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## A dynamic aggregate model for the simulation of short term power fluctuations

Luciano De Tommasi<sup>a</sup>, Madeleine Gibescu<sup>b</sup>, Arno J. Brand<sup>a</sup>

<sup>a</sup>*Energy Research Center of the Netherlands, Wind Energy Unit, 1755ZG Petten, the Netherlands. E-mail: detommasi@ecn.nl, brand@ecn.nl*

<sup>b</sup>*Department of Electrical Sustainable Energy, Delft University of Technology, the Netherlands. E-mail: m.gibescu@tudelft.nl*

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### Abstract

An important aspect related to wind energy integration into the electrical power system is the fluctuation of the generated power due to the stochastic variations of the wind speed across the area where wind turbines are installed. Simulation models are useful tools to evaluate the impact of the wind power on the power system stability and on the power quality. Aggregate models reduce the simulation time required by detailed dynamic models of multiturbine systems.

In this paper, a new behavioral model representing the aggregate contribution of several variable-speed-pitch-controlled wind turbines is introduced. It is particularly suitable for the simulation of short term power fluctuations due to wind turbulence, where steady-state models are not applicable.

The model relies on the output rescaling of a single turbine dynamic model. The single turbine output is divided into its steady state and dynamic components, which are then multiplied by different scaling factors. The smoothing effect due to wind incoherence at different locations inside a wind farm is taken into account by filtering the steady state power curve by means of Gaussian filter as well as applying a proper damping on the dynamic part.

The model has been developed to be one of the building-blocks of a model of a large electrical system, therefore a significant reduction of simulation time has been pursued. Comparison against a full model obtained by repeating a detailed single turbine model, shows that a proper trade-off between accuracy and computational speed has been achieved. © 2012 Published by Elsevier Ltd.

**Keywords:** wind farm, variable speed wind turbine, wind power fluctuations, multiturbine model, aggregate model

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### 1. Introduction

In a power system, the balance between produced and consumed power has to be continuously maintained. Imbalance results in frequency deviations of the system voltages and currents from the nominal value, which must be controlled in order to prevent instability phenomena and guarantee the power quality [1], [2], [3]. In the future, the power system will be coping with large scale wind energy integration [4], wind energy becoming a more and more significant fraction of the total produced power. In this scenario, wind power fluctuations, due to the stochastic nature of the wind, may significantly affect the system balancing and frequency stability. In particular, power fluctuations due to the wind turbulence may impose a limit to the amount of wind power which can be installed [5], [6]. Simulation models are therefore of paramount importance to evaluate these effects and design effective control systems.

A modern wind turbine is a complex non-linear dynamical system. Detailed simulation models describing the dynamical behavior of a single wind turbine have been developed at Energy research Center of the Netherlands (ECN) [7],[8],[9] as well as at other research institutes and companies, e.g. [10], [11].

The models are typically developed in simulation environments which enable a graphical representation of the model components as interconnected blocks. In this section we introduce state space representations for discussion purposes. A wind turbine generator is a (time-invariant) dynamical system which admits the state space representation:

$$\begin{aligned} \frac{d\underline{x}}{dt} &= \tilde{f}[\underline{x}(t), u(t)], \\ \tilde{y}(t) &= \tilde{h}[\underline{x}(t), u(t)], \end{aligned} \quad (1)$$

where  $\underline{x}$  is the state vector,  $\tilde{y}$  is the output and  $u$  is the input. In this work we assume that  $\tilde{y}$  is the (active) power, whereas  $u$  is the rotor-effective wind speed acting on the turbine.

Nowadays, wind turbines are typically part of farms consisting of tens to hundred turbines. Assuming that the output  $y$  of a wind farm including  $N$  turbines can be obtained by adding the outputs  $\tilde{y}_i$  of the single turbine models [7],[8], the detailed wind farm model is:

$$\begin{aligned} \frac{d\underline{x}_i}{dt} &= \tilde{f}[\underline{x}_i(t), u_i(t)], i = 1 \dots N \\ \tilde{y}_i(t) &= \tilde{h}[\underline{x}_i(t), u_i(t)], i = 1 \dots N \\ y(t) &= \sum_i \tilde{y}_i(t). \end{aligned} \quad (2)$$

However, this repetition of an individual turbine model is not computationally efficient. A behavioral model can reduce the computational cost of simulations, while preserving, at the same time, the fundamental characteristics of the full model dynamic response. It is a model of reduced complexity which approximates (2) such that  $y_a(t) \approx y(t)$ ,  $y_a(t)$  being the output of the approximated model.

*Aggregate models* are behavioral models obtained by modelling several identical subsystems (e.g. the turbines of a wind farm) by means of a single instance of the subsystem model [3], [12], [21]. Aggregation may be partial or full. Examples of partially aggregated models are the *cluster* and *compound* representations [12]. Their description is omitted in this paper due to a lack of space. This class of models can satisfactorily reproduce the time domain response of the full model. On the other hand, in the single machine representation all the different turbines of the full model are represented by means of a single instance of a turbine model. In this work, we introduce a new single machine model by extending the model [9] to variable-speed-pitch-controlled wind farms. As in [9], our aim is to approximate just the power spectral density of the full model's output, instead of the time domain response.

A typical single machine equivalent [18], [19], [20] uses “equivalent” parameters. This means that the physical parameters of the single turbine model are rescaled to take into account the presence of multiple turbines (e.g. the rated power of the equivalent electrical machine is the sum of the rated powers of the single electrical machines). The state space representation is:

$$\begin{aligned} \frac{d\underline{x}}{dt} &= f[\underline{x}(t), u(t)], \\ y_{a1}(t) &= h[\underline{x}(t), u(t)], \end{aligned} \quad (3)$$

where the effect of parameters rescaling is taken into account in the functions  $f$  and  $h$  which replace  $\tilde{f}$  and  $\tilde{h}$  of the single turbine model.

Other (single machine) aggregate models (e.g. [14],[15],[16],[17]) are steady state models, which give the output power as an instantaneous function of the wind speed (power curves):

$$y_{as}(t) = y[u(t)]. \quad (4)$$

The proposed model differs on the models [14],[15],[16],[17] because it relies on the full dynamic turbine behavior. Furthermore, it differs on the models [18],[19],[20] because it retains the physical parameters of the single turbine

dynamic model and produces the aggregate model's output by filtering its output (see also [9],[17]):

$$\begin{aligned} \frac{d\underline{x}}{dt} &= \tilde{f}[\underline{x}(t), u(t)], \\ y_{a2}(t) &= h'[\underline{x}(t), u_0, u(t)], \end{aligned} \quad (5)$$

where  $\bar{u}(t) = u_0 + u(t)$ ,  $u_0$  is the mean wind speed in a given time interval (e.g. 10 minutes) and  $u$  usually is a stochastic function, known as turbulence<sup>1</sup>. It is remarked that the function  $\tilde{f}$  in the first of (5) is the same one used in the first of (1).

The proposed model aims to model the smoothing effect due to the incoherence of the wind at different locations within the wind farm. In the following of this paper, we show that this goal is pursued by filtering the steady state part of the single turbine model (power curve) by means of a Gaussian filter as well as by properly scaling the output variations due to its dynamic part.

The rest of the paper is organized as follows. Section 2 introduces the power fluctuations as consequence of the wind speed variation and defines the fluctuation width. Section 3 describes the proposed aggregated model and reviews the Gaussian smoothing applied to the steady state part of the model. Section 4 presents the simulation results obtained with the aggregate model (5) and compares them against those ones obtained by means of the full model (2). Comparison includes both average power and fluctuation width. Conclusions are summarized in section 5.

## 2. Wind speed and power fluctuations

The main cause of wind power fluctuation is the natural variation of the wind speed. As already explained in section 1, the wind speed is often expressed as the sum of its mean value  $u_0$  in a given time interval (e.g. 10 min.) and turbulence  $u(t)$  [4]. The term  $u(t)$  is usually modelled as a stochastic function. It is characterized by the intensity  $I_u$ , which is expressed as the standard deviation  $\sigma_u$  of  $u(t)$  normalized by the mean wind speed:

$$I_u = \sigma_u / u_0. \quad (6)$$

Several spectral characterizations of wind turbulence have been proposed in the literature. A common assumption is that the turbulence at any point of the space is described by the Kaimal spectrum [22]:

$$S_u(f) = \frac{\sigma_u^2}{f} \frac{4fL/u_0^{(hub)}}{(1 + 6fL/u_0^{(hub)})^{\frac{5}{3}}}, \quad (7)$$

where  $S_u$  is the single sided power density spectrum,  $f$  is the frequency,  $L$  is the integral length scale of the wind speed at hub height,  $u_0^{(hub)}$  is the 10-minute average wind speed at hub height. However, the interaction of wind with the rotating blades and the tower modifies the spectrum so that the rotor effective wind speed has no longer a Kaimal shape.

Another possible assumption is that the probability density function  $p(u)$  of the fluctuations  $u$  is Gaussian [4]:

$$p(u) = \frac{1}{\sigma_u \sqrt{2\pi}} e^{-\frac{u^2}{2\sigma_u^2}}. \quad (8)$$

In the development of the aggregate model, we follow the assumption (8).

Wind speeds at different geographical locations are only partially correlated, therefore the power fluctuations of different turbines partially compensate each other (smoothing effect). The coherence of wind speeds at the two points  $i$  and  $j$  is defined as:

$$C(f) = \frac{|S_{ij}(f)|}{\sqrt{S_{ii}(f)S_{jj}(f)}}, \quad (9)$$

<sup>1</sup>Sometimes the function  $u_t$  is assumed as deterministic, for example it can describe a wind gust.

where  $S_{ii}$  and  $S_{jj}$  are the auto-power-spectral-density functions at locations  $i$  and  $j$ , and  $S_{ij}$  is the cross-power-spectral-density function between  $i$  and  $j$ . A commonly accepted expression for the coherence is due to Davenport (e.g. [17]):

$$C(f, r, u) = e^{-d \frac{r}{u_0} f}, \quad (10)$$

$r$  being the distance between two points and  $d$  the decay constant. The parameter  $d$  in this expression or parameters of other similar expressions can be found by means of least-squares fitting of measured data [17]. From (10) it is seen that the coherence is reduced when turbines are dispersed on a larger geographical area; therefore the smoothing effect is increased in such case. Moreover, sufficiently high frequency components are incoherent.

The coherence of the wind is of course reflected on the coherence of the power fluctuations of different turbines as well. The smoothing effect is maximum when the wind coherence is zero (incoherent wind). According to [17], in a wind farm, power fluctuations with frequencies higher than about  $10^{-2}$  Hz are independent, whereas in the frequency band from  $2 \cdot 10^{-3}$  Hz to  $10^{-2}$  Hz there may be some correlation. For frequencies lower than  $2 \cdot 10^{-3}$  Hz, there is definitely correlation.

In this work, we study the measure proposed in [24], i.e. the *fluctuation width*. In the time interval  $[0, T]$ , it is defined as:

$$F_W(T, N) = P_{\max}^{[0, T]} - P_{\min}^{[0, T]}, \quad (11)$$

where  $P_{\max}^{[0, T]}$  and  $P_{\min}^{[0, T]}$  are respectively the maximum and minimum power in the time interval  $[0, T]$  generated by a wind farm with  $N$  turbines. For given values of  $T$  and  $N$ ,  $F_W$  is a random variable whose probability density function depends on the wind stochastic characterization. For a given  $T$ , the expected value  $E[F_W]$  is a decreasing function of  $N$ , since smoothing effects are more and more pronounced as the number of turbines increases (see e.g. [23]). For a given wind speed realization  $u(t)$  (and number of turbines  $N$ ), it is easily understood from the definition (11) that  $F_W$  is an increasing function of  $T$ .

In section 4, we use both the proposed aggregate model (5) and the full wind farm model (2) to compute the fluctuation width (11), and compare the results.

### 3. The proposed model

In this work, the focus is on short term simulations [5],[6]. Therefore, the proposed model takes into account both the wind turbulence and the system dynamics. In more long term studies, e.g. [14],[15],[16], the dynamic behavior of the wind turbines is neglected and the output power is averaged over sufficiently long time intervals (1 minute in [15], 10-15 min. in [16] and 1 hour in [14]).

In [9] an aggregate model of fixed speed wind farms was developed in Matlab/Simulink. The model relies on the separate rescaling of dynamic and quasi-steady-state components of the output of a single turbine model. We extend that model to Variable-Speed-Pitch-controlled (VSP) wind farms.

The variable speed concept is nowadays the most widespread technology among the wind turbines. It enables to vary the rotational speed of the turbine such that the best aerodynamic efficiency is achieved for a given wind speed. This way, the achieved results are the maximum energy extraction from the wind as well as the reduction of mechanical stress for the turbine components.

The Simulink implementation of the proposed VSP Doubly-Fed-Induction-Generator (DFIG) [13] aggregate model is depicted in Fig. 1. Said  $P_a$  the wind farm aggregate model's output,  $P_d$  the single turbine dynamic model's output,  $P_{ss}$  the single turbine steady state model's output,  $\bar{u}(t) = u_0 + u(t)$  the wind speed, with  $u_0$  mean and  $u$  turbulence, the model in Fig. 1 computes<sup>2</sup>:

$$P_a[\bar{u}(t)] = N \cdot P_{ss}[u_0] + \sqrt{N} \cdot \{P_d[\bar{u}(t)] - P_{ss}[u_0]\}. \quad (12)$$

The dynamic model block computing  $P_d$  is documented in the ECN reports<sup>3</sup> [7],[8],[9] and will not be reviewed in this paper. The steady state block computes the output  $P_{ss}$  as function of the wind speed by means of a power curve.

<sup>2</sup>The notation  $P[\bar{u}(t)]$  here denotes the model's output  $P$  when the wind speed realization  $\bar{u}(t)$  feeds the model.

<sup>3</sup>The reports can be downloaded via [www.ecn.nl](http://www.ecn.nl).

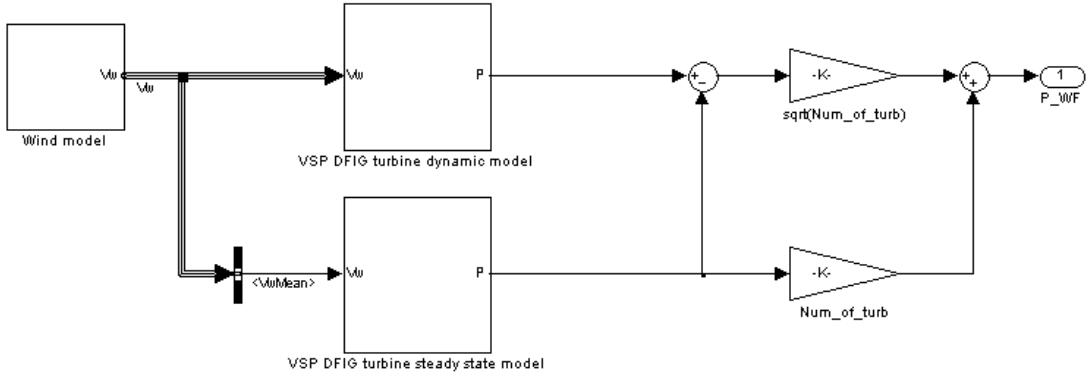


Figure 1: Matlab/Simulink implementation of the proposed aggregate model.

The fact that each turbine of the wind farm full model (2) is fed by a different wind speed realization  $\bar{u}_i(t) = u_0 + u_i(t)$ , where deviations  $u_i$  from the mean  $u_0$  are assumed Gaussian (see equation (8)), can be taken into account in the aggregate model by applying the Gaussian smoothing [14],[15],[16], to the single turbine power curve and then feeding it with the mean wind speed  $u_0$ . The smoothed power curve is computed as follows:

$$P_{ss}(v) = \tilde{P}_{ss}(v) * \frac{1}{\sqrt{2\pi}\sigma_g} e^{-\frac{v^2}{2\sigma_g^2}}, \quad (13)$$

where  $*$  is the convolution operator and  $\sigma_g$  is the standard deviation or width of the Gaussian filter. A good estimation of the optimal filter width is the standard deviation of the turbulence  $\sigma_u = I_u u_0$ .

In Fig. 2, three different power curves are compared: the power curve  $\tilde{P}_{ss} = \tilde{P}_{ss}(v)$  of a single turbine (blue) and two power curves  $P_{ss} = P_{ss}(v)$  smoothed by means of Gaussian filters with different standard deviations (green, red). The filter used to obtain the green curve has a bigger standard deviation than the filter corresponding to the red curve, so resulting in a more pronounced smoothing of the original power curve.

The lowest wind speed at which the output power of a wind turbine equals the turbine rated power is named rated wind speed ( $u_{rat}$ ). Since the energy production should be maximized, the wind turbines are chosen such that their rated wind speed is close to the mean wind speed of the site where they are installed ( $u_{rat} \approx u_0$ ). However, because of wind speed variations  $u_i(t)$ , some turbines will be fed with a wind speed lower than the rated one, so producing less power, and some others will be fed with a wind speed higher than the rated, still producing the rated power. Hence, the mean total production will be lower than the rated turbine power multiplied by the number of turbines  $N$ .

In section 4.3, we show that, when the output of the single turbine power curve is multiplied by  $N$  and  $u_0 \approx u_{rat}$ , the mean output power of the aggregate model is greater than the mean output power of the full model. As already explained, this difference has to be compensated by replacing the single turbine power curve with a smoothed curve.

The scaling factor  $\sqrt{N}$  applied to the dynamic part of the output is justified by the assumption of incoherent fluctuations. In fact, when fluctuations are incoherent, the ratio between the fluctuation amplitude of a wind farm and of a single turbine is  $\sqrt{N}$  [17],[24]. Since wind coherence is directly reflected on the coherence of wind turbine outputs. It is however worthwhile to note that Davenport's coherence expression (10) shows that only sufficiently high frequency components are truly incoherent and therefore damped with the factor  $\sqrt{N}$ . Coherence of low frequency components might be taken into account by weighting them with a factor closer to the one occurring in steady state [17].

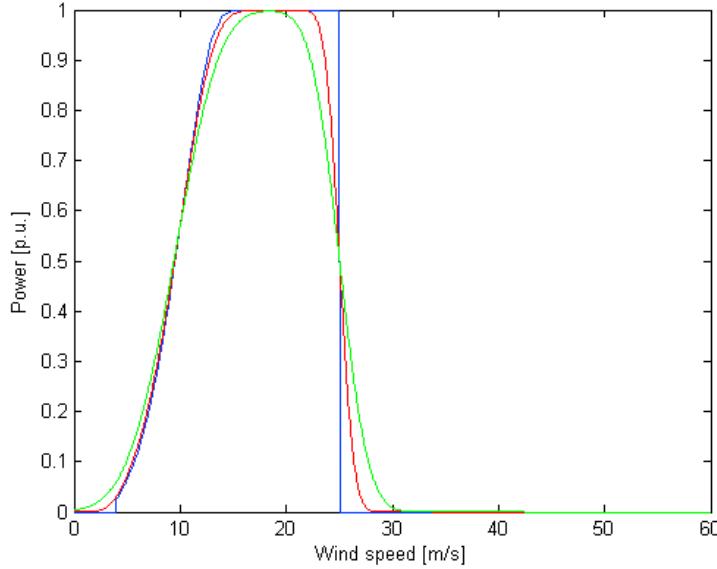


Figure 2: Wind turbine steady-state model (blue curve). Smoothing effect obtained by means of the Gaussian filter (green and red curves).

## 4. Simulation results

### 4.1. Outline

To generate the output power of a wind farm with  $N$  wind turbines, we performed  $N$  simulations of a single turbine and summed the so obtained outputs. In fact, we assume that the output of a single VSP-DFIG turbine does not influence the output of the others, see equations (2).

In each simulation, the turbine model (1) is fed by a different wind speed. Wind speed realizations, representing the wind at different wind farm locations, have been obtained by means of the ECN Control Design Tool [25]. We assume that they all have the same mean, for  $i = 1..N$ ,  $u_{0i} = u_{rat}$ , where  $u_{rat}$  is the rated wind speed of the turbines. The turbulence variations  $u_i(t)$ ,  $i = 1..N$ , are realizations of statistically independent processes. They have the Kaimal spectrum (7) (see also [9] and references therein).

With these assumptions, it is clear that the simulation of the aggregate model is about  $N$ -times faster than simulation of the full model. This is a significant reduction of the computational time, since the simulation of a detailed turbine model may take several tens of seconds even on a modern personal computer.

A comparison between the output power obtained by means of the full model (2) and the aggregate model (5) is shown in Fig. 3. It is worthwhile to note that the aggregated model has to be fed with a single wind speed realization  $u(t)$ , representing the wind in all the area where the turbines are installed. On the other hand, the full model is fed with  $N$  different wind speed realizations  $u_i(t)$ ,  $i = 1..N$ . This leads to a significant loss of information in the aggregate model. To give an idea of the behaviour of the aggregated model when its input wind speed realization is varied, Fig. 3 shows two results obtained using two different wind speed realizations (A1 and A2)<sup>4</sup>. However, it is worthwhile to remark that outputs of the full and aggregate models shown in Fig. 3 have similar Power Spectral Densities (PSDs), see Fig. 4. The PSDs of the output of the full model has been compared with the one of the aggregate model. They have been estimated by means of the Welch's averaged, modified periodogram method [26].

<sup>4</sup>In all the figures, the output power is expressed in p.u. of the rated wind farm power.

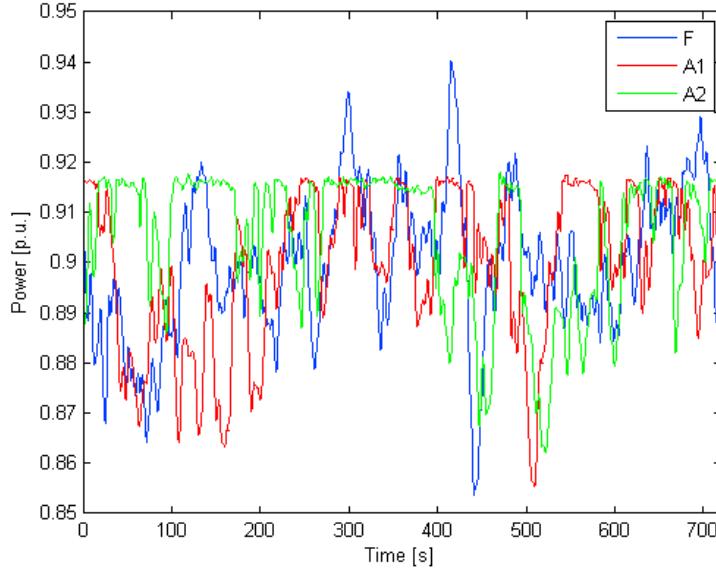


Figure 3: Comparison between output power of the full model (F) and of the aggregate as obtained, respectively, by means of two different wind speed realizations (A1, A2).

#### 4.2. Gaussian filter width

To verify that the the turbulence standard deviation  $\sigma_u = I_u u_0$  is a good estimation of the optimal Gaussian filter width  $\sigma_g$ , we computed  $\sigma_g$  by means of optimization. This way,  $\sigma_g$  is varied until the deviation between the output of the full model and the aggregated model is minimized. The optimization method used is the golden section search with parabolic interpolation<sup>5</sup>. The optimization process has been repeated three times, for  $N = 10, 50, 100$ . In all cases, it converges in seven iterations when the minimum is searched in the interval  $[0, 5]$ . The obtained optimal widths computed by optimization are:  $\sigma_{10} = 1.9196$ ,  $\sigma_{50} = 2.0755$  and  $\sigma_{100} = 2.0689$ . They are close to the turbulence standard deviation  $\sigma_u = 1.9689$ .

#### 4.3. Average power

Average output powers  $\langle P \rangle$  in  $[0, T]$  as given by the full (F) and aggregate models without and with Gaussian smoothing (respectively ANS and AS), are compared for  $0 \leq T \leq 12$  min. Results in Fig. 5 show that Gaussian smoothing enables a much better agreement between aggregate and full model for  $N = 10, 50, 100$ .

#### 4.4. Fluctuation width

Power fluctuation widths  $F_W$  in  $[0, T]$  as given by the full (F) and aggregate models (A), are compared for  $0 \leq T \leq 12$  min.

Results in Fig. 6 show that the aggregate model mostly leads to an underestimation of  $F_W$  for  $N = 10, 50, 100$ . This especially holds for  $T > 4$  min. The curve representing the aggregate model prediction (A) has been obtained averaging 100 simulations each of them obtained with a different wind speed realization.

It is however remarked that the damping factor  $\sqrt{N}$  finds its justification in the frequency domain, enabling an adequate approximation of the full model power spectral density (Fig. 4).

Finally, the bottom-right panel in Fig. 6 represents the standard deviation of the power fluctuation width, referred to the 100 simulations performed, as function of  $T$  and for  $N = 10, 50, 100$ . It can be seen that the standard deviation is a decreasing function of both  $T$  and  $N$ .

<sup>5</sup>For further information, see documentation of the *Matlab*<sup>(c)</sup> function `fminbnd`.

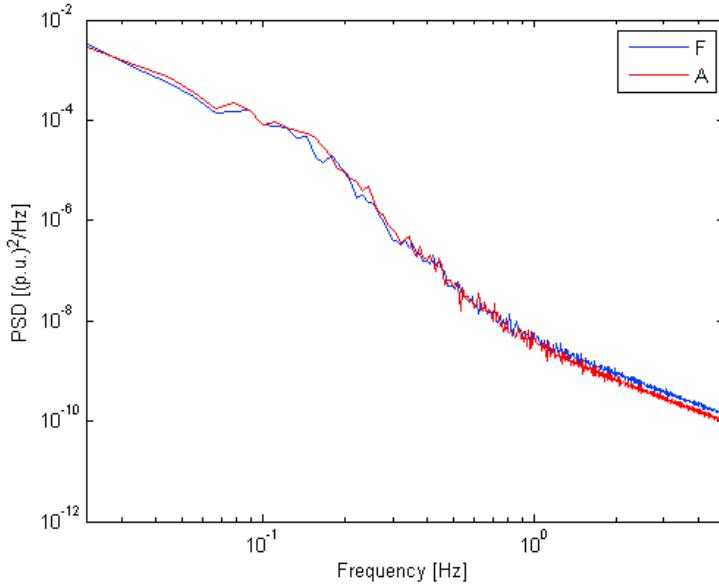


Figure 4: Comparison between power spectral densities of the outputs of the full (F) and aggregate (A) models.

## 5. Conclusions

A new dynamic aggregate model of variable-speed-pitch-controlled wind farms for the simulation of wind power fluctuations has been proposed. The smoothing effect due to incoherence of power fluctuations of different wind turbines has been introduced by applying Gaussian filtering to the steady state turbine model part of the model (power curve) as well as by rescaling the power variations due to the dynamic behavior of the single turbine model.

Comparison against non-reduced model obtained by adding the output of individual turbine models revealed that the proposed model enables an accurate approximation of the average output power as well as of the power spectral density.

Finally, a time domain power fluctuation measure, namely the power fluctuation width [24], has been studied as function of the time interval length, using both full and aggregate models.

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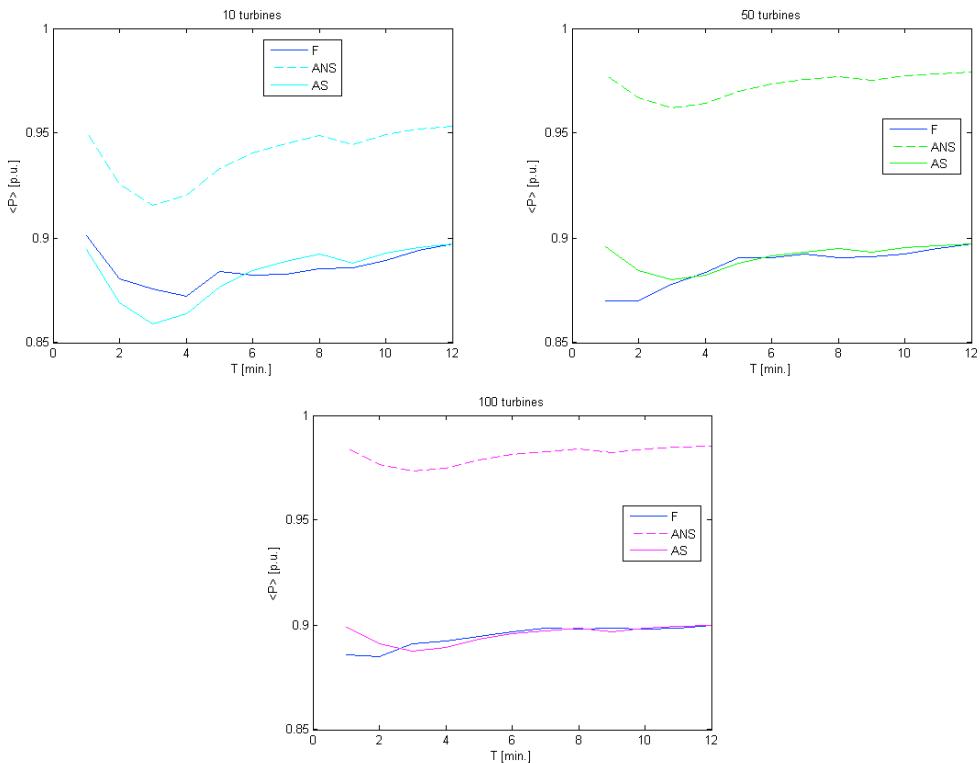


Figure 5: Comparison between mean powers of the full model (F) and of the aggregate model with and without Gaussian smoothing (AS, ANS) for  $N = 10, 50, 100$ .

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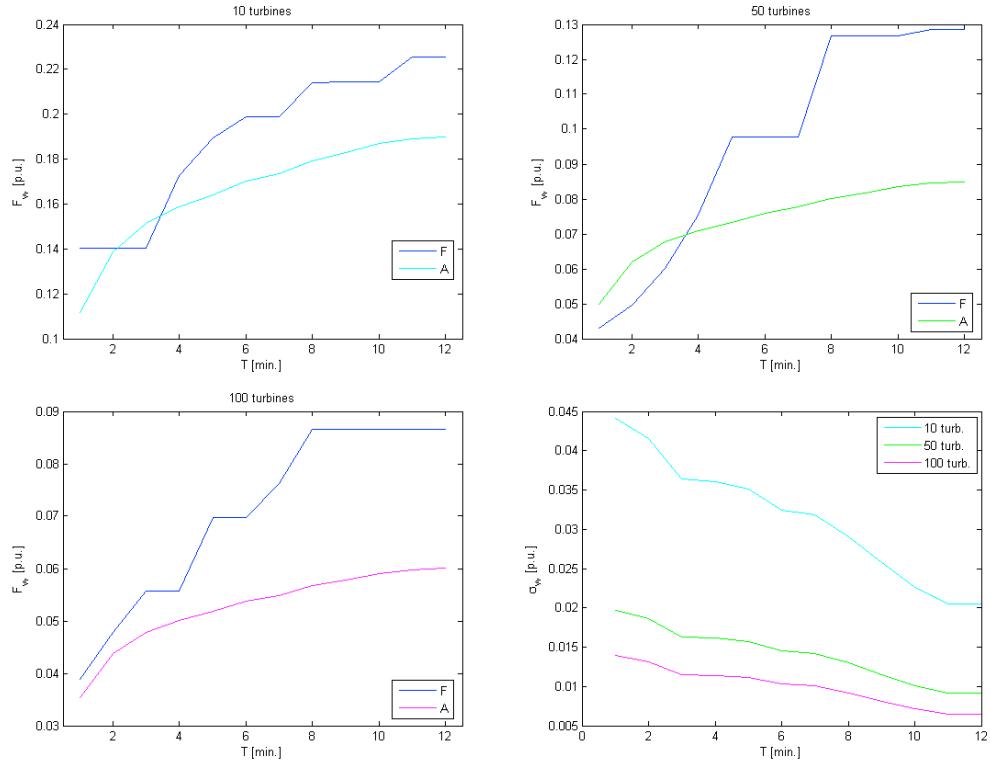


Figure 6: Comparison between fluctuation widths of the full model and of the aggregate model for  $N = 10, 50, 100$  (top panels and bottom-left panel). Standard deviation of fluctuation widths as function of  $T$  referred to 100 simulations (bottom right panel).

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