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Fault Detection and Load Distribution for the Wind Farm Challenge ⋆

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Abstract: In this paper a fault detection system and a fault tolerant controller for a wind farm model is designed and tested. The wind farm model is taken from the wind farm challenge which is a public available challenge where a wind farm consisting of nine turbines is proposed. The goal of the challenge is to detect and handle different faults occurring in the individual turbines on farm level.
The fault detection system is designed such that it takes advantage of the fact that within a wind farm several of the turbines will be operating under similar conditions. To enable this the turbines are grouped into several groups of similar turbines, then the turbines within each group are used to generate residuals for the turbines in the group. The generated residuals are then evaluated using dynamical cumulative sum. The designed fault detection system is cable of detecting all three fault types occurring in the model. All the detections are not within the requirement of the challenge thus room for improvement.
To take advantage of the fault detection system a fault tolerant controller for the wind farm has been designed. The fault tolerant controller is a dispatch controller which is estimating the possible power at each individual turbine, using these estimates to set the reference to the turbines accordingly. The fault tolerant controller has been compared to the reference controller from the challenge. And the fault tolerant controller is better than the reference controller on all measures both under normal and faulty conditions.
Thus a fault detection system and a fault tolerant controller has been designed and combined. The fault tolerant control system has then been tested and compared to the reference system and shows improvement on all measures.

Keywords: Fault detection, Wind, Fault-tolerant systems, Parameter estimation, Modeling, Wind farm

1. INTRODUCTION

As wind turbines and wind farms becomes larger and larger, it becomes more important to keep the turbines running both seen from an economical perspective but also from a grid perspective. Seen from the grid it is important that wind farms follow the power reference to ensure the stability of the grid. The economical perspective is to make wind energy price competitive to fossil fuel energy. Operation and maintenance is contributing to 25–30% of the total cost of wind energy, Blanco (2009), Hassan et al. (2013), therefore methods for reducing the cost of operation and maintenance are needed in the wind industry. A way of reducing the cost is by making the maintenance more planned than now, where 80% of all maintenance performed is unplanned, Borchersen et al. (2012). Unplanned maintenance is both causing production losses but also affecting the grid since an unplanned break down of a turbine is affecting the production.

One way to improve the operation and maintenance is to reduce the load on a faulty turbines, and thereby allow them to run till the next planned maintenance for that turbine. This should be achieved without loosing track of the power reference demanded by the grid to ensure the stability even in case of faulty turbines. Thus if the faulty turbine is running in reduced production to minimize the loads, the other turbines in the wind farm should compensate for this by producing more.

To enable this, methods for detecting faults in wind turbines in wind farms are needed, and then to take advantage of such a detection system a new controller for the wind farm is needed which can distribute the loads among the other wind turbines in the wind farm. The fault detection and fault tolerant control for an individual turbine has been widely investigated, see Sloth et al. (2010), Wei et al. (2008), Blesa et al. (2011), Odgaard and Stoustrup (2012). Thus to come a step closer the

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fault tolerant wind farm a challenge has been proposed in Odgaard and Stoustrup (2013b). The wind farm model proposed in the challenge is used in this paper to detect and accommodate for individual faults at farm level.

The paper is structured such that the model is introduced in Section 2, then in Section 3 a fault detection system for the wind farm is designed and evaluated through Monte Carlo simulations. The output of the fault detection system is then feed into a load distributing dispatch controller which is presented in Section 4. The design of the load distribution for the controller is in Section 5. A final conclusion for the paper is drawn in Section 6

2. WIND FARM MODEL

The wind farm model used in this paper is the one proposed in Odgaard and Stoustrup (2013b). The layout of the proposed wind farm is shown in Fig. 1. In the model it is assumed that wind only can come from two directions, both of the directions are shown in Fig. 1. The wind farm model consists of nine 4.8MW turbines, for further details about the individual turbine see Odgaard et al. (2009). The model of the individual turbine has previously been used for the study of fault detection of an individual turbine, a summary of these results can be found in Odgaard and Stoustrup (2012). The numbering of the turbines are change in this paper compared to numbering used in the challenge. The turbines are numbered from one to nine, and when referring to the turbines it is done subindex t. In the figure the rows are numbered for the two wind cases such that it is easy to identify which turbine there are on the same row depending on then wind direction. Several of the modeling parameters are used from the challenge thus not rewritten in this paper.

The following three types of faults can occur to each of the individual turbines in the farm:

(1) Blade debris build-up
(2) Pitch offset due to misalignment
(3) Change in drive train damping

It should be noted that it is assumed that only one fault is present at any time. The following requirements for the fault detection system has been specified in Odgaard and Stoustrup (2013b); the detection time should be less than 3 seconds and the maximum of false positive pr 1000 seconds should be less than 1.

The sampling frequency of the model is 10 Hz both for the fault detection system and for the wind farm controller. A met mast is located in front of the wind farm, and the met mast is assumed to be in front of the farm in both wind cases. Thus a measurement of the wind speed from the met mast is also available for the fault detection system and the controller. The individually wind turbines have higher sampling frequency, but this is of no interest in this work since the focus is on the farm level.

3. FAULT DETECTION

The fault detection systems for the wind farm consists of several parts. The first part is an estimation of which of the two possible wind directions that are occurring. Then the wind speed is estimated for each turbine using the wind measurement from the met mast. Then depending on the wind direction and the wind speed, the turbines are grouped into groups of similar turbines. These groups are then used for performing the fault detection.

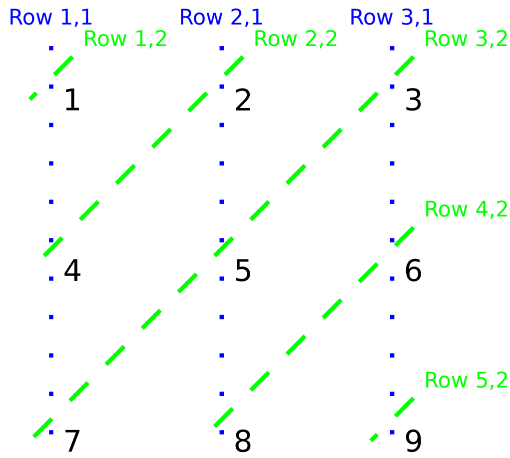

Fig. 1. The layout of the wind farm with the nine turbines and the different rows for the two wind cases.

3.1 Wind Direction Estimation

Since the wind only can come from two directions, the estimation of the wind direction is fairly simple. From Fig. 1 it is seen that in case 1 Turbine 1 and Turbine 4 should be affected by the same mean wind. Where in case 2 Turbine 1 is in the front row and Turbine 4 are in the second row thus a difference in power is expected.

The wind direction is therefore estimated by taking the first 500 samples, and then use those to compare the power production from the two turbines using (1). The wind direction is then found using the decision rule in (2)

$$p_{w_m} = \left| \frac{1}{500} \cdot \sum_{k=1}^{500} P_1[k] - P_4[k] \right| \tag{1}$$

$$w_{case} = \begin{cases} 1 \text{ if } p_{w_m} \leq 10 \cdot 10^3 \\ 2 \text{ if } p_{w_m} > 10 \cdot 10^3 \end{cases} \tag{2}$$

3.2 Wind Speed Estimation

When the wind direction has been found, the wind speed is estimated using variable time delays. The length of the delays are calculated by using the distance between the measuring point and the turbines, combined with the average wind speed found by the transfer function (3), both the distance and the transfer function has been specified in Odgaard and Stoustrup (2013b).

$$H(s) = \frac{1}{s+1} \tag{3}$$

The wind speed is then found for each row depending on the wind direction. The row wind speeds are then used as an estimate for the wind speed for the turbines in each row.

3.3 Fault 1 Blade Debris

Fault 1 is debris build up on the blades which causes the power production from the faulty turbine to decrease. To detect this an estimate of the power based on the rotor speed is used. The reason for using the rotor speed is that this is not affected by the debris on the blades. The power is estimated using (4), the residual is generated using (5).

$$P_{e_t}[k] = f_\omega^{-1}(\omega_{m_t}[k]) \tag{4}$$
$$P_{res_t}[k] = P_{m_t}[k] - P_{e_t}[k] \tag{5}$$

where $f_\omega(P)$ is the function describing the relationship between the power and generator speed, the function is a lookup table which can be found in the implementation of the model,Odgaard and Stoustrup (2013a). All the residuals are evaluated using CUSUM Basseville and Nikiforov (1993). The CUSUM is implemented such that they change dynamically according to the estimated power production since the fault is a 3% reduction of the power output for the faulty turbine.

$$g_{1_t}[k] = S_{1_t}[k] - \min_{1\leq j\leq k} S_{1_t}[j] \tag{6}$$

$$S_{1_t}[j] = \sum_{k=1}^{j} \frac{\mu_{1f1_t}[k] - \mu_{0f1}}{\sigma_{f1}^2} \cdot \left(P_{res_t}[k] - \frac{\mu_{0f1} + \mu_{1f1_t}[k]}{2}\right) \tag{7}$$

Table 1. CUSUM parameters Fault 1

μ_{0f1}	=	0
$\mu_{1f1_t}[k]$	=	$P_{e_t}[k] \cdot Amp_{f1}$
Amp_{f1}	=	0.027
σ_{f1}^2	=	3000

3.4 Fault 2 Pitch Offset

Fault 2 is pitch offset of 0.3 degree. To detect this fault the nearby turbines are used. This is done by comparing the turbines to other turbines standing in the same row. As show in Fig. 1 there are turbines in wind case 2 which do not share rows with any turbine. Therefore the fault will not be detected for these turbines. The fault detection is done by using the measurements from turbines in the same row as an estimated of the pitch angle for the other turbines in the row. The difference between the estimated pitch angle and the measured pitch angle is then used for generating a residual.

$$\beta_{res_t}[k] = \beta_t[k] - \beta_{comp_t}[k] \tag{8}$$

$\beta_{comp_t}[k]$ is found by taking the average of the turbines in the same row as turbine with pitch measurement $\beta_t[k]$. Thus $\beta_{comp_t}[k]$ change depending of the wind direction. If there are three turbines it is the average value of the two others turbine in the row, this is the applying for all turbines in case 1, for case 2 the turbines 1 and 9 do not share row with any turbines thus β_{comp_t} is not estimated for these turbines.

The residuals are evaluated using CUSUM, since the fault is a fixed offset the CUSUM parameters are fixed compared to those used for Fault 1. The CUSUM equations for detecting fault 2 are listed in (9) and (10) the parameters for the CUSUM are listed in Table 2.

$$g_{2_t}[k] = S_{2_t}[k] - \min_{1\leq j\leq k} S_{2_t}[j] \tag{9}$$

$$S_{2_t}[j] = \frac{\mu_{1f2} - \mu_{0f2}}{\sigma_{f2}^2} \cdot \sum_{k=1}^{j} \left(\beta_{res_t}[k] - \frac{\mu_{0f2} + \mu_{1f2}}{2}\right) \tag{10}$$

Table 2. CUSUM parameters for Fault 2

μ_{0f2}	=	0
μ_{1f2}	=	0.2
σ_{f2}^2	=	0.05

3.5 Fault 3 Drive Train Dynamics

Fault 3 is a change in the drive train dynamics which causes the turbine to have increase in vibrations and thereby the damage. Detection of change in the drive train dynamics is done by filtering out the 3P frequency content of the generator speed and then compare the turbines in the same row since they are under approximately the same condition. In the case of a turbine being alone in a row, the generator speed is compared to an estimated of the generator speed found using (11) and (12).

$$\omega_{gest_t}(t) = f_\omega\left(P_{cest_t}(t)\right)\left(1 + \frac{\gamma_\omega}{\omega_{g,max}} \cdot \sin\left(\sigma_p \cdot 2\pi \cdot t\right)\right) \tag{11}$$

$$\hat{P}_{ag_t}(s) = \frac{\tau_w\left(v_{est_t}\right)}{s + \alpha_w\left(v_{est_t}\right)} P_{a_t}(s) \tag{12}$$

$$P_{cest_t}(t) = P_{ag_t}(t) - \mathrm{pos}\left(P_{ag_t}(t) - P_{ref_t}(t)\right) \tag{13}$$

Where P_{a_t} is the aerodynamic power available at the turbine, $\hat{P}_{ag_t}(s)$ is the estimated dynamically available using the estimated wind speed v_{est_t}, $P_{cest_t}(t)$ is the estimated power. The residuals are generated using:

$$\omega_{res_t}[k] = \omega_t[k] - \omega_{comp_t}[k] \tag{14}$$

Where ω_{comp_t} is ω_{gest_t} if the turbine is not sharing row with any other turbine, but if there is other turbines in the row, ω_{comp_t} is the mean generator speed of the other turbines in the row. The residuals are evaluated using the CUSUM shown in (15) and (16).

$$g_{3_t}[k] = S_{3_t}[k] - \min_{1\leq j\leq k} S_{3_t}[j] \tag{15}$$

$$S_{3_t}[j] = \frac{\mu_{1f3} - \mu_{0f3}}{\sigma_{f3}^2} \cdot \sum_{k=1}^{j} \left(\omega_{res_t}[k] - \frac{\mu_{0f3} + \mu_{1f3}}{2}\right) \tag{16}$$

Table 3. CUSUM parameters for fault 3.

μ_{0f3}	=	0
μ_{1f3}	=	0.1
σ_{f3}^2	=	0.3

3.6 Decision Rules

Since all three faults are using CUSUM for detection of faults, the decision rules are following the same structure. The structure for the decision rules for all three faults is:

$$f_{id_t}[k] = \begin{cases} 1 \text{ if } g_{i_t}[k] \geq h_{1_{fi}} \\ 0 \text{ if } g_{i_t}[k] \leq h_{1_{fi}} \\ 0 \text{ if } \left| g_{i_t}[k] - \max_{1 \leq j \leq k} g_{i_t}[j] \right| \geq h_{0_{fi}} \\ \quad \wedge f_{id_t}[k-1] == 1 \end{cases} \tag{17}$$
$$\text{for } i \in \{1, 2, 3\}$$

Here the maximum, minimum, and the running sum are all reset when f_{id_t} changes from 1 to 0. The decision parameters for each of the three faults are listed in Table 4.

Table 4. Decision parameters.

$h_{1_{f1}}$	=	$0.25 \cdot 10^6$
$h_{0_{f1}}$	=	$0.1 \cdot 10^6$
$h_{1_{f2}}$	=	60
$h_{0_{f2}}$	=	0.1
$h_{1_{f3}}$	=	3
$h_{0_{f3}}$	=	0.5

3.7 Fault Detection Performance

To evaluated the performance of the fault detection system the output of the fault detection system has been combined using logical operations. The logic is designed such that only one fault can be detected at a time. Thus if Fault 1 has been detected in Turbine 2, that would be the only output of the fault detection system until Turbine 2 is seen as faulty free by the fault detection system.

The performance has been evaluated through 200 simulations, 100 for each wind case. In each simulation the three faults each occurred twice. The faults occurred at the same time instance in all simulations. Thus the only difference between each simulation is the seeds used for generating the model noise. The results from the 200 simulations are listed in Table 5.

Fault 1 is the only fault which is detected within the specified requirements. For Fault 2 there is small difference in detection time from the required 3 seconds, and the detection rate is only 50% for case 1 and 0% for case 2. Thus the fault detection system is not fulling the requirements. The reason for the fault detection system not fulling the requirements for fault 2, is to some extend caused by the fault being fixed of only 0.3 degree and when the wind turbine is operating in high wind speed this small change can not be detected by the proposed method without leading to a high number of false positive.

For Fault 3 the detection time is a bit higher than the specified but on the other hand all faults are detected and the detection of the fault is consistent for all wind speeds. From the figures in the table it should be noted that the performance of the FDI system is better for wind case 1 than for wind case 2. This is caused by the fact that the fault detection system is relying on the turbines to have nearby turbines that can be compared against. And in wind case 2 this is not the case for turbine 1 and turbine 9. Thus the fault detection system is not working properly for these two turbines in wind case 2. Which is why Fault 2 is not detected in wind case 2 since it occurs in turbine 1.

Table 5. The results for the fault detection system.

		Detect time	Missed	False positive
Case1	F1	0.795 [s]	0%	0.061 [pr 1000 s]
	F2	4.114 [s]	50%	3.464 [pr 1000 s]
	F3	6.752 [s]	0%	0.546 [pr 1000 s]
Case2	F1	0.775 [s]	0	1.746 [pr 1000 s]
	F2	NaN	100%	3.836 [pr 1000 s]
	F3	6.946 [s]	0	1.477 [pr 1000 s]

4. WIND FARM CONTROLLER

To take advantage of the previous designed fault detection system, the standard PI controller implemented in the challenge is exchanged with a load distributing dispatch controller.

The controller is design as a dispatch controller which first calculates the possible power for each turbine and then distributing the available power among the turbines. The individual power reference for turbine t is found by first estimating the power available at the turbine and then (18) is used to calculate the individual reference for each turbine, similar control strategy has been used and implemented in Grunnet et al. (2010).

$$P_{ref_t}[k] = \frac{P_{avail_t}[k]}{P_{avail_p}[k]} \cdot P_{ref_p}[k] \tag{18}$$

$$P_{avail_p}[k] = \sum_{t=1}^{N} P_{avail_t}[k] \tag{19}$$

where P_{avail_t}, P_{avail_p}, and P_{ref_t} is; the available power at the turbine, the available power for all turbines within the farm, and the power reference for the wind farm respectively. It should be noted that the dispatch controller is only active if the power reference for the farm is below the theoretical maximum production for the farm.

4.1 Power Estimation

The dispatch controller is depending on having a good estimate of the possible power for each turbine. Thus an estimate of the maximum available power for each turbine if found, the estimate is denoted P_{avail_t}. The estimate is based on the pitch angle and the power measurement coming from the turbine. The estimate of the available power is found by first estimating the wind speed from the pitch angle using (20). Then the available power is found using (21), this estimate is then corrected to fit to the actual power measurement from the turbine using (22).

$$w_{est_t}[k] = h^{-1}\left(\frac{P_{ref_t}[k]}{g^{-1}(\beta_t[k])}\right) \tag{20}$$

$$\hat{P}_{a_t}(s) = \frac{\tau_w(w_{est_t})}{s + \alpha_w(w_{est_t})} P_{a_t}(s) \tag{21}$$

$$P_{avail_t}[k] = \text{pos}(P_{a_t}[k] - P_{ref_t}[k]) + P_{m_t}[k] \tag{22}$$

4.2 Controller Performance

To evaluate the performance of the dispatch controller, the dispatch controller and the PI controller are compared

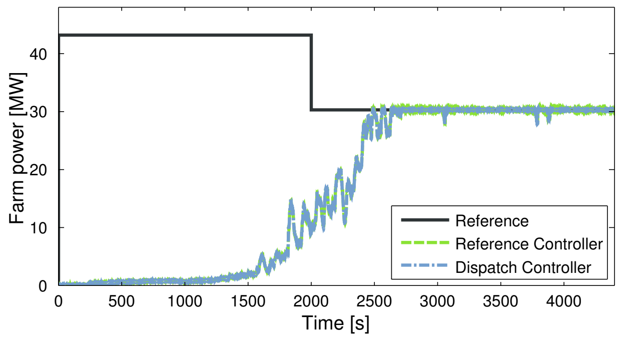

Fig. 2. The power output using the two different controllers.

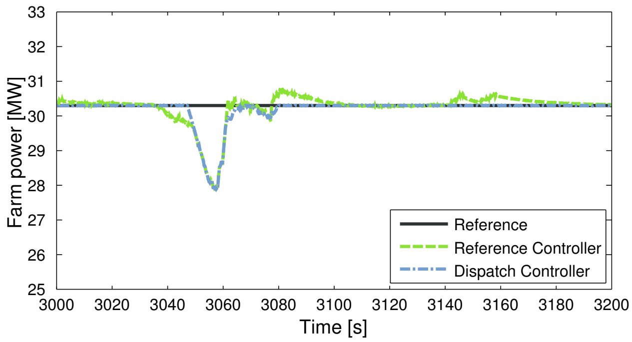

Fig. 3. Zoom of Fig. 2 to give a better view of the performance.

using the two wind cases without any faults. The output for wind case 1 is shown in Fig. 2 and Fig. 3.

The controllers are compared by looking at how much power they are missing compared to the power reference, and the amount of over production they generate, these figures are listed in Table 6. From the numbers it is seen that the dispatch controller is outperforming the PI controller on all measures. Thus the dispatch controller is used as a starting point for designing the fault tolerant wind farm controller.

Table 6. Controller performance of the dispatch controller compared to the reference controller (lower is better).

Test case		Over	Missing
Case 1	Ref	18.2	1.0003
	Dis	1	1
Case 2	Ref	24.93	1.00006
	Dis	1	1

5. FAULT ACCOMMODATION

The three faults can be divided into two groups regarding how accommodate for the fault. The first group consist of Fault 1 which cause a reduction in the power production from the turbine but without any increase in the damage. The second group consist of Fault 2 and Fault 3 since they both increases the damage when they occur. The effect of the different faults are defined in Odgaard and Stoustrup (2013b). Thus to handle these two groups of faults, two different strategies for fault accommodation are presented in this section.

5.1 Fault 1

In the case of Fault 1 it is simply the possible power and the power production which is reduced from the turbine thereby this must be taken into account when calculating the possible power of the faulty turbine. The accommodation is done by first down scaling the possible power from the turbine, since this number is used in the calculating of the reference in (23), and then the reference is increase afterwards such that the faulty turbine produces the specified by the controller, this is achieved by using (24). Since the amplitude of the fault is known it is fix in the accommodation, if the amplitude was unknown an estimator of the reduction should be designed which should also be fairly easy.

$$P_{availf1_t}[k] = P_{avail_t}[k] \cdot 0.97 \tag{23}$$

$$P_{reff1_t}[k] = P_{ref_t}[k] \cdot \frac{1}{0.97} \tag{24}$$

5.2 Fault 2 and Fault 3

In turbines where Fault 2 or Fault 3 are detect the power reference is lowered as mush as possible to reduce the damage in the faulty turbine. The reduction in power must not effect the overall power output of the park. Thus the power is only lower when the reduced power from the faulty turbine can be accommodated by other non faulty turbines within the farm. Therefor the power reduction is based on the extra amount of available power P_{over}, which can be found using (25). The available power for the faulty turbine is then lowered according to the amount of available power (26). It should be noted that a minimum reference for the power has been set to avoid having a turbine standing still, since this will set all outputs from the turbine to zero and thereby disable the fault detection, furthermore this behavior is assumed to be an unwanted. To find the new reference for the faulty turbine (18) is used, with the available power taking the fault into account.

$$P_{over}[k] = P_{avail_p}[k] - P_{ref_p}[k] \tag{25}$$

$$P_{availf_t}[k] = \max\left(\text{pos}\left(P_{avail_t}[k] - P_{over}[k]\right), P_{min}\right) \tag{26}$$

where $P_{min} = 50 \cdot 10^3[W]$.

5.3 Performance of the Fault Accommodation

To compare the effect of accommodating for the faults, the damage numbers with and without load distribution are listed in Table 7. From the table it seen that the damage numbers from Fault 3 are reduced in both cases. The damage caused by Fault 2 is not reduce, this is caused by the fault detection system is not detecting the fault in high wind speeds, which is required for reducing the loads.

The difference between accommodating for the faults and not, is clearly seen in Fig. 4. The detection time for the fault is seen in the beginning, but when the fault has been detected the accommodating is reducing the loads to all most the same level as the fault free case. The reason for the damage increase near the end of the fault period, is due to the over all wind speed for the wind farm is reduced. Which requires the faulty turbine to produce more power, to follow the power reference for the farm, which has the highest priority for the controller.

Table 7. Damage numbers with and without fault accommodation.

Test case		Damage 2	Damage 3
Case 1	No accommodation	inf	1.0201
	With accommodation	inf	1.0040
Case 2	No accommodation	inf	1.0190
	With accommodation	inf	1.0032

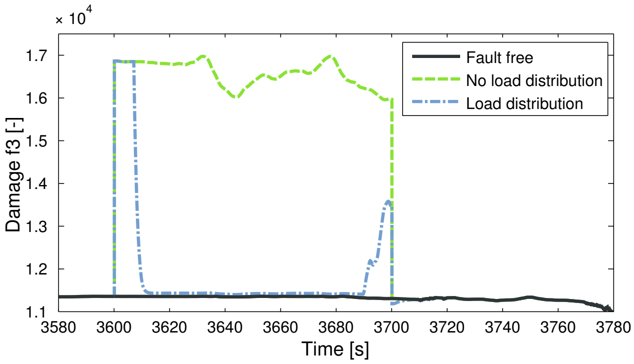

Fig. 4. Plot of how the damage number changes when Fault 3 occurs at 3600 [s]. The fault free case is also plotted to give a lower reference for the damage number.

6. CONCLUSION

In this paper a fault detection system for a wind farm has been designed and tested using the model purposed in the wind farm challenge. A load distributing controller has been designed and tested together with the fault detection system. The fault detection system is taking advantage of that turbines standing in the same row are under similar operation condition thus the other row turbines are used to generated residuals which are evaluated using CUSUM. The designed controller is a dispatch controller using an estimate of the available power for each turbine to calculate an individual reference for each turbine. The controller is accommodating for the faults by reducing the power reference for the faulty turbines, if the avaible power for the other turbines allows the power reference for the farm to be followed. This ensures that the wind farm will follow the power reference before accommodating any faults.

From the simulations it is seen that the performance of the wind farm has increased even with the load distributing controller compared to the reference controller, this is both the case where the wind farm is subject to faults and in the case of normal operation. This is achieved even though the fault detection system is not fulfilling the requirements regarding detection time for all three faults. The proposed fault detection system still has room for improvements, but it shows that several faults can be detected at wind farm level using nearby turbines as the reference. Furthermore it is shown that by connecting a fault detection system to a fault accommodating dispatch controller the load of the faulty wind turbines can be reduced without losing track of the power reference for the wind farm.

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