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Research Article

Effect of Energy Storage on Variations in Wind Power

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Key words:
energy storage;
wind power systems;
power fluctuation;
lowpass filter;
exponentially weighted moving average filter

Irregularities in power output are characteristic of intermittent energy, sources such as wind energy, affecting both the power quality and planning of the energy system. In this work the effects of energy storage to reduce wind power fluctuations are investigated. Integration of the energy storage with wind power is modelled using a filter approach in which a time constant corresponds to the energy storage capacity. The analyses show that already a relatively small energy storage capacity of 3 kWh (storage) per MW wind would reduce the short-term power fluctuations of an individual wind turbine by 10%. Smoothing out the power fluctuation of the wind turbine on a yearly level would necessitate large storage, e.g. a 10% reduction requires 2–3 MWh per MW wind. Copyright © 2005 John Wiley & Sons, Ltd.

Introduction

Sporadic fluctuation of power output is characteristic of intermittent energy sources such as wind energy. This may in turn impose special requirements on the surrounding power system and may even restrict the use of wind energy in certain conditions. Thus wind power systems challenge equally the power quality, energy planning and power flow controls in the local grid.

Wind data consist basically of two overlapping effects, namely macro-meteorological and micro-meteorological fluctuations.[1] The macro-meteorological fluctuations indicate the movements of large-scale weather patterns such as the day and night cycle and the movement of depressions and anticyclones. The micro-meteorological fluctuations originate from the atmospheric turbulence with typical time scales of 1–600 s. Similar fluctuation patterns appear in wind power systems, although modified by the physical and electrical characteristics of the wind turbine itself.[2]

The fluctuations in wind power influence both power quality and energy planning. The power quality problems that cannot be handled with power electronics mainly arise from the local voltage variation caused by the imbalance of the power generation and the local power demand. This can be problematic in weak networks, where an expansion in local wind power capacity may result in undesired voltage levels.[3,4] In an extreme situation a whole wind power system may need to be disconnected from the grid.[5]

The aim of this work is to assess how energy storage could smooth out fluctuations in wind power generation on a time scale from 1 s to hours and a few days. We focus on small or intermediate energy storage capacities which may improve the power quality of an individual wind power turbine. The concept may be expanded to large wind power systems when the corresponding system data are analysed. The effects due to fluctuation for less than 1 s, causing e.g. flickering,[6] are excluded here.

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In the article a methodology is presented to describe the smoothing out of wind turbine power variations when combined with energy storage. The system output is modelled by introducing to the output data a time constant corresponding to energy storage capacity. This method is applied to two sets of data with a time resolution of 1 s and 1 h respectively. The method allows us to directly relate the size of the energy storage with wind power variation on a short- and medium-term time scale.

Previous work on wind power and storage includes mainly economic issues and autonomous wind–storage systems. Integration of wind power into the power system has been reported e.g. by Bindner and Lundsager,[7] Tande[8] and Koch *et al*.[9] Economic benefits of combining grid-connected wind power with energy storage on open electricity markets have been reported by Bathurst and Strbac[10] and Korpaas *et al*.[11] Using storage for compensating reactive power in a wind farm has been discussed by Muljadi *et al*.[12] Bindner[3] reports storage among competitive alternatives to increase wind power in weak grids. Electric storage has also been applied to non-grid wind–diesel or autonomous wind–storage systems.[13,14] The compensation of fluctuations in a wind–diesel system using fuzzy logic was reported by Leclercq *et al*.[15] The kind of analysis presented in this study has not been reported previously.

Defining the Characteristics of Wind Power Fluctuation

A statistical approach is first applied to characterize the different wind power conditions and their specific behaviour, as the effect of energy storage will depend much on the prevailing wind speed conditions. The time scale and relative intensity of the wind speed or power fluctuation are of primary importance here.

Based on the work by Van Der Hoven,[16] Rohatgi and Nelson[1] divide the fluctuations of horizontal wind speed into two distinct regions, namely macro-meteorological and micro-meteorological. The macro-meteorological region results from the large-scale movement of the air masses due to depressions and anticyclones, while the micro-meteorological fluctuations originate from the atmospheric turbulence. As Figure 1 shows, the typical power density peaks in the macro region are found at 12 and 100 h, while the peak in the micro region is at about 1 min only.[1]

Classification of wind data is typically done by analysing the wind turbulence intensity and integral time and length scale from 10 min samples.[17] The normalized power level and standard deviation together with the integral time scale are used to characterize the statistical details of the power data sets. The integral time scale describes the average time over which the fluctuations in the data are correlated with each other,[1] while the normalized standard deviation is applied to identify the level of smoothing in the power series.

The integral time scale of the wind speed fluctuation is calculated with the autocorrelation of the wind data.[17] In a similar way the autocorrelation is used to define the integral time scale of the wind power fluctuation as shown below. First we define the sample autocorrelation function r for a given lag m as[18,19]

$$r_m = \frac{\sum_{i=1}^{n-m} (p_i - \overline{p})(p_{i+m} - \overline{p})}{\sum_{i=1}^{n} (p_i - \overline{p})^2} \quad \text{for } m = 1, 2, 3, \ldots, n/4 \tag{1}$$

where $\overline{p} = \frac{1}{n}\sum_{i=1}^{n} p_i$, n being the number of sample data points. Next the power integral time scale (PITS) is defined as

$$\text{PITS} = \int_{m=1}^{m_{r=0}} r_m \mathrm{d}t = \sum_{m=1}^{m_{r=0}} r_m \Delta t \tag{2}$$

Here Δt is the sampling interval for the data set and $m_{r=0}$ is the point where r_m for the first time equals zero or becomes negative. The normalized standard deviation (STD) of the wind turbine power is defined as

$$\text{STD} = \frac{1}{P_{\text{nom}}} \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (p_i - \overline{p})^2} \tag{3}$$

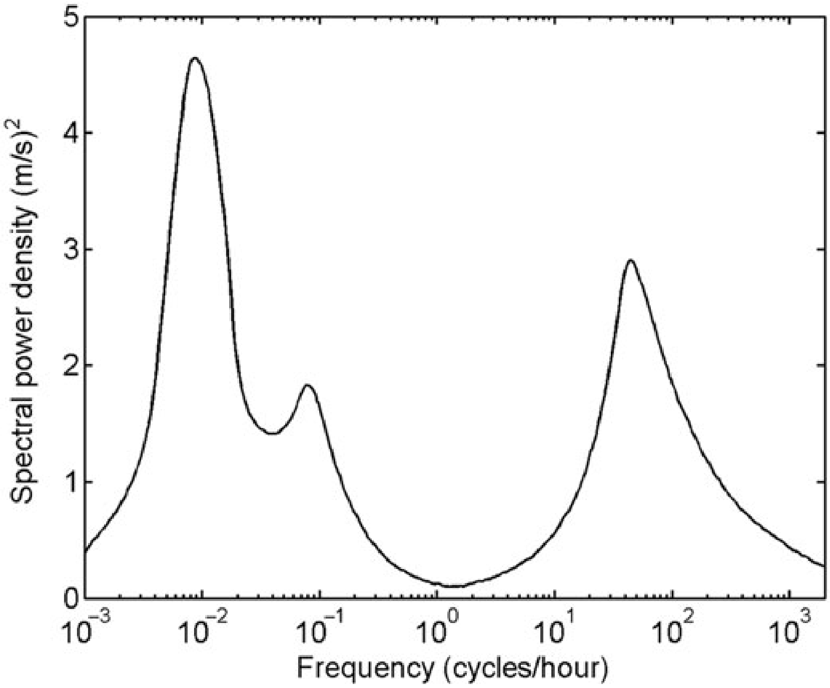

Figure 1. Spectral power density of horizontal wind speed showing the macro-meteorological and micro-meteorological fluctuations (adopted from Reference 1)

where P_{nom} is the nominal power of the wind turbine. Correspondingly the normalized mean power level (PFR) is

$$\text{PFR} = \frac{\bar{p}}{P_{nom}} \tag{4}$$

Two different sets of wind power data are used here. The first data set contains measured wind turbine power output data with $\Delta t = 1$ s. The blade-passing effects and other very-short-term phenomena typically handled with power electronics do not appear in the data series, but it includes the effects originating from the micro-meteorological fluctuations.[20]

The $\Delta t = 1$ s data PITS analysis is done with fixed and successive 10 min (600 point) data windows, giving altogether 20–44 data periods whose results will be averaged over the whole sample. This assures the comparability of different samples and puts weight on their short-term patterns.

The second data set has $\Delta t = 1$ h and comprises two different types of data. The first subset comprises measured wind turbine power data that have been averaged over 1 h intervals. The second part contains simulated wind turbine output that has been calculated using height-corrected hourly wind data together with wind turbine power curves. The samples cover a period of 1 year, except for the two smaller turbines where the sample period is 202 days. Only limited statistical analysis is done to the hourly data ($\Delta t = 1$ h), as the averaging process has eliminated all short- and intermediate-term fluctuations.

Storage Analysis

In our approach the fluctuations in wind power output are described as undesirable short-term noise in the signal output. The effect of energy storage is modelled by introducing a filtering time constant to the wind power data. This is done with a discrete lowpass filter that is typically used to remove high-frequency noise from a signal.[21]

The lowpass filter suggests an increase or a decrease to the level of wind power output, which is comparable to discharging or charging of the storage with corresponding power. In the analysis it is assumed that the energy storage has no efficiency losses and that it gives an immediate response to the filtering suggestions.

The suggested method allows the influence of energy storage to be studied through different time constants corresponding to energy storage capacity.

The first-order passive lowpass filter is mathematically described as[21,22]

$$\tau Y' + Y = X \tag{5}$$

where τ is the filtering time constant corresponding to energy storage capacity, Y is the filter output function corresponding to the wind turbine output together with the storage unit, Y' is the derivative of Y and X is the filter input function that corresponds to the wind turbine output without energy storage.

When discrete data with a time step Δt are used interconnected with a lowpass filter and the derivative of Y is expanded into discrete form, equation (5) can be written for time step k as

$$\tau \frac{Y_k - Y_{k-1}}{\Delta t} + Y_k = X_k \tag{6}$$

Solving for Y_k gives

$$Y_k = \frac{\tau}{\tau + \Delta t} Y_{k-1} + \frac{\Delta t}{\tau + \Delta t} X \tag{7}$$

Defining a constant $\alpha = \tau/(\tau + \Delta t)$, equation (7) can be rewritten as

$$Y_k = \alpha Y_{k-1} + (1 - \alpha) X_k \tag{8}$$

Now equation (8) has the form of an exponentially weighted moving average (EWMA) filter.[22] The subscript k corresponds to time, i.e. $t_k = t_0 + k\Delta t$, where Δt is the time step and t_0 is the starting point of the analysis.

The improvement in the quality of the filtered power output data has been evaluated through the changes in the wind power fluctuation characteristics. The PITS value is periodically re-evaluated and averaged, while the STD is recalculated for the whole sample.

With an EWMA filter the response of the energy storage is

$$P_{\mathrm{st},k} = Y_k - X_k \tag{9}$$

where $P_{\mathrm{st},k}$ is the power taken from the storage unit. Inserting equation (8) into equation (9), we obtain

$$P_{\mathrm{st},k} = \alpha Y_{k-1} + (1 - \alpha) X_k - X_k = \alpha (Y_{k-1} - X_k) \tag{10}$$

Solving equation (9) for Y_{k-1} and inserting it into equation (10) yields

$$P_{\mathrm{st},k} = \alpha (P_{\mathrm{st},k-1} + X_{k-1} - X_k) = \alpha (P_{\mathrm{st},k-1} - \Delta X_k) \tag{11}$$

At start-up ($k = 1$) the initial value $P_{\mathrm{st},0} + X_0$ needs to be defined. The initial value is found here by using periodic boundary conditions iteratively so that the storage capacity is minimized.

The energy state of the storage, representing the energy content in it, is defined in discrete form as

$$E_k = -\sum_{m=1}^{k} P_{\mathrm{st},m} \Delta t \tag{12}$$

The energy storage capacity used for damping the fluctuations is then defined as

$$Q = \max_{k=1\ldots n} E_k - \min_{k=1\ldots n} E_k \tag{13}$$

where n is the total number of time points in the data sample.

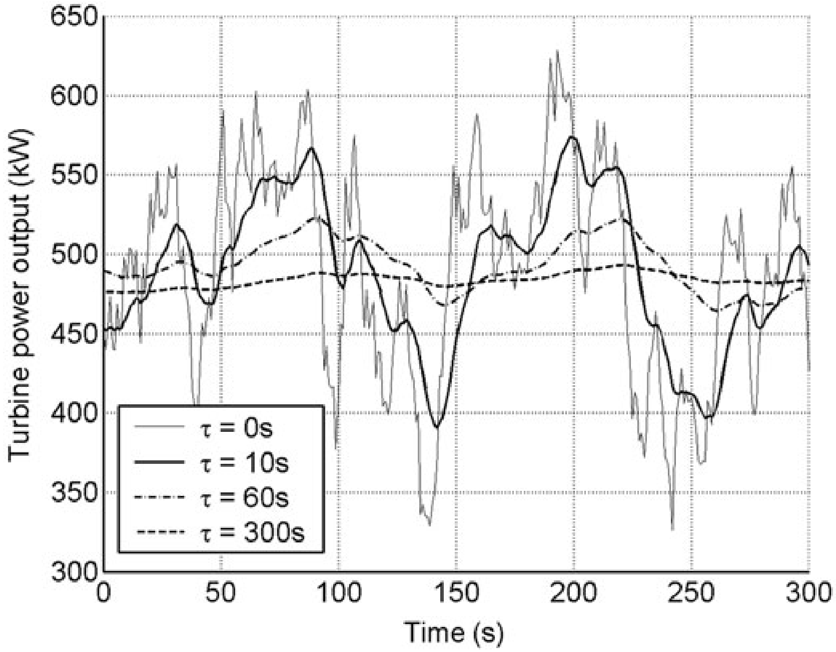

Figure 2. Demonstration of the effects of increasing τ (energy storage capacity) on the amplitude of the wind power fluctuation for a real wind power case

Figure 2 shows how the time constant affects a wind power data sample in practice. The τ values in the figure correspond to energy storages with different capacities.

Input Data Used in the Analysis

The analysis in this work is based on measured data of wind speed and wind turbine power output at different locations around Europe, as presented in Table I. The table includes the site and sample names, location and data-sampling interval. Both synchronous and asynchronous turbines are included, as well as one older wind turbine model with passive stalling.

The data-sampling intervals are 1 s and 1 h. As data with $\Delta t = 1$ s are difficult to obtain, only three different sites in Finland could be used. The turbine data with hourly interval are available from three sites in Finland. Three additional sites around Europe are simulated based on hourly weather data.[23] The simulated data are generated by applying the power curve[24] and turbine tower height (65 m) of the actual turbine located at the site Riutukari. The logarithmic wind profile is used to estimate the wind speed at the tower height.[17]

The $\Delta t = 1$ s data are used to analyse the effect of storage on short-term fluctuations that originate from the micro-meteorological-scale weather phenomena combined with the turbine dynamics. The data samples in Table II mainly correspond to power levels up to 80% of nominal power. These levels are considered more interesting, as the relative fluctuations are large and effects from the active stalling are absent. The statistical qualities of the sample data are shown in Table II.

The classification of the data samples with 1 s interval is presented in Figure 3. Class A includes low-power data with high PITS, hence dominated by slow fluctuations with large amplitude. Class B includes low-power data with low PITS, hence dominated by fast small-amplitude fluctuation. Classes C and D include likewise the high-power data, class C having high PITS and slow fluctuation and class D having low PITS and fast fluctuation.

Table I. Wind turbine sites and types of data sets used as input in the analysis

Site	Country	Wind turbine[a]	Location	Sample name	Sample interval Δt
Pori	Finland	1000 AA	61°22′N 21°18′E	Pori	1 s
Oulu	Finland	1000 SA	65°02′N 25°01′E	Oulu	1 s
Pyhätunturi	Finland	220 AP	68°15′N 23°22′E	Pyhä	1 s
Föglö	Finland	600 SA	60°00′N 20°19′E	Fögl	1 h
Vårdö	Finland	500 SA	60°14′N 20°24′E	Vård	1 h
Riutukari	Finland	1300 AA	65°00′N 25°12′E	Riut	1 h
Trapani	Italy	1300 AAS	37°55′N 12°30′E	Trap	1 h
Lerwick	Great Britain	1300 AAS	60°08′N 01°11′W	Lerw	1 h
Copenhagen	Denmark	1300 AAS	55°48′N 12°30′E	Cope	1 h
Paris	France	1300 AAS	48°42′N 06°12′E	Pari	1 h

[a] AA = asyncronous turbine, active stalling; SA = syncronous turbine, active stalling; AP = asyncronous turbine, passive stalling; AAS = asyncronous turbine, active stalling, simulated.

The hourly (Δt = 1 h) power data represent a 1 h power integral value of the turbine output or a simulated power value from the weather data. All the short-term effects are smoothed out, leaving only the effects from macro-meteorological phenomena. The statistical characteristics of the hourly data are shown in Table III.

Results of the Short-term Data Analysis

By using the EWMA filtering approach, it was possible to analyse how τ influences the normalized power standard deviation (STD) and the power integral time scale (PITS) of the data samples. Also the corresponding storage capacity needed could be determined. With these results the reduction of STD can be directly related to the storage capacity requirements. The STD in the short-term analysis corresponds to the standard deviation of a 3–7 h long data sample.

The effects of the filtering of the Δt = 1 s data are shown in Figures 4–7. The reduction of the fluctuation over all the samples is presented in Figures 4a–4c. For example, with τ = 1 min the reduction of fluctuation in classes A and C is 11%–24%, in class B 23%–30% and in class D over 40%.

The increase of the PITS against τ is shown in Figures 5a–5c. As each of the PITS values is averaged from the values of the 10 min data windows, they elucidate the typical time scales in those windows only. The rapid increase of PITS values indicates that fluctuations in the 10 min range are effectively dampened. PITS values saturate at about τ = 5 min to a value of 75–90 s for samples A–C and 65–70 s for samples D. Going for higher τ would not be possible owing to the 10 min data window used.

The relation of τ and the energy storage capacity is shown in Figures 6a–6c. The storage capacity is expressed in units of kWh storage per MW of nominal wind turbine power (kWh/MW). The capacity equivalent to τ = 1 min is 2·7–6·5 kWh/MW for classes A–C and (slightly higher) 6·1–8·5 kWh/MW for class D. For τ = 10 min we have 17–34 kWh/MW for classes A and B, 48 kWh/MW for class C and 28–40 kWh/MW for class D.

In Figure 7 the results from Figures 5 and 6 are combined to relate the wind power fluctuation and storage capacity. It can be seen that with a storage capacity of 3 kWh per wind power MW the STD is reduced in all cases by at least 10%. In the wind power classes B and D, 1 kWh/MW is adequate to provide 10% reduction in the STD. Going beyond the 10% suppression, the storage capacity needed will increase rapidly, with large differences between the power classes A–D.

Assuming an available energy storage capacity of 5 kWh per MW reduces the STD by 12% (class C), 14%–23% (class A), 23%–28% (class B) and 37%–51% (class D). The large spread stresses the importance of good knowledge about local wind conditions to judge the usefulness of energy storage. When the wind conditions are dominated by turbulence with high integral time constant, the fluctuations in the wind power output are strong in the low-frequency region, which is the most capacity-intensive to compensate. From a practical

Table II. Statistical characteristics of the data sets with $\Delta t = 1$ s. Letters A–D refer to the wind power fluctuation classes defined in Figure 3

Characteristic[a]	Oulu A1	Oulu A2	Pori A	Pyhä A	Oulu B	Pori B	Pori C	Oulu D	Pori D1	Pori D2
Nominal power (kW)	1000	1000	1000	220	1000	1000	1000	1000	1000	1000
Mean power (kW)	155	300	209	92	444	483	949	595	854	1014
Power SD (kW)	42·9	97·7	43·1	20·3	79·4	101	107	124	177	153
Normalized mean power	0·155	0·300	0·209	0·417	0·444	0·483	0·949	0·595	0·854	1·01
Normalized power SD	0·043	0·098	0·043	0·092	0·079	0·101	0·107	0·124	0·177	0·153
Mean PITS (s)	33·8	35·2	28·1	32·6	20·1	19·5	25·0	18·6	14·2	8·51
PITS SD (s)	20·2	14·3	16·4	18·1	13·3	15·1	16·4	11·9	7·65	4·98

[a] SD = standard deviation; PITS = power integral time scale.

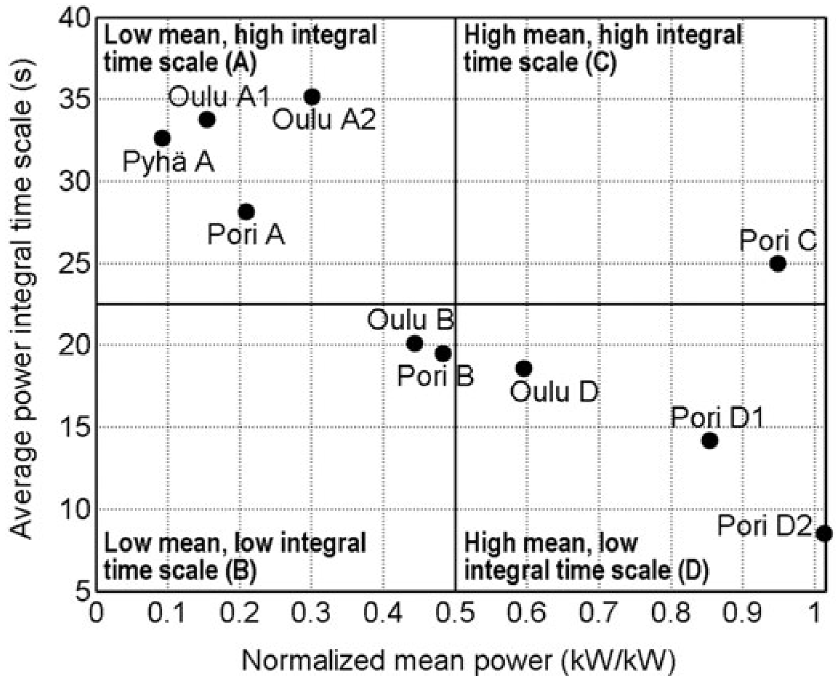

Figure 3. Classification of Δt = 1 s wind power data used in the analysis according to mean power and power integral time scale

Table III. Statistical characteristics of the data sets with Δt = 1 h

Characteristic[a]	Pari	Cope	Trap	Lerv	Fögl	Vård	Riut
Nominal power (kW)	1300	1300	1300	1300	600	500	1300
Mean power (kW)	232	370	343	469	165	94·1	338
Power SD (kW)	314	417	435	465	168	107	366
Normalized mean power	0·179	0·285	0·264	0·361	0·274	0·188	0·260
Normalized power SD	1·35	1·13	1·27	0·99	1·02	1·13	1·08

[a] SD = standard deviation.

point of view a modern flywheel energy storage module could provide up to 25 kWh energy storage capacity,[25] suggesting that in most conditions a single storage unit could reduce the short-term STD of a 1 MW wind turbine by 50% (not shown in Figure 7). Alternatively, such a unit could provide 10% reduction in STD for a 10–50 MW wind power park, depending on the wind power class.

Results of the Long-term Data Analysis

The hourly data sets were studied to investigate how the macro-meteorological phenomena in wind speed could be compensated through storage. As Δt and τ are now large and smooth out the micro-meteorological effects and since the long data sets include many kinds of wind behaviour, the previous classification of Δt = 1 s wind power data (classes A–D) is not feasible. The data sets contain a 1 year sample (202 days for Fögl and Vård).

The reduction of the deviation in the hourly data through the increased time constant is shown in Figure 8. The upper part shows the absolute reduction of STD, while the lower part shows the reduction of STD in per-

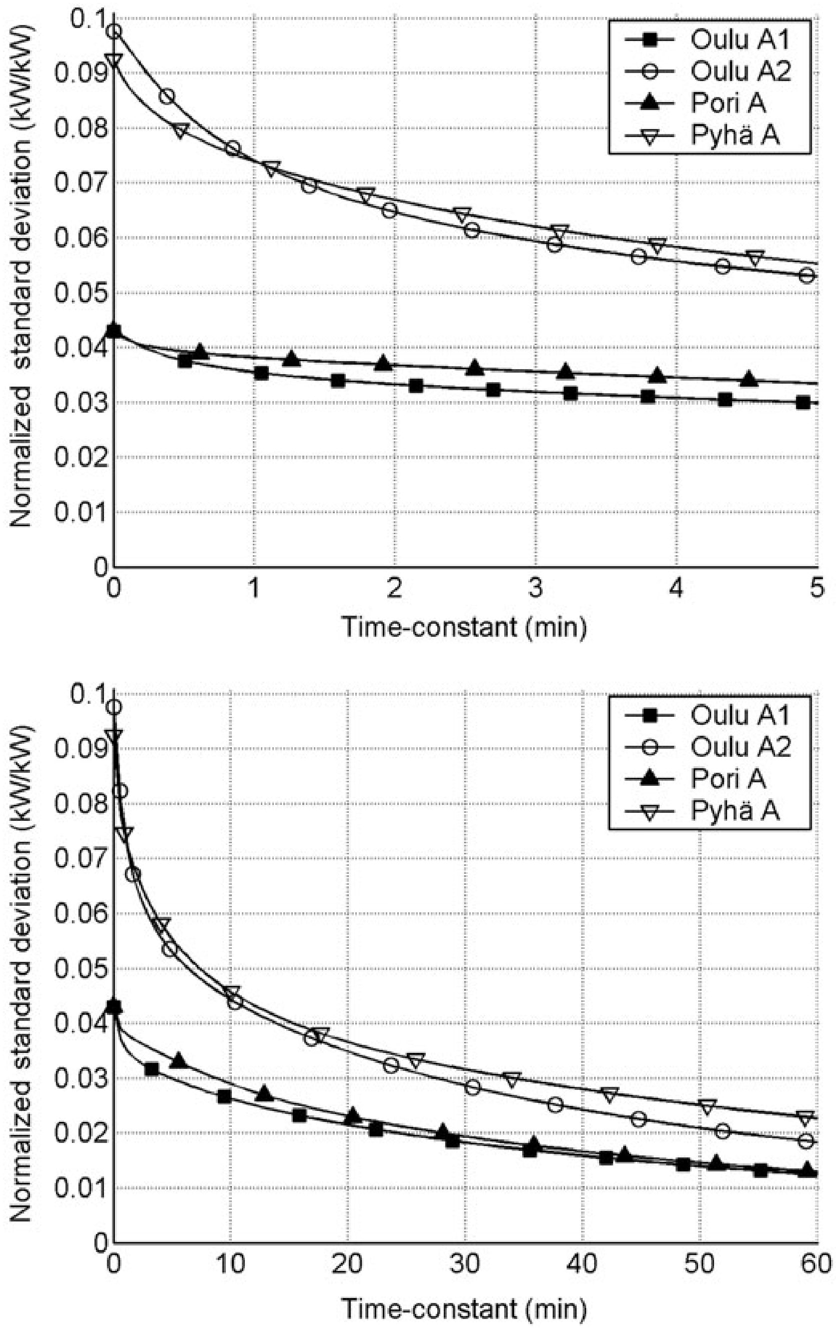

Figure 4a. Short-term influence of time constant τ on the relative standard deviation of the wind turbine power output. Turbine data sets with Δt = 1 s and fluctuation class A

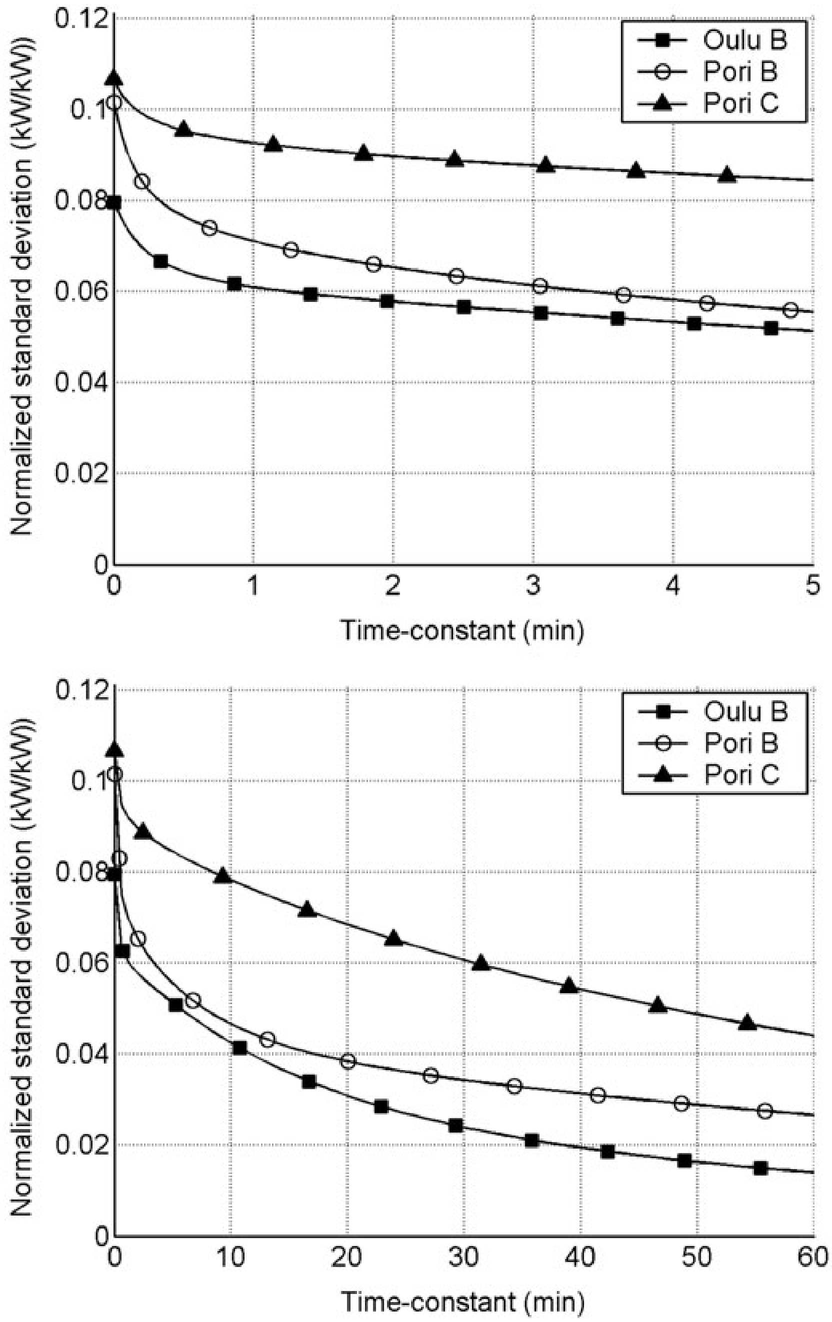

Figure 4b. Short-term influence of time constant τ on the relative standard deviation of the wind turbine power output. Turbine data sets with $\Delta t = 1$ s and fluctuation classes B and C

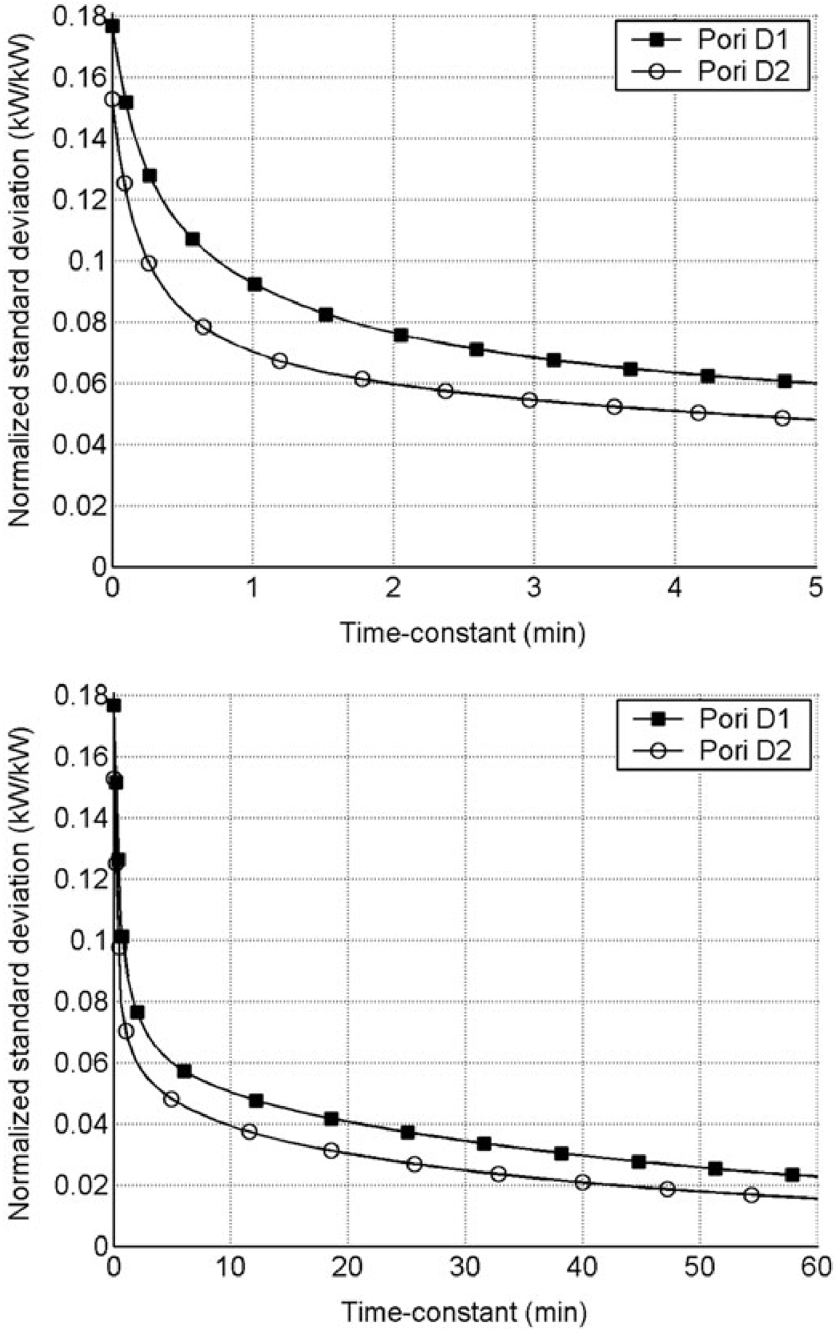

Figure 4c. Short-term influence of time constant τ on the relative standard deviation of the wind turbine power output. Turbine data sets with Δt = 1 s and fluctuation class D

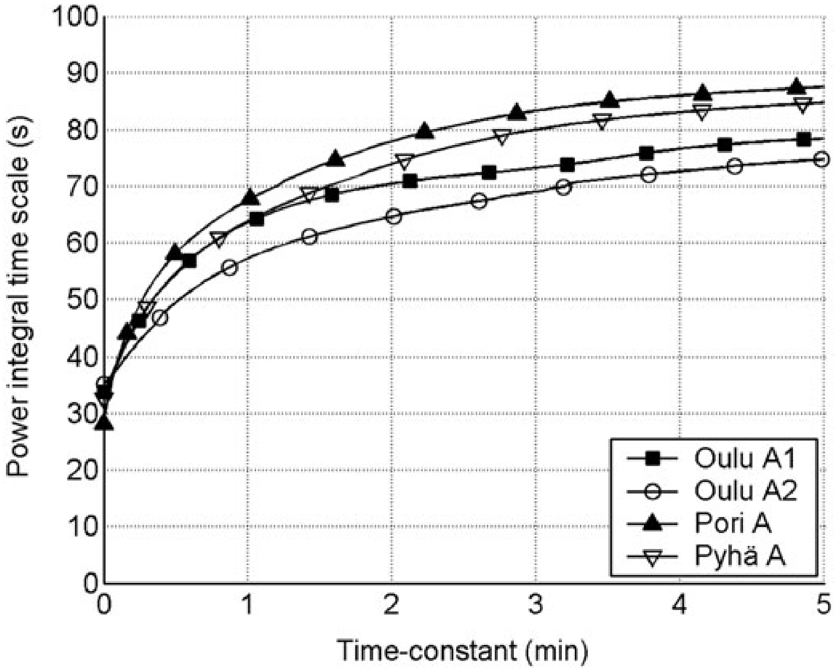

Figure 5a. Short-term influence of time constant τ on the power integral time scale of the wind turbine power output. Turbine data sets with Δt = 1 s and fluctuation class A

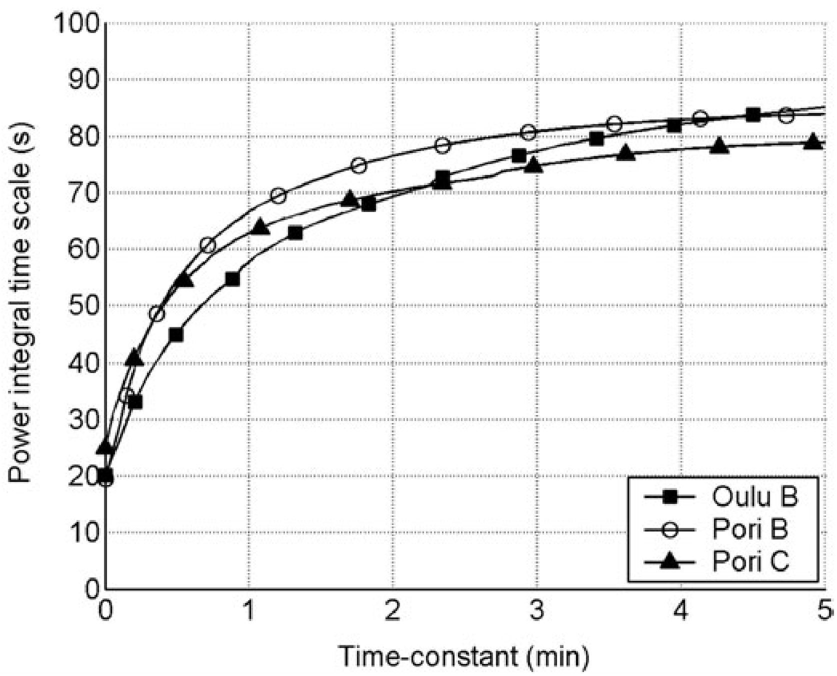

Figure 5b. Short-term influence of time constant τ on the r power integral time scale of the wind turbine power output. Turbine data sets with Δt = 1 s and fluctuation classes B and C

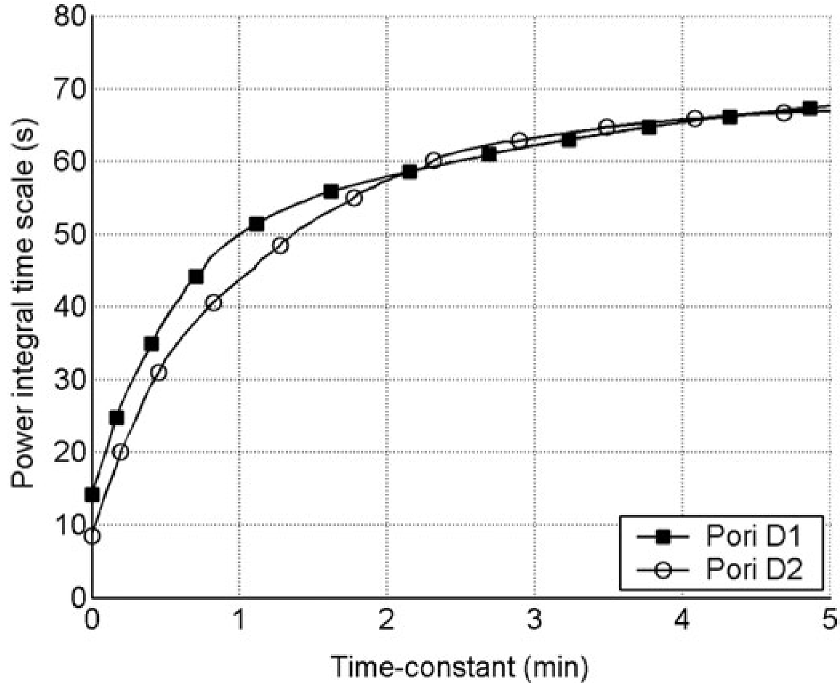

Figure 5c. Short-term influence of time constant τ on the power integral time scale of the wind turbine power output. Turbine data sets with Δt = 1 s and fluctuation class D

centages. With $\tau = 12$ h a 23%–27% reduction was achieved in the yearly fluctuation for most of the samples. With τ as high as 24 h a roughly 34%–38% reduction is achieved. The Trapani sample differs from the others, most likely owing to a difference in local weather fluctuation cycles. Energy storage with τ = 12–24 h corresponds for example to pumped hydro storage, typically applied in energy-planning schemes.

The comparison of energy storage capacity and τ is shown in Figure 9. With τ up to about 12 h the energy storage capacity values are very similar for all the samples, but the differences become pronounced with larger τ.

In Figure 10 the results from Figures 8 and 9 are combined to present the storage capacity as a function of long-term wind power fluctuation. To achieve a 10% reduction in the yearly fluctuation, a 2–3 MWh storage capacity per MW of wind power is required. Similarly, a 30% reduction can be achieved with a capacity of 10–15 MWh per MW.

The above energy storage capacities indicate that a large storage system set-up, such as an array of flywheel modules,[25] is needed when the local network cannot accommodate the voltage changes due to the long-term power fluctuations of a wind turbine. Alternatively, there are multiple ways to reduce the voltage changes induced by embedded generation, as discussed by Masters.[4] The optimal combination of wind power, energy storage and other installations, e.g. reactive power compensators or voltage controllers, becomes a site-connected economic issue which is beyond the scope of this paper.

Conclusions

Integration of energy storage into an individual wind turbine and the corresponding effects have been modelled using a filter approach in which a time constant (τ) is applied to describe the energy storage capacity.

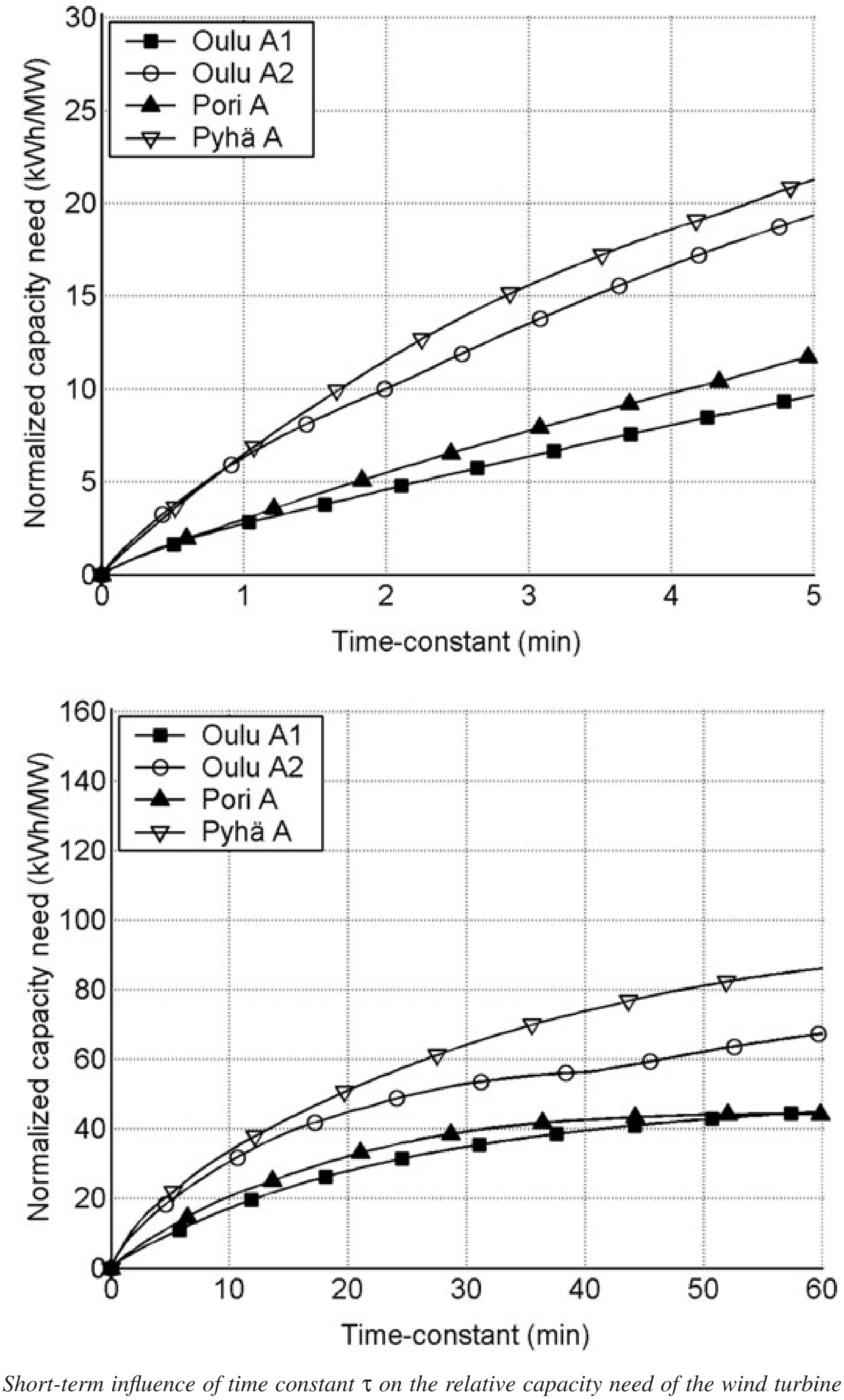

Figure 6a. Short-term influence of time constant τ on the relative capacity need of the wind turbine storage unit. Turbine data sets with Δt = 1 s and fluctuation class A

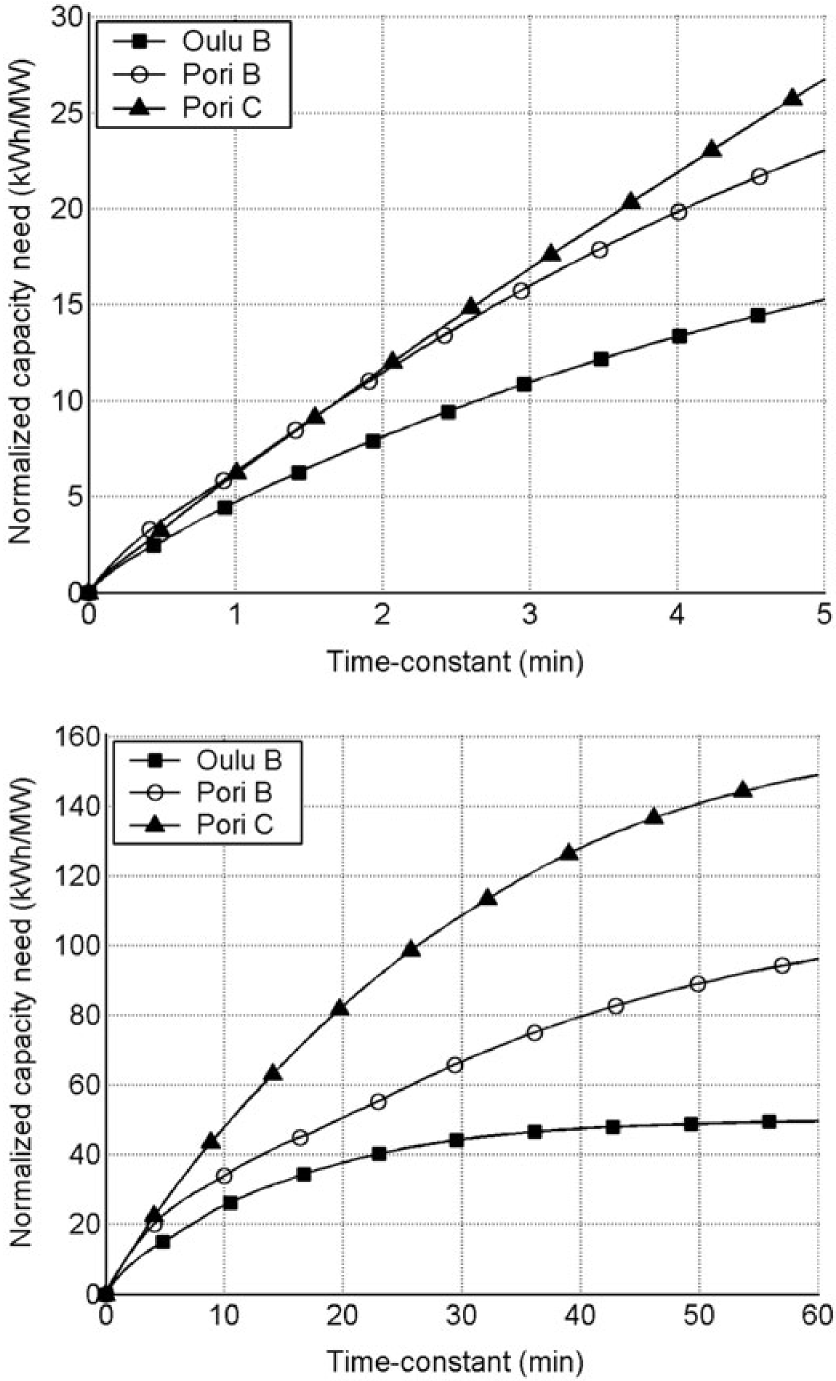

Figure 6b. Short-term influence of time constant τ on the relative capacity need of the wind turbine storage unit. Turbine data sets with Δt = 1 s and fluctuation classes B and C

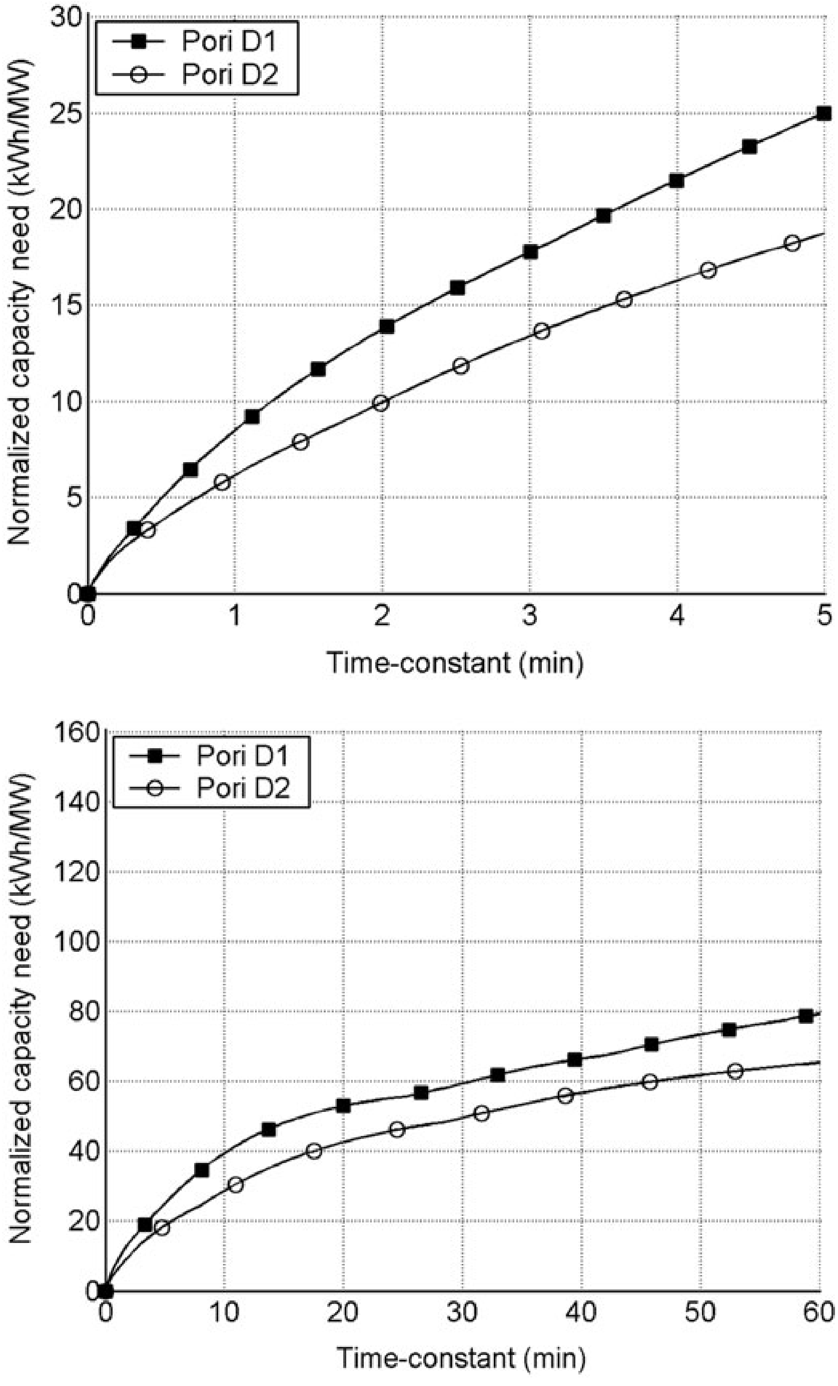

Figure 6c. Short-term influence of time constant τ on the relative capacity need of the wind turbine storage unit. Turbine data sets with Δt = 1 s and fluctuation class D

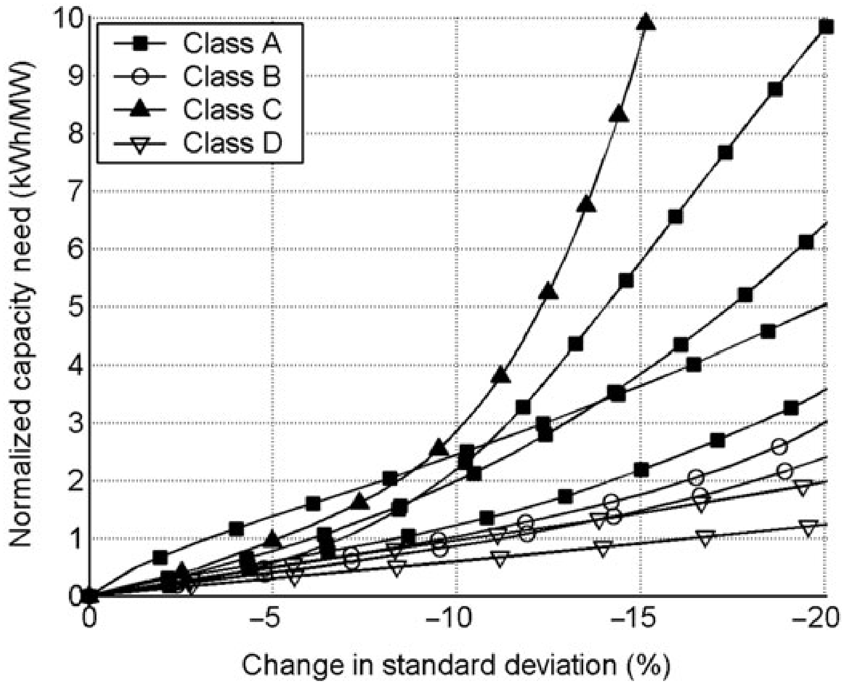

Figure 7. Relation of short-term energy storage capacity and relative standard deviation of the wind turbine power output. Turbine data sets with Δt = 1 s and power fluctuation classes A–D

The relationship between the standard deviation of the wind turbine power output and the corresponding energy storage capacity was solved. The effects of storage were studied for European conditions with time steps Δt = 1 s and Δt = 1 h to identify the effects from both micro-meteorological and macro-meteorological wind fluctuations. The data sets comprised measured power data from six Finnish wind turbines and simulated power data based on European mean weather data from four different cites.

The micro-scale analyses showed that applying already relatively small time constants and hence small energy storage capacities would reduce the short-term fluctuations of wind power. A storage capacity of 3 kWh per MW of wind power shows at least a 10% reduction in the short-term deviation (4–7 h) of the power data, while in some wind conditions only 1 kWh per MW is needed to obtain the same effect. With 5 kWh capacity per MW the reduction of standard deviation varies from 12% to 50% between the sites, showing the importance of understanding the local wind conditions for storage sizing and design. By introducing a storage capacity of 25 kWh per MW, still within the limits of a modern flywheel energy storage unit, the standard deviation of wind power would be reduced by 50% in most cases.

The macro-scale analyses showed that large storage capacities would be needed as expected to significantly smooth out the yearly fluctuation of the power output from an individual wind turbine. Reducing the yearly deviation by 10% would require an energy storage capacity of 2–3 MWh per MW wind power, while a 30% reduction would require 10–15 MWh capacity per MW. Such energy storage capacity requirements can easily become economically unfeasible. When necessary, the fluctuations could be levelled out with a storage system, possibly in combination with a system such as a reactive power compensator or a voltage controller, to reduce the system sensitivity to wind power fluctuations.

Our further work on this energy storage will include more detailed numerical energy system modelling of wind–storage schemes using the results from the present study as input. In this context the control schemes for storage and their effects will be quantified in more detail for practical cases.

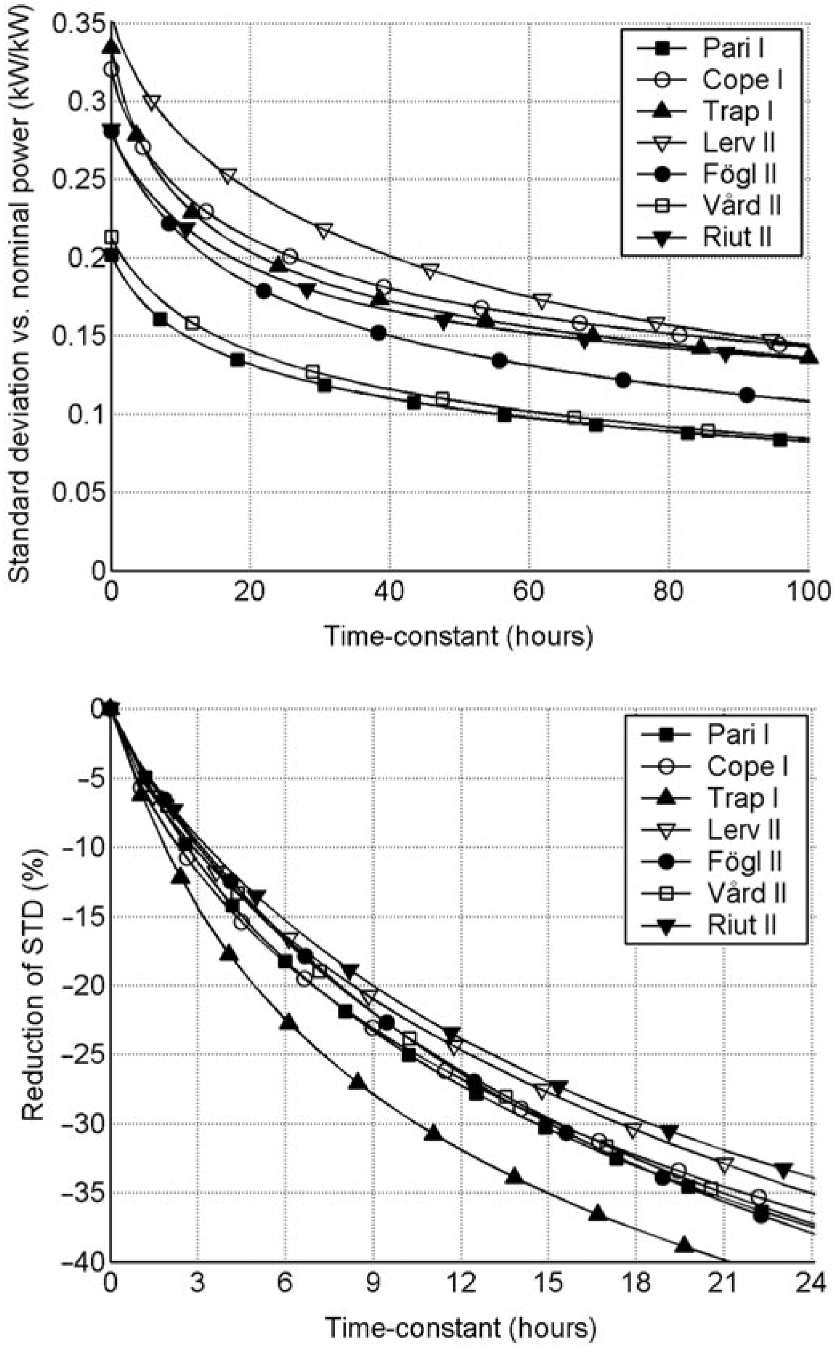

Figure 8. Influence of long-term time constant τ on the macro-scale standard deviation of the wind turbine power output. Turbine data sets with Δt = 1 h

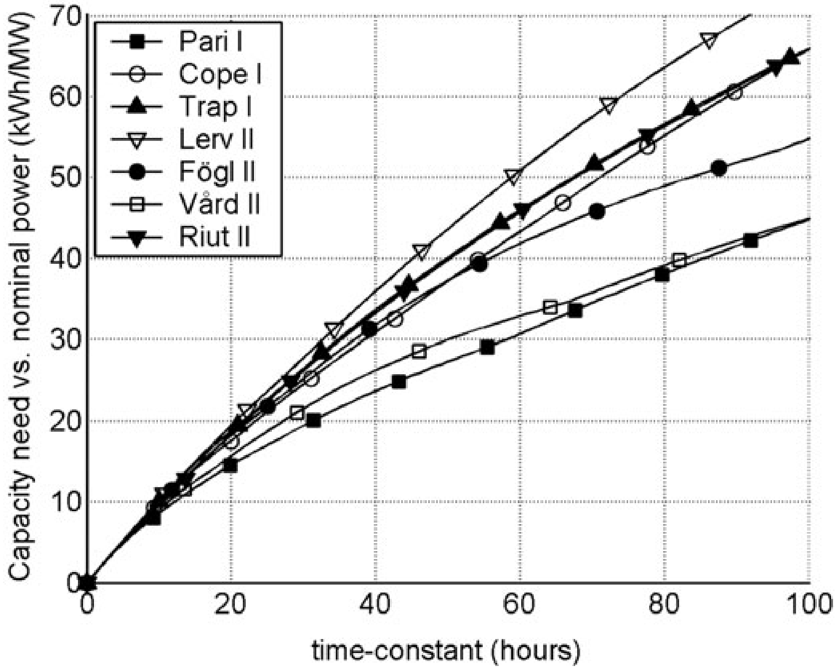

Figure 9. Influence of time constant τ on the relative energy storage capacity per MW wind turbine capacity. Turbine data sets with Δt = 1 h

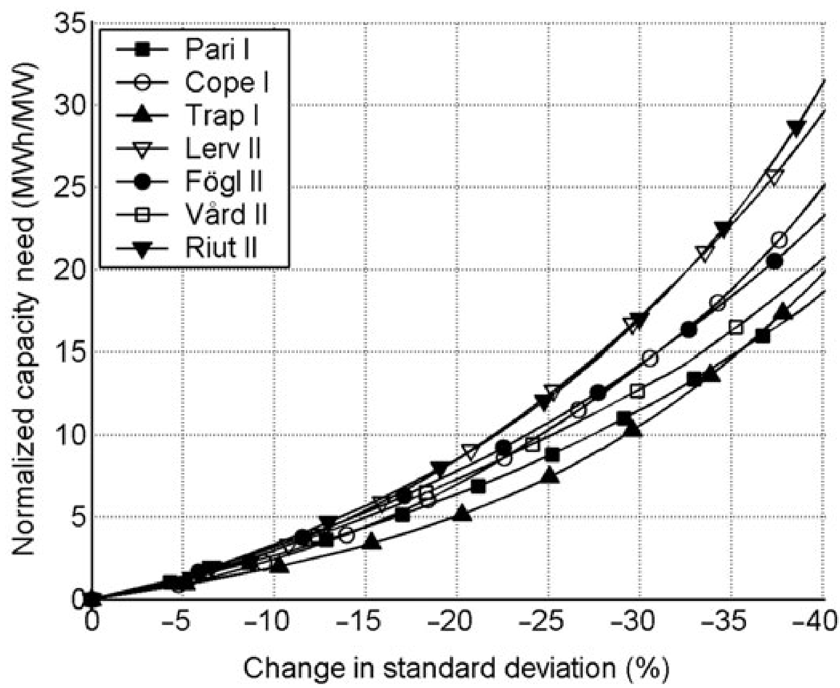

Figure 10. Relation of long-term energy storage capacity and relative standard deviation of the wind turbine power output. Turbine data sets with Δt = 1 h

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Appendix: Nomenclature

r_m	autocorrelation function with lag m
p_i	power data sample value with index i
$\bar{p}$	average power of a data sample
PITS	power integral time scale
STD	normalized standard deviation
PFR	normalized mean power level
Δt	sampling interval for a data sample
τ	filtering time constant corresponding to energy storage capacity and control strategy
Y	filter output corresponding to wind turbine output together with response from storage unit
Y'	time derivative of Y
X	filter input corresponding to wind turbine output without energy storage
k	step number for discrete analysis
n	number of data points in a data sample
Δt	time step applied in discrete data
α	constant used in the exponentially weighted moving average filter
t_0	initial time for an analysis
t_k	corresponding time for step k
$P_{st,k}$	power taken from an energy storage at step k
E_k	energy state of an energy storage at step k
Q	energy storage capacity used for damping fluctuations in a data sample

References

1. Rohatgi JS, Nelson V. *Wind Characteristics—an Analysis for the Generation of Wind Power.* Alternate Energy Institute, West Texas A&M University: Canyon, TX, 1994; 171.
2. Sørensen P, Hansen A, Janosi L, Bech J, Bak-Jensen B. Simulation of interaction between wind farm and power system. *Risø-R-1281(EN)*, Risø National Laboratory, Roskilde, 2001.
3. Bindner H. Power control for wind turbines in weak grids: project summary. *Risø-R-1117(EN)*, Risø National Laboratory, Roskilde, 1999.
4. Masters CL. Voltage rise: the big issue when connecting embedded generation to long 11 kV overhead lines. *Power Engineering Journal* 2002; **16**: 5–12.
5. Sørensen P, Madsen P, Vikkelsø A, Jensen K, Fathima K, Unnikrishnan A, Lakaparampil Z. Power quality and integration of wind farms in weak grids in India. *Risø-R-1172(EN)*, Risø National Laboratory, Roskilde, 2000.
6. Jenkins N, Allan R, Crossley P, Krischen D, Strbac G. *Embedded Generation.* Institution of Electrical Engineers: London, 2000; 139–142.
7. Bindner H, Lundsager P. Integration of wind power in the power system. *28th Annual Conference of the Industrial Electronics Society, IEEE*, vol. 4, 2002; 3309–3316.
8. Tande JOG. Grid integration of wind farms. *Wind Energy* 2003; **6**: 281–295.
9. Koch F, Shewarega F, Bachmann U. The effect of large offshore and onshore wind farms on the frequency of national power supply system; simulation modelled on Germany. *Wind Engineering* 2003; **27**: 393–404.
10. Bathurst GN, Strbac G. Value of combining energy storage and wind in short-term energy and balancing markets. *Electric Power Systems Research* 2003; **67**: 1–8.
11. Korpaas M, Holen AT, Hildrum R. Operation and sizing of energy storage for wind power plants in a market system. *International Journal of Electrical Power and Energy Systems* 2003; **25**: 599–606.
12. Muljadi E, Butterfield CP, Yinger R, Romanowitz H. Energy storage and reactive power compensator in a large wind farm: preprint. *NREL/CP-500-34701*, 2003.

13. Muljadi E, Bialasiewicz JT. Hybrid power system with a controlled energy storage: preprint. *NREL/CP-500-34692*, 2003.
14. Elhadidy MA, Shaahid SM. Promoting applications of hybrid (wind+photovoltaic+diesel+battery) power systems in hot regions. *Renewable Energy* 2004; **29**: 517–528.
15. Leclercq L, Robyns B, Grave J. Control based on fuzzy logic of a flywheel energy storage system associated with wind and diesel generators. *Mathematics and Computers in Simulation* 2003; **63**: 271–280.
16. Van Der Hoven I. Power spectrum of horizontal wind speed in the frequency range from 0·007 to 900 cycles per hour. *Journal of Meteorology* 1957; **14**: 160–164.
17. Manwell JF, McGowan JG, Rogers AL. *Wind Energy Explained—Theory, Design and Application.* Wiley: Chichester, 2002; 37–45.
18. Pindyck RS, Rubinfeld DL. *Econometric Models and Economic Forecasts* (4th edn). McGraw-Hill/Irwin: Boston, MA, 1997; 494–497.
19. Keller PA. Autocorrelation function. In *Quality Encyclopedia* [Online]. 2001. Available: http://www.qualityamerica.com/ [21 April 2004].
20. Davidson M. Wind farm power quality and network interaction. In *Wind Energy Conversion; Proceedings of the 1996 18th British Wind Energy Association Conference*. Anderson M. (ed) Mechanical Engineering Publications: Bury St Edmunds, 1997; 227–232.
21. Nilsson JW, Riedel SA. *Electric Circuits* (6th edn). Prentice-Hall: Upper Saddle River, NJ, 2001; 277–286, 702–711.
22. Tham MT. Dealing with measurement noise—a gentle introduction to noise filtering. [Online]. 1998. Available: http://lorien.ncl.ac.uk/ming/filter/filter.htm [21 April 2004].
23. CEC. *Test Reference Years TRY, Weather Data Sets for Computer Simulations of Solar Energy Systems and Energy Consumption in Buildings.* Commission of the European Communities, Directorate General XII for Science, Research and Development: Brussels, 1985.
24. Nordex AG. Nordex N60 and N62 product brochure. [Online]. 2002. Available: http://www.nordex-online.com/ [21 April 2004].
25. Rojas A. Flywheel energy matrix systems—today's technology, tomorrow's energy storage solution. [Online]. 2004. Available: http://www.beaconpower.com/products/EnergyStorageSystems/DocsPresentations.htm [21 April 2004].

