COMPARISON OF WIND FARM AGGREGATE MODELS FOR TRANSIENT STABILITY STUDIES

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Abstract – The paper presents and compares four different methods for aggregation of wind farms (WFs) for system dynamic studies. The methods compared include single equivalent turbine model, cluster representation of the WF, probabilistic clustering model and a compound aggregation model. In the first method wake effects are ignored whereas in the other methods these are taken into account. Probabilistic clustering technique has been applied to a large 49 turbine WF. Dynamic responses of the WF represented using different aggregation methods are compared against responses of the full WF model for various wind scenarios to analyse aggregation method suitability for system dynamic studies including the required simulation time.

Keywords: Wind farm modelling, model aggregation, transient analysis, clustering methods, stability studies

1 INTRODUCTION

Energy targets for most European countries call for massive increase in electricity supplied by renewable sources in the coming years. Significant increase in number of wind farms (WF) connected to power networks is expected both onshore and offshore. The capacity of the WFs has increased dramatically over the last decade and most of the future supply of electricity will be through large-scale wind power (WP) projects distributed all over power systems.

In order to carry out system dynamic studies relevant dynamic models of WF are needed. In general, several differential equations are required to model a single wind turbine (WT). For the entire WF this can easily exceed hundreds of differential equations which can contribute considerably towards simulation time required to carry out dynamic system studies. In order to efficiently perform transient stability studies aggregate models of WFs are used.

There are cases when WFs with a large number of WTs have been aggregated in a single equivalent machine [1] and [2], or sometimes two or more reduced models have been used to represent equivalent wind generators [3] and [4]. Some aggregation models use identical incoming wind speeds (WSs) for all WTs within the WF, others consider different input wind speeds, but neglect wake effects.

The choice of an aggregation technique depends largely on the type of study it will be used for. Single machine equivalent model and probabilistic clustering [5] based aggregate model of the WF remain fixed for the entire year. The number of equivalent turbines in cluster representation [4] of the WF is variable throughout the year and depends on wind speed (WS) and/or wind direction (WD) at the site. Therefore, these three types of aggregate models result in different number of equivalent turbines used to represent the entire WF as well as in different simulations times for various wind conditions. Some aggregation methods may be suitable for studies of integration of large WF into the power system replicating a general dynamic behaviour of a WF at the point of common coupling (PCC), while other might be useful when both accurate and fast analysis is needed.

This paper provides an overview of the four methods for WT aggregation for system dynamic studies. The aggregate models of WF include aggregation of connecting cables which was typically ignored in past studies.

2 WF AGGREGATION METHODOLOGIES

Energy extraction by a WT from oncoming wind causes reduction in energy at the back of the turbine. Due to this reason wind leaving the turbine has less kinetic energy and lower speed compared to incoming wind. This deficit in WS and added turbulence (at the back of the turbine) is called wake effect. Since power production from a turbine is directly dependent upon the WS it receives, turbines in the wake of another turbine will produce less power than upfront ones. Turbulent behaviour of a wake is ignored in this paper though, and only the velocity deficit is considered. The wake effect is not only dependant on the WS but also on spacing among the turbines as well as on design of the rotor blades. A detailed wake model considering single, partial and multiple wakes was used for this study. Detailed description of the wake model used is given in [6].

2.1 Types of Aggregation

The main requirement for aggregation of a WF is that the active and reactive power output at the PCC obtained with aggregate WF model are the same as those obtained with a detailed WF model. Another requirement is that the aggregate model should be able to adequately represent the dynamic behaviour of a WF in case of disturbance. Accuracy of aggregation methods is verified by comparison of resulting active and reactive power exchanges and responses with those obtained with a full WF model. Four different types of WF model aggregation used in this study are described in the sequel.

2.1.1 Single Unit Representation

This method assumes that all wind turbines (WTs) inside the WF receive the same WS (normally WS coming to the WF or an average value) therefore all wind turbines in the farm can be replaced by a single equivalent wind turbine [7]. Rated apparent power of this equivalent turbine is the sum of rated powers of all individual turbines (1):

$$S_{eq\_WT} = \sum_{i=1}^{n} S_{individual\_WTs} \tag{1}$$

where n is the number of turbines aggregated, $S_{individual\_WTs}$ is the rated apparent power of each WT and S_{eq_WT} is the rated apparent power of the equivalent WT. The equivalent transformer connecting the equivalent turbine to the grid is also scaled appropriately to allow the rated power transfer of the aggregate generator.

The equivalent WF model consists of all mechanical and electrical components and controllers scaled appropriately. The advantage of this approach is that the order of WF model and required computation time can be massively reduced. However, the disadvantage of this approach is that it ignores the variation of WS inside the WF, i.e., the wake effect. Since different wind turbines produce different powers based on their location inside the WF, this method can over-estimate the total WF power output which can affect the dynamics of the WF as well as total active and reactive power injected into the grid. Details about aggregation of constant speed and variable speed wind turbines to a single equivalent turbine can be found in [1] and [8], respectively.

2.1.2 Cluster Representation

In this method, wind turbines in a WF receiving similar wind speeds are replaced by a single equivalent unit. Rated voltage at the terminal of the equivalent turbine should be the same as at individual turbines. Rated apparent power of this equivalent unit is the sum of rated apparent powers of the turbines that it replaced. The aggregation method assumes that turbines receiving similar WS operate at the same operating point. The number of equivalent turbines used to represent a WF at a particular time depends on the incoming WS, WD, WF layout and the level of accuracy required during clustering. Multi-machine WF equivalent models are generally more accurate [8]. The wind turbine has a soft shaft system which accumulates potential energy when twisted during normal operation and some of this energy is released when a fault occurs in the network. This potential energy stored in the turbine shafts depends on the operating point and a single turbine equivalent model cannot accurately represent the WF during disturbances as it assumes the same operating point for all wind turbines in the WF.

The advantage of multi turbine equivalent model is therefore its ability to account for different acceleration of individual turbines in the farm based on their actual operating points. This method however, works best for incoming wind speeds up to rated speed of the turbine. At higher wind speeds all turbines can be grouped into a single turbine equivalent because they work at the same operating point producing rated power.

A disadvantage of multi turbine aggregate models is that a new set of equivalent turbines has to be modelled every time a WS or WD changes. This constant update of equivalent model can be cumbersome for the operator as parameters of equivalent WTs would have to be computed very often. Also in some cases this aggregation method may result in many equivalent turbines needed to represent WF which can result in long simulation time and extra effort to develop aggregate model.

Results about the number of equivalent turbines needed to represent a WF for particular WS and WD in this study are stored in a Coherency matrix whose size is determined as in [4]:

$$S_{coh\_mat} = n_{WDi}.n_{WTs}.n_{WSi} \tag{2}$$

where n_{WDi} is the number of wind directions, n_{WTs} is the number of turbine inside a WF, n_{WSi} is the number of wind speeds. The number of WDs and WSs are dictated by a step size.

2.1.3 Compound Representation

This method is a compromise between the two methods discussed above. The method described in [9] can represent the entire WF consisting of DFIGs by a single equivalent turbine taking into account the difference in wind speeds and turbines operating at different operating points. In this method, a WF is represented by a single electrical generator with an appropriate control system. The representation of mechanical system however, is different. To take into account the variation in WS at each turbine the mechanical torque produced by aerodynamic rotor of each turbine is aggregated and the resultant torque is applied to the equivalent electrical generator. One main disadvantage of using this approach is that in order to calculate mechanical torques for each turbine they must have rotor model, drive-train, induction generator, rotor speed controller and pitch angle controller. Even though simplified turbine models in this case can be used the number of differential equations required to model all the components involved is still reasonably large. Secondly, the implementation of this aggregation method in some commercial software packages may not be straight forward as the user typically has limited possibility to adjust predefined models in the package. This type of aggregate model can be particularly useful in case of modelling very large WFs at sites with significant WS fluctuation [10].

2.1.4 Probabilistic Clustering

In this method, a set of equivalent turbines are determined which would be used to represent the WF for an entire year. The number and rated power of each equivalent turbine is dependant on the statistical analysis of the site. The method of probabilistic clustering of wind turbines was originally proposed in [5] using a WF consisting of 9 WTs. The dynamic equivalent models of wind turbines were not shown there. Methodology to determine most probable set of equivalent generators to represent the WF is described below.

Dynamic behaviour of turbines during a fault in the system is influenced by the controller action which is dependant on the WS faced by the turbine. If turbines are under less WS, the controller would try to track the optimal point of operation whereas if facing higher WS the controller would attempt to keep angular speed inside acceptable range to maintain power production. Therefore it can be expected that WTs facing the similar wind speeds will also have a similar dynamic behaviour during a fault in the system. Aggregation by wind speeds [9] and [4] is also performed in Cluster Representation approach. Turbines with a similar wind profile are clustered and represented by a single aggregate WT.

Turbines facing free-stream wind receive wind at full speed while those downwind receive reduced amount due to wake effects. In order to identify turbines facing similar wind speeds a clustering algorithm using Support Vector Clustering (SVC) was employed. It is a further step of support vector machine concept described in [11]. The goal of the SVC algorithm is to assign multidimensional data features to groups and obtain accurate and non-overlapped clusters. Clustering is performed for each incoming WS for all wind directions (0 to 360^o) in steps of 1^o.

Once clustering of WTs is achieved, these clusters are further arranged into groups of clusters. Groups are found for each WS and WD. Groups formed can be unique or non-unique (exist more than once at any WS or WD). Most of the time the same group is valid for a range of WS and WD while in other cases new groups have to be formed. The main requirements for identification of unique groups are:

1) Number of clusters in any two groups are different
2) Number of clusters in any two groups are same, but number of turbines in the clusters are different

The 'number of clusters' inside a group represents the number of equivalent turbine(s) needed for WF representation while 'number of turbines' inside each cluster is used to calculate the rated power of the equivalent turbine(s). Therefore, a group is unique if either the number of equivalent turbines it needs to represent the WF or the rated power of the equivalent turbines is different.

It was noticed that the same group can occur more than once per year as WS and direction changes; therefore identification of most frequently occurring groups is performed to come up with most probable group to represent WF for most time in a year. This would determine the number of equivalent turbines needed to represent the WF during the year as well as their rated powers. Site information is necessary to establish the probability of incoming WS and WD at a site.

Wind speed and direction data at the WF site is required for at least one year. Based on wind site information the frequency of WS and WD for the whole year is determined. In case study, data from a site in Sweden for years 1999, 2000 and 2002 was used and it was evident from the measurements and from [12], that wind during the year is prevailing from two directions. Similarly, the probability of different wind speeds at a site can be found from wind data and represented as Weibull distribution as shown in Figure 3. Figure 2 shows a wind rose at the site illustrating frequency of WS from each WD. From this figure it can be seen that WD is very probable from two sectors i.e. 100^o to 180^o and from 280^o to 360^o.

As described above the clustering of WTs is dependant on the WD and WS therefore, groups of clusters are formed based on these two factors. To find the probability of a group during the year, the probability of the WS and WD when that group should be used needs to be determined first. For example, if a group X is used when incoming WS is 4, 5 and 6 m/s for WDs between 100^o and 101^o, then the probability of occurrence of group X during the year can be determined as follows:

$$p_{groupX} = \left(\sum_{i=1}^{n} p_{WS} \right) . p_{WD} \qquad (3)$$

where p_{WS} is the probability of a particular WS and p_{WD} is the probability of a particular WD range.

Equation (3) can be employed if group X occurs at several wind speeds but one WD range. If however, Group X occurs with different combination of WS and direction, i.e., once for WS is 4m/s and direction 100^o to 101^o, and then for WS is 6m/s and direction 101^o to 102^o then equation (4) should be used:

$$p_{groupX} = \sum_{i=1}^{n} (p_{WS} . p_{WD}) \qquad (4)$$

where n is the total number of occurrences of group X.

By using (3) and (4), the probability of any group during the year can be determined for any site. The number of groups can vary based on size and layout of the WF, direction interval of the SVC and wind characteristic at a site during the year.

Depending on the site's wind characteristics and WF layout one or more groups may have higher probability of occurrence. If one group is found highly probable, then it becomes an obvious choice to represent the whole WF for the entire year. If however, several groups have comparable probabilities of occurrence, then one of the following two scenarios can occur.

Firstly, identified groups may have the same number of clusters. The WF can then be represented by same number of equivalent WTs by any of these groups. In this case any group can be chosen.

Secondly, identified groups may have different number of clusters. In this case any of the groups can be used to represent the WF. The preference however, should be given to the group with smallest number of clusters as it simplifies the representation of the WF.

2.2 *Equivalent Turbine and Cable Representation*

Equivalent turbines are connected to the bus bar using cables having equivalent resistances and reactances calculated as shown below. Firstly, losses inside each string of WTs are calculated through detailed model (in radial connection) as follows:

$$P_{loss} = \left[I_1^2 R_1^2 + (I_1 + I_2)^2 R_2^2 + ... + (I_1 + I_2 + .. + I_n)^2 R_n^2 \right] \quad (5)$$

$$Q_{loss} = \left[I_1^2 X_1^2 + (I_1 + I_2)^2 X_2^2 + ... + (I_1 + I_2 + .. + I_n)^2 X_n^2 \right] \quad (6)$$

Losses inside the whole WF are calculated as sum of losses inside each string. Equivalent current flowing out of the WF is calculated as:

$$I_{eq,WF} = \frac{S_{eq,WF}}{\sqrt{3}V} \quad (7)$$

Using total active and reactive power loss as well as equivalent current the value of equivalent resistance ($R_{eq,WF}$) and reactance ($X_{eq,WF}$) can be calculated using:

$$R_{eq,WF} = \frac{P_{loss,WF}}{3I_{eq,WF}^2} \quad (8)$$

$$X_{eq,WF} = \frac{Q_{loss,WF}}{3I_{eq,WF}^2} \quad (9)$$

where $P_{loss,WF}$, $Q_{loss,WF}$ are total active and reactive power losses inside the detailed WF. $I_{eq,WF}$ is the current flowing out of the WF, $S_{eq,WF}$ is the power produced by the detailed WF and V is the rated voltage used inside the WF.

Once values for $R_{eq,WF}$ and $X_{eq,WF}$ are calculated they are used with aggregated wind turbines to account for loss inside the cables in all three methodologies. Further details for cable aggregation can be found in [4].

3 CASE STUDY

A WF consisting of 49 wind turbines is used for case study. Turbines used are variable speed, pitch controlled Vestas V80 with doubly-fed induction generators, each with a rated capacity of 2 MW. The rated power of this WF is 98MW. It is assumed that all individual turbines inside a WF are of same type with same parameters. Distance between two turbines next to each other and directly behind one another is 400m. A symmetrical WF layout is chosen for case study as shown in Figure 6 however the methodology can be applied to any size and layout of a WF. Simulations were performed using commercially available power system analysis software DIgSILENT PowerFactory™ [13]. Built-in model of DFIG inside this software package was scaled to 2MW with appropriate scaling of mechanical and electrical parameters. Each turbine is connected to the collector system by a tertiary 0.69/3.3/30 kV transformer for modelling purposes.

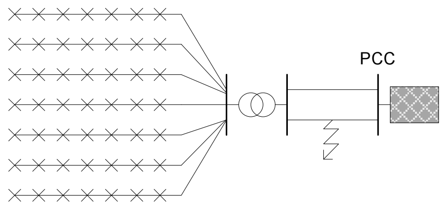

Figure 1: Radial connection of WF

A 3-phase, 200ms, self clearing fault was simulated at one of the transmission lines connecting WF to the PCC. Figure 1 shows the layout and electrical connections inside the WF. The internal WF voltage is 30kV. The voltage is then stepped up to 132kV through a 30/132kV transformer. The voltage at PCC (slack bus) is fixed at 1 p.u.. Equivalent cables are used in all simulations and for all aggregation methods.

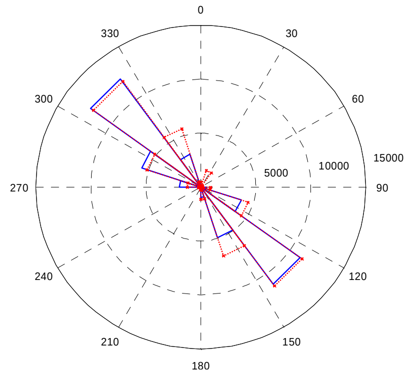

Figure 2: Plots of wind roses for a site in Sweden for years 2000 (red line) and 2002 (blue line).

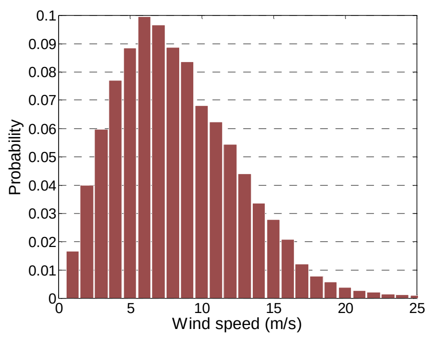

Figure 3: Weibull distribution of wind speeds at the site in year 2000

3.1 *Probabilistic clustering approach*

Using a WF of 49 turbines arranged as shown in Figure 6, 321 unique groups were identified after applying wake effects, clustering data and through probabilistic grouping. These results were obtained after analysing wind speeds received by each turbine for all incoming wind speeds within the operating range (4m/s to 25m/s) and from all directions (0 to 360^{o}). Figure 4 shows possible ways to model a WF by number of equivalent turbines. For instance, if number of equivalent turbines is 1 then there is only one unique way to represent the WF (by representing all WF by a single turbine), however if the number of equivalent turbines is 4 then there are 90 different ways to represent WF with 4 aggregate

WT. It can be seen from Figure 4 that a WF can be represented by a maximum of 10 WTs.

In order to choose only one group, out of 321, to represent WF during the year, probabilities of each have to be analysed. Therefore, site analysis is brought in to see probability of usage of each group during the year. Figure 5 shows that only four groups are found to have noticeable probabilities whereas the rest of them have probabilities of less than 0.001. Table 1 shows four highly probable groups and their cluster information.

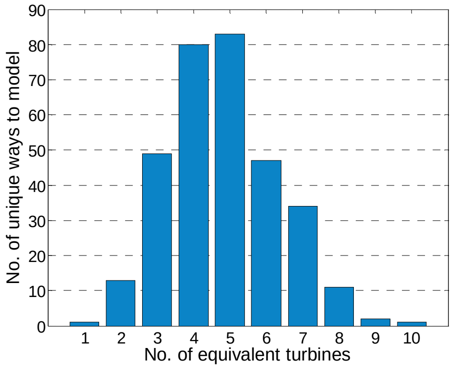

Figure 4: Equivalent number of turbines that can represent a WF and number of possible ways to model them

Groups	No. of Eq. WTs	Rated powers [MW]	Probability	WTs Clustered (high to low WS)
A	3	26; 22; 50	0.1028	13; 11; 25
B	3	38; 30; 30	0.089	19; 15; 15
C	2	38; 60	0.062	19; 30
D	1	98	0.0244	49

Table 1: Most probable groups to represent the WF

It is evident from Table 1 that probability of representing a 49 turbine WF by 1, 2, or 3 equivalent turbines is higher than representing it by up to 10 equivalent turbines.

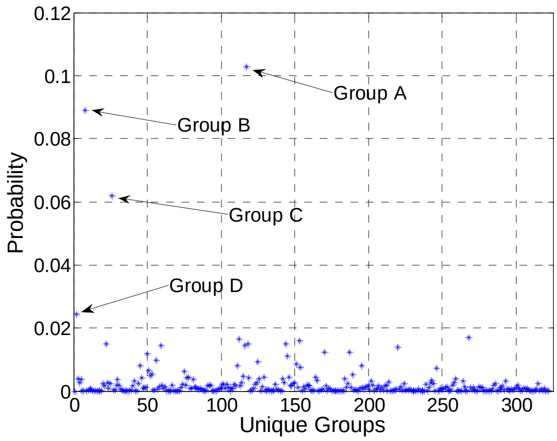

Figure 5: Probability of every unique group found

Groups A and B both have higher probability than the others and suggest the use of 3 equivalent turbines. Since Group A has the highest probability, it is used in this paper to represent the WF during the whole year.

3.2 Cluster representation

If coherency matrix approach is used, as proposed in [4], it would require creation of a 22 x 360 x 49 = 388,080 entry matrix from which relevant clustered information would have to be used every time WS and WD change. If either or both WS and WD change this would require a new number of equivalent turbines to be selected from 7920 possible combinations. Also if different number of equivalent turbines is used they may differ in parameters and therefore those will have to be adjusted every time.

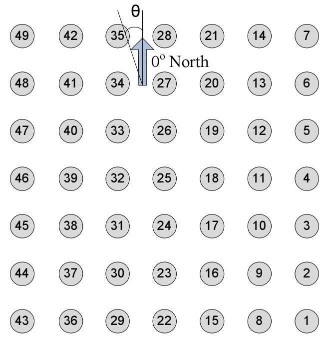

Figure 6: Layout of a 49 turbine WF

Clustering algorithm proposed in [4] was run with accuracy of 0.1m/s to identify turbines receiving similar wind speeds. Results for two wind scenarios are shown in Table 2 and 3.

3.3 Single Unit Equivalent representation

In this case, all 49 wind turbines are represented by a single equivalent turbine with rated capacity of 98 MW. Cables with equivalent parameters are used to ensure that losses are similar and that powers flowing out of the aggregated WF are the same as with detailed WF model.

4 RESULTS

Time domain simulations comparing active and reactive power behaviour are performed. Two different wind conditions are considered and performance of each aggregation method in terms of number of WTs needed as well as simulation time for running transient study for 10 seconds, are shown in Table 2 and 3. First, the wind entering WF at 10m/s from 100^{o} is considered to model partial load operation. Secondly, the wind entering WF at 24m/s from 0^{o} is simulated to model full load operation.

Model	Sim Time (s)	No. of WTs
Detailed WF	925	49
Single-Eq Turbine	14.6	1
Probabilistic Clustering	44.9	3
Cluster Representation	60	5

Table 2: WF modelling with incoming WS = 10m/s, WD =100 deg. Using constant step size of 0.00075 sec

When WS entering the WF is low, wake effects have major influence inside the WF and turbines can receive completely different wind speeds and operate at different operating points producing different amount of power. Whereas at higher WSs (usually above rated) turbines produce similar powers and run at nominal operating points. Due to this reason at higher wind speeds cluster representation and single-unit representation model the WF by a single turbine. Probabilistic clustering however models WF using 3 equivalent turbines (most probable Group, A from Table 1). It can be seen from Table 2 that detailed modelling significantly adds to the simulation time.

Model	Sim Time (s)	No. of WTs
Detailed WF	925	49
Single-Eq Turbine	18.9	1
Probabilistic Clustering	34.8	3
Cluster Representation	18.9	1

Table 3: WF modelling with incoming WS = 24m/s, WD = 0 deg. Using constant step size of 0.00075 sec

For both considered wind scenarios single-turbine equivalent is the fastest. At higher WS cluster representation groups all WTs into one equivalent WT so the simulation time is similar as in previous case. Probabilistic clustering, on the other hand, always represents the WF by 3 equivalent WTs, therefore, the time of simulation in the second case (24m/s) is the longest compared to two aggregation methods. At WS of 10m/s however, cluster representation results in 5 equivalent clusters and therefore the simulation time is longer than in case of probabilistic clustering which used 3. Number of equivalent WTs for cluster representation depends on the WS, WD and wake effects and therefore the simulation time can be different at different wind scenarios.

4.1 Dynamic Response Analysis

Results of transient simulations for two wind scenarios are illustrated in Figures 7, 8, 9 and 10. Wind farm represented by detailed model regains stability after fault clearance in both scenarios considered. (Peaks in real and reactive power responses observable at 2.2 sec are due to WF reconnection and then operation of crowbar protection to reconnect rotor-side converter.)

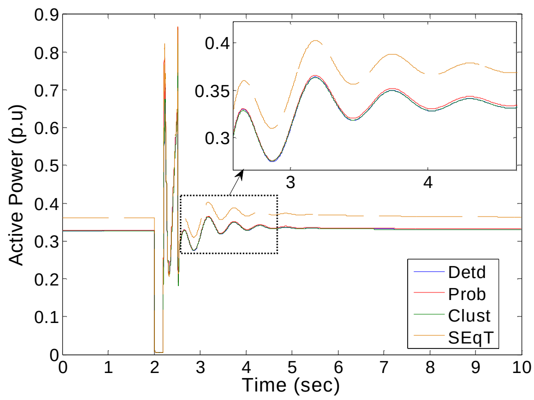

Figure 7: Active power response for all three aggregation methods and detailed model at WS=10m/s, WD=100deg

It can be seen that for lower WS (10m/s), single-equivalent turbine over-estimates the power produced and so the response is offset as compared to detailed model. Probabilistic clustering and Cluster representation model on the other hand accurately capture the WF response. For higher WS (24m/s) when turbines operate at rated power all aggregation methods model the response of the WF with sufficient accuracy. Number of equivalent WTs used in each case is given in Table 2 and 3. For all methods described in this analysis, the WS is considered to be constant during the time frame of the dynamic simulation.

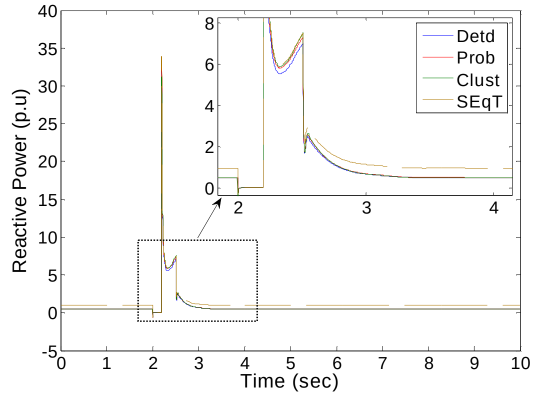

Figure 8: Reactive power response for all three aggregation methods and detailed model at WS=10m/s, WD=100deg

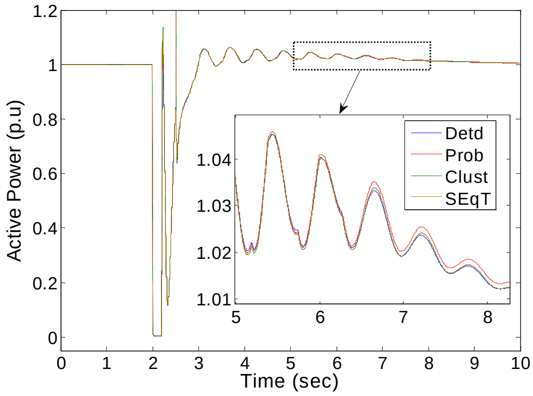

Figure 9: Active power response for all three aggregation methods and detailed model at WS=24m/s, WD=0deg

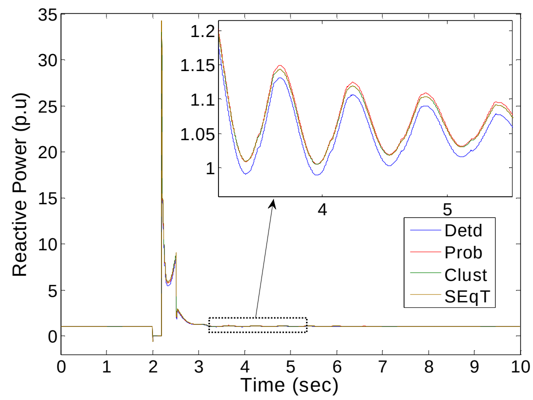

Figure 10: Reactive power response for all three aggregation methods and detailed model at WS=24m/s, WD=0deg

5 CONCLUSION

Reduction of WF models is required to reduce complexity of the overall model and the simulation time. Four aggregation methods are discussed in this paper, namely, Single-Unit equivalent, Cluster Representation, Compound Aggregation and Probabilistic Clustering. Three of these methods are tested and their results compared with detailed model of a 49 wind turbine WF. It is shown that a large WF can be represented by fewer equivalent turbines by all three aggregation models.

From the computation time point of view and reduction in model complexity it is obvious that the single-unit representation is the best. This method can be used during system stability studies when a fault is being simulated far away from the WF and a general response of the WF would be sufficient. It can however overestimate power flow into the grid for WSs below rated.

Compound aggregation can take long time to simulate (not illustrated in this paper) since the model of the mechanical part of the system does not get reduced. It is also harder to implement using commercial software packages as they typically provide limited user programming flexibility.

Cluster representation gives accurate results and it can be used for replicating dynamic behaviour of a WF for any incoming WS and WD. But, it can (depending on wind conditions) result in a higher number of equivalent turbines which may lead to longer simulation times and more complex aggregate model of the WF.

Probabilistic clustering gives sufficient level of accuracy at almost all wind conditions, but inherently it will work more efficiently for highly probable WSs and WDs. On the other hand, it does require initial off-line analysis of wind data to determine the most probable equivalent model of the WF. This analysis may be time consuming but subsequently leads to simple aggregate model and short simulation times.

Dynamic simulations with Probabilistic Clustering and Cluster Representation aggregate models showed good agreement with detailed WF model responses. These methods were found more accurate than Single Equivalent model and faster than Compound Aggregation. Both models can be used when replicating faults near the wind farm (such as at PCC) or for system stability studies. However, Probabilistic Clustering method is more practical as the same number of equivalent turbines (derived through probabilistic analysis) can be used during most of the time in the year reducing operator effort. In Cluster Representation, if either WS or WD changes the equivalent model becomes invalid and aggregate number of equivalent turbines would need to be recomputed, which means readjustment of several mechanical and electrical parameters every so often.

Based on the analysis performed it can be concluded that each method has its pros and cons. A trade-off exists between accuracy and computation time which makes the choice of aggregation model very user application specific.

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