

# Case Study: Vibration trip and post-event Analysis with Auto-Associative Neural Networks on a Large Steam Turbine.

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## ABSTRACT

This 300 MW steam turbine at a coal-based thermal power plant is equipped with a protection system, a condition monitoring analysis software and an automatic diagnostic tool. The Machine Protection System (MPS) and Condition Monitoring System (CMS) configuration combines sensors, electronic hardware, firmware and software specific to this application. The protection system initiated a trip having identified high vibration. The trip prevented further damage. Subsequent analysis of the data using the condition monitoring software established the bearings most affected and pin pointed the source of high vibration. The data is post processed using an Auto-Associative Neural Networks (AANN) that has been trained with healthy data recorded several hours prior to the trip. AANN are methodologies widely used for novelty and anomaly detection. The AANN results indicates that such approach would be capable of detecting the failure event in advance compared to the automatic diagnostic system based on rules, demonstrating the validity of the approach in this context. Various aspects related to vibration: protection, condition monitoring, analysis, automatic diagnostics using rules and Neural Networks are presented and their results discussed.

## 1. INTRODUCTION

This coal-fired power plant (Figure 1) located in India, has two 300 MW units, each unit is based on a steam turbine-generator (STG) equipped with 7 bearings and running at 3000 RPM (Figure 2).



Figure 1. Coal-fired power plant with 2 x 300 MW STG.

On 31<sup>st</sup> March 2012 at 17h00, while near full load, Unit 1 tripped on high vibrations. The analysis revealed a severe mechanical fault involving blade loss in the low pressure turbine.

The plant is equipped with a Meggitt VM600, with:

- Protection system that was tuned to react to any event within a 3 seconds delay. This system is composed of absolute and relative vibration sensors and electronics, and monitors.
- Condition Monitoring system, using the same VM600 system infrastructure (sensors, cabling, racks, power supplies, etc) but using different signal processing approach and settings
- An expert system based on rules, for which standard rules had been written and then were executed regularly in real time.

In the post-analysis stage, we replayed also the data through an automatic detection application using neural networks algorithms. The results of these various methods are discussed. The system succeeded to protect this large and valuable facility against further damages and permitted analyzing the information recorded in the CMS to

understand the mechanical situation enough to drive the mechanical inspection of the machine and discover the cause of the trip. But not all tools provided the results in line with our expectations, so we will eventually come with conclusions on what to use, and how, amongst these different concepts and tools along the decision chain. How to configure parameters in details to get valuable information out of the vibration signals on similar machines, for that goal, is also shown.

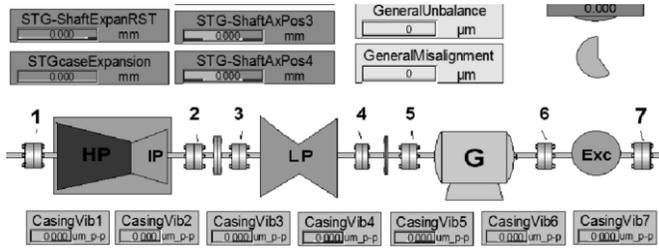


Figure 2. Main Steam Turbine Generator with arrangements of HP, IP, LP turbine bodies and bearings (extract from an on-line mimic).

## 2. MACHINE PROTECTION

### 2.1. General arrangement

As suggested by the asset assessment process, the main Steam turbine-generator is the first, indeed critical machine monitored and protected in this plant, amongst other “not-so-critical” machineries involved (Table 1) mostly in cooling the rest of the plant, also referred to as “Balance of Plant” machines. All other functions are achieved by 2 or 3 redundant units.

Table 1. Machines whose vibrations are monitored, and protect installations (total numbers for 2 units).

Tag	N°	Description
FWP	3+3	Boiler Feed Water Pump
CoWD	3+3	Condensate Water Pumps
CWP	3+2	Circulating Water Pumps
ACWP	2+2	Auxiliary Cooling Water Pump
DMCWP	2+2	De-Mineralised water Cooling Pump
AC	4	Air Compressor
TAC	3	Transport Air Compressor
CC	2	Coal Crusher
AWSP	2	Ash Water Slurry Pump

For this turbine, other sensors are for:

- Speed, 1/REV signal required for synchronization between all channels, and phase reference.
- Expansion measurements
- Axial displacement at the thrust
- Rotor eccentricity

The protection on vibration generated a trip signal, sent to the Distributed Control System (DCS) through a relay. This was followed by a controlled load drop in the steam turbine, then a normal stop of the machine. This procedure avoids an over-speed transition phase that is usually the case for an emergency stop, but also cumulates additional damages to the shaft.

After the trip event, it was clear that all bearings were affected. At this point there had been a doubt whether the measurement system could be incriminated, by an electrical short-circuit, or by a general failure of a protection system. However this was not possible because of the general fundamental architecture of the system installed.

In this system the protection function is insured locally and independently in each of the modules inserted in the system rack, so the event could not come suddenly at the same time from independent sources for not a good reason. If power supply were lost, then there is a logic by which a Normally Energized relay opens, therefore showing the system as “not operational”, as with a “watchdog”. But this was not the scenario for this trip.

As the system had shown a good reliability and no false trip event in the previous 3~4 years of operation, the trip event was considered seriously and probably originating from a mechanical origin.

So, after all it is a success at this stage for the Machine Protection System (MPS), considering that the system was able to decide to stop automatically the machine within a 3 seconds decision loop, while it was running several years already without false trips.

### 2.2. Configuration setup

These are some of the parameters (Figure 3), configured in the system, which were used, therefore recommended for this type of large Steam Turbine protection (extracted from the Configuration Summary).

Interesting parameters involved are: the filter allows up to 1500 Hz, this as per §5.2.3 in (ISO-comitee, ISO 10817-1, 1998). The delay is 3 seconds. All decision are routed to 2 redundant relays, and the trip signal, at 254 micrometers Peak-to-Peak is validated by the [ok] of each channel. The threshold is a little bit higher than in (ISO-comitee, ISO 10817-1, 1998). This achieves both a good reactivity in case of a real trip event, as well as rejection of false events due to, for example, a failure at the sensor or at its connection to the system.

At some bearings, critical speeds generated trip during run-ups. Adaptive monitoring (Figure 4) is used, then to allow passing, indeed rapidly, these critical speeds to reach nominal speed. This is an improvement to the “Trip Multiply” method, for which the multiplier on the threshold is unique across all speed layers. This “Adaptive Monitoring” is one of the features participating to improve the accuracy of the protection. The adaptive does not affect the protection at normal operation at 3000 RPM.

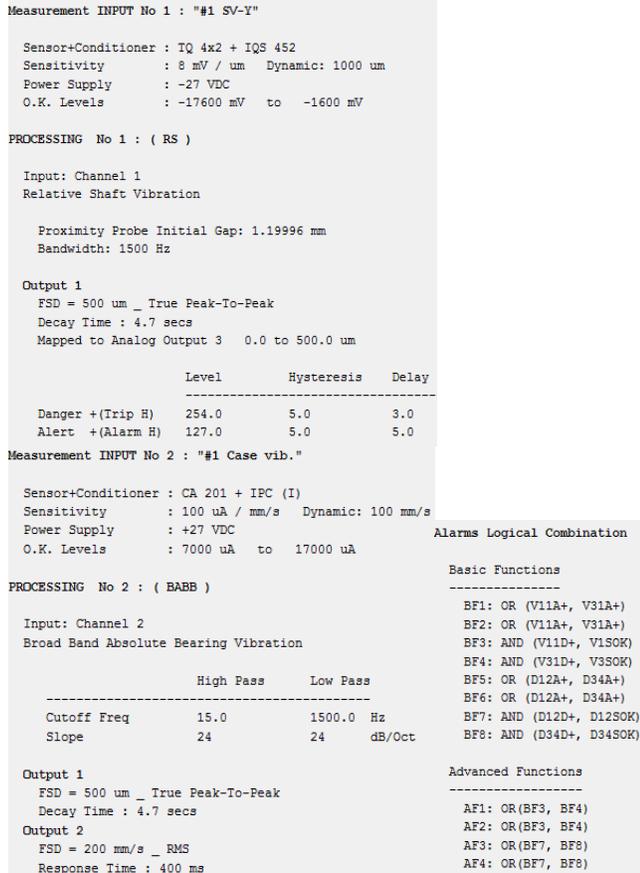


Figure 3. Vibration configuration for protection: Relative shaft channel (left), Absolute bearing channel (middle) and logical combination for the trip logic sent to relays.

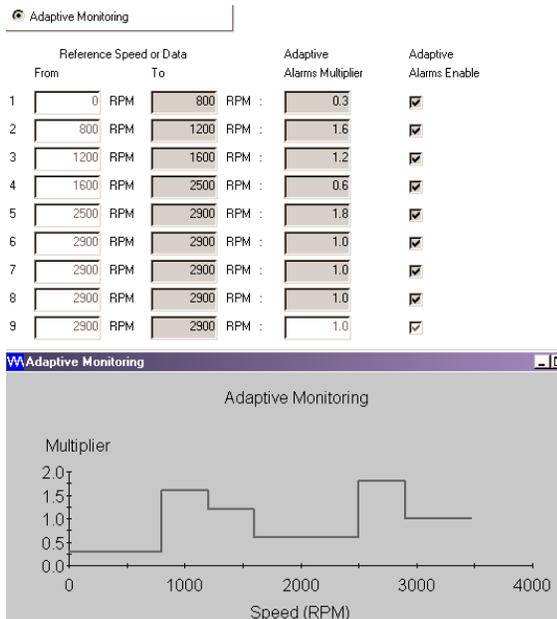


Figure 4. Example of adaptive monitoring configuration for critical speeds (shaft resonances) allowances, applied to the the threshold.

### 3. TRIP EVENT

#### 3.1. As recorded in the DCS

The Distributed Control System (DCS) of the plant recorded the absolute shaft vibrations, which were sent by Modbus from the Machine Protection System (MPS). We have no change before the trip (Figure 5) and all levels increased suddenly within less than 10 seconds, while several of them jumped to 500 microns corresponding to the maximum range (Figure 7 and 11).

The background level before the trip is approx. 25  $\mu\text{m}_{\text{Pk-Pk}}$  on an average, and always less than 50  $\mu\text{m}_{\text{Pk-Pk}}$ . The vibration levels jumped suddenly by a factor of 10, at least.

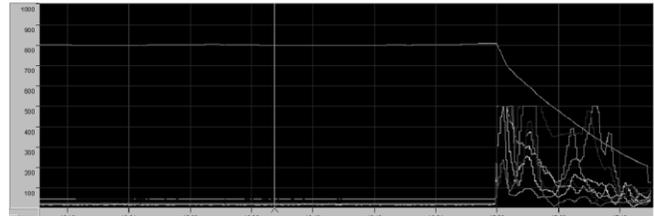


Figure 5. Vibration Trip, as recorded in the DCS during one hour before machine stop at 17 h00.

Other parameters were affected: in particular bearing temperature rose on bearing 4 (Figure 6), but the maximum was reached only 9 minutes after the trip.

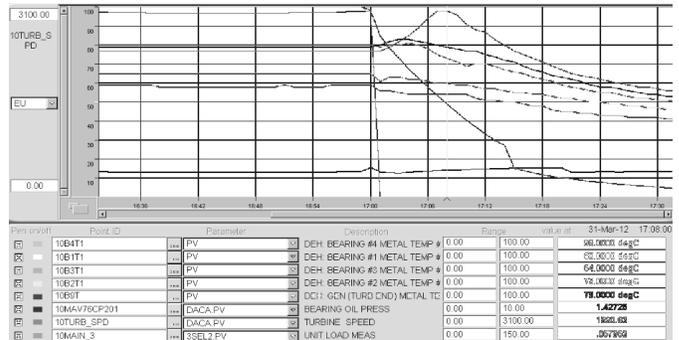


Figure 6. Other parameters during the trip. The maximum temperature is on bearing 4 and 9 minutes after the trip.

Had the protection been triggered by temperature alone, the late response due to temperature diffusion to the probe would have delayed the decision by several minutes in this case. This would have caused to more damage to the machine meantime. We also checked that oil pressure was in normal range before and after the trip ensuring proper lubrication at all times.

But not all bearings were involved in the incipient change. We observed that bearing 4, then 3, surrounding the LP turbine, responded first to the incident. This confirmed the "First-out-Event" in the Protection System.

We could confirm this, after looking at the vibration data recorded in the CMS. Our recommendation then followed: to open LP turbine body on the side of bearing 4.

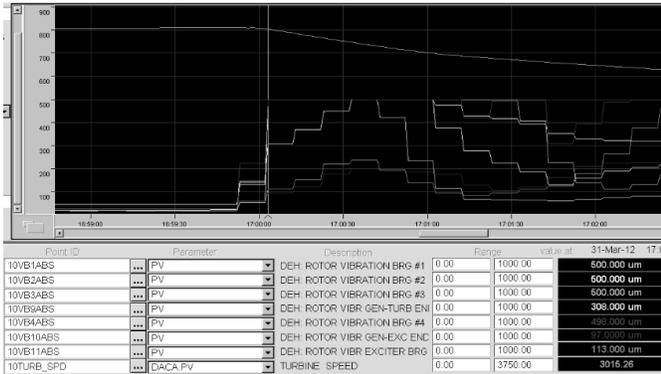


Figure 7. Incipient change of vibration levels: bearing 4 increases the most and the fastest in the first 10 seconds before reaching maximum level. The cursor is on the event.

### 3.2. As recorded in the Condition Monitoring System

The CMS ran independently on a separate PC and a reference clock was not available for its synchronization. As a result there was 2 minutes drift difference between systems. The event list (Figure 8) shows that the events occurred first on bearing 4.

Event Name	Date/Time	Station Name	Machine Name	Point Name	Output Name
High Alert	31.03.12 17:08:38	MainT/G#1	Steam Turbine	STG-SV-X3	1X
DB Log file has b...	31.03.12 17:01:24				
High Alert	31.03.12 16:58:19	MainT/G#1	Steam Turbine	STG-SV-Y6	1X
Normal Event	31.03.12 16:58:19	MainT/G#1	Steam Turbine	STG-SV-X7	Hi
Normal Event	31.03.12 16:58:04	MainT/G#1	Steam Turbine	STG-SV-Y6	1X
Normal Event	31.03.12 16:58:02	MainT/G#1	Steam Turbine	STG-SV-Y1	Hi
High Alarm	31.03.12 16:58:01	MainT/G#1	Steam Turbine	STG-SV-Y1	1X
Normal Event	31.03.12 16:58:01	MainT/G#1	Steam Turbine	STG-SV-Y7	Hi
Normal Event	31.03.12 16:58:01	MainT/G#1	Steam Turbine	STG-SV-Y6	Hi
High Alarm	31.03.12 16:58:00	MainT/G#1	Steam Turbine	STG-SV-X1	1X
High Alert	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y7	1X
High Alert	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X5	1X
High Alert	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X1	1X
High Alert	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y6	1X
High Alert	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y1	1X
High Alarm	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X5	1X
High Alarm	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X4	1X
High Alarm	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X3	1X
High Alarm	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X2	1X
High Alarm	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y2	1X
High Alarm	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y3	1X
High Alarm	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y5	1X
High Alarm	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y4	1X
Normal Event	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X6	1X
Normal Event	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X5	Hi
Normal Event	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X4	Hi
Normal Event	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X2	Hi
Normal Event	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-X1	Hi
Normal Event	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y2	Hi
Normal Event	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y5	Hi
Normal Event	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y4	Hi
Normal Event	31.03.12 16:57:59	MainT/G#1	Steam Turbine	STG-SV-Y4	0.5X

Figure 8. Event list in the CMS, by their order of arrival even though the time only shows the second resolution.

The sequence of events shows how the fault developed and, more importantly, that almost all probes (relative vibrations) were going directly from “normal” (green) to “Alarm” (red), having no time even to be in “Alert” (yellow) status in between. The band 1X (extraction of the signal at the

frequency of the rotation) is always involved. The change was so quick that the resolution in time was not enough to pick up the fast increasing slope on the level; due to cutting the signal in FFT blocks before processing. This is not the case for the protection system, which uses fast and reactive digital filtering techniques instead of the slower FFT technique (Fromageat, 2000).

There was no sign in the trends, whatsoever, that could indicate the failure before it occurred. This is well known in literature (McCloskey, 2002) that a sudden blade failure can well happen without any preliminary change on vibration parameters. Within 2 years of operation, the machine showed same vibration behavior with thermal transients after run-ups, and some fluctuations with load and daily temperature changes (Figure 9).

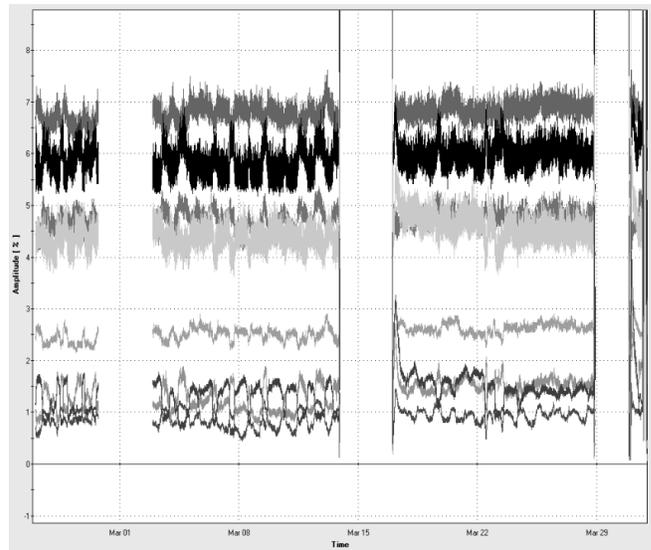


Figure 9. Vibration trends observed one month before the event, on bearings x extraction {3,4}x{Overall,(1X)}. Normal fluctuations are due to daily load and temperature changes.

All vibration bands and gap show the same flat curve a few hours before the trip. From Figure 10 it is possible to observe that after the trip none of the sensors give less vibration than the maximum observed before.

At the time of the event, some “pre-trip” data was stored every second in a CMS buffer. This was analyzed together with all the transient trends of all bands and Polar plots (example Figure 11).

The response is much bigger (over 500 μm\_pk-pk), compared to previous transients, and this strong (1X) means “unbalance” as per general diagnostic rules.

Polar, Bode, Cascade for all bearings and directions were plotted. They are not all presented here. On bearing 3 and 4, the rundown signature is way-off the normal behavior of the shaft.

Concerning the spectral signatures during rundown, as soon saturations occur the integrity of the data is lost. Signal

Saturations are distortions which prevent spectra to represent the signals accurately.

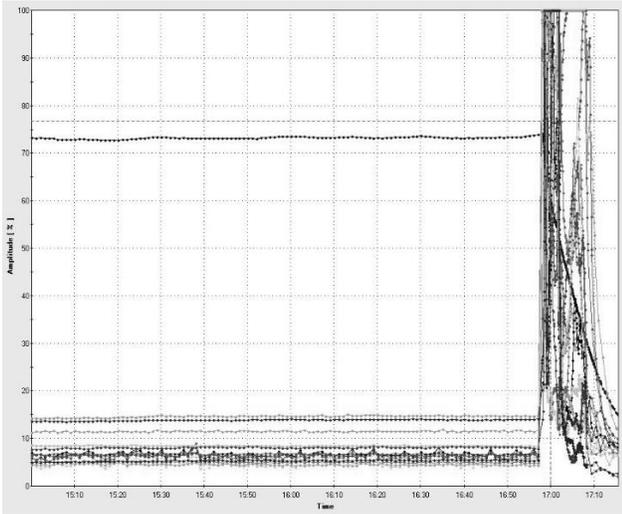


Figure 10. Vibration trends 2 hours before the failure.

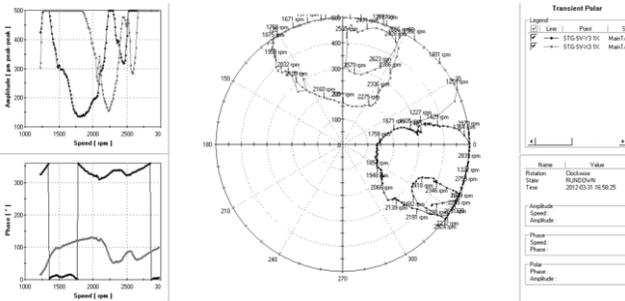


Figure 11. Example of Polar plot on bearing 3.

But, we can still make use of the signal that were not saturated. This is the case for bearing 6 signals, even just after the trip. Bearing 6 is located on the other side of the generator. In this signature there is a strange subtle change that had never been seen before on this machine. It consists of additional  $1/3$ ,  $2/3$ ,  $1+1/3$ ,  $1+2/3$ , etc. signatures in the spectra (Figure 12) and can be seen almost on all bearings just after the event.

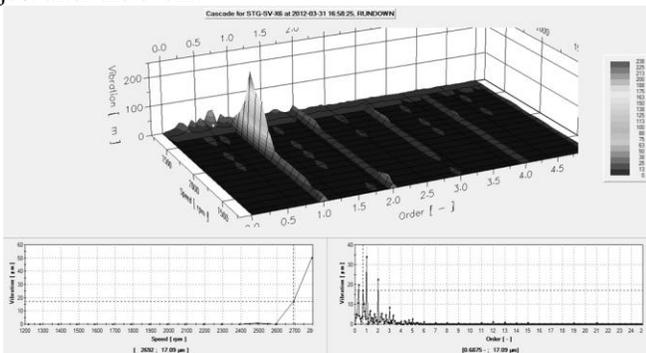


Figure 12. Valid cascade plot on a non-saturating sensor. Strange inter-harmonics can be seen in the early stage of the rundown (details are on the spectrum, left-bottom).

In this early stage, the sub-harmonics represent a large part of the signal, as shown in Figure 13. They mostly consist in this  $1/3$  harmonic and multiples.

We think these inter-harmonics, both sub- and higher -harmonics signatures, at fractional ratio of harmonics, can be related to a well known effect due to “Erratic loose parts” in rotating machines. This type of signature is known to be due to non-linear, chaotic movements of lost parts inside a rotor, rotating within a certain specific range of speed, which depends on the weight of the part.

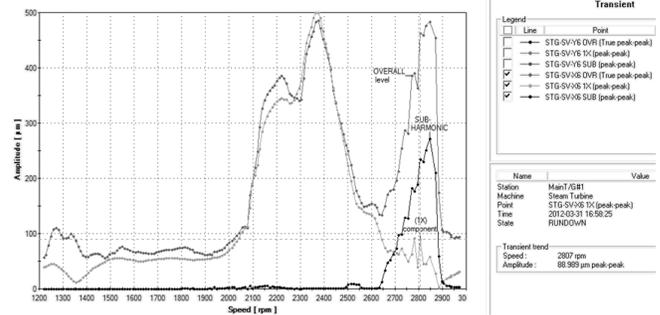


Figure 13. Transient (rundown) trend of the bands: Overall, 1X, and sub-synchronous. Between 2900 and 2700 RPM, the SUB harmonics is abnormally high.

This leads to quasi-periodic behavior, with a certain degree of randomly controlled movement (resulting in following a fractal-shaped trajectory in space).

### 3.3. Machine Damage

When opening the machine, 2 blades were discovered inside the LP body. Eventually a total of 4 blades were detached from the rotor (Figure 14).



Figure 14. Rests of blades found in LP turbine after the trip.

The rotor showed the 4 missing slots on disk #5, out of the 7 disks. Most blades have been de-rooted from the shaft (Figure 15), shrouds being gone.

There is almost a periodicity of 6 in the blade loss. This is because, on this side, blades are attached by groups of 6 to the same shroud. Also 2 fixed blades were off in the stage between 5 and 6. We believe these were a consequence of rotating blades loss, because they could have been hit by the “flying” blades, downstream the steam path afterwards.

Whatever be the reason of the de-rooting of blades (McCloskey, 2002) whether before or after the de-shrouding, we can estimate the consequence on vibration.



Figure 15. Rotor showing missing shrouds and 4 blades off, at positions: 7, 13, 19, 38 on stage 5 that has a total of 124 blades. On this side, 2 blades had been de-rooted.

Let us calculate the consequence on the unbalance, in the approximation of a rigid rotor. More information, are in (nPower-RWE, 2007)

The weight of a blade is:  $w = 1.045 \text{ Kg}$  and the radius to consider corresponds to its center of gravity, that is: distance between the root and the rotor axis, plus half a blade length:

$$R = R_{\text{root}} + \frac{1}{2}BL \quad (1)$$

$$R = 0.91 + 0.42/2 \text{ (m)} \quad (2)$$

Assuming a rotor weight  $W = 29441 \text{ Kg}$ , of which half of it is supported by this bearing, the order of magnitude of the specific unbalance is then, for one blade:

$$Ub = (w.R) / W \approx 80 \text{ g.mm/Kg} (=80.10^{-6}\text{m}^{-1}) \quad (3)$$

The total specific unbalance of the 4 blades is the vector composition of the individual unbalances at their respective angle.

$$Ub_{\text{total}} \approx 230 \text{ g.mm/Kg} \quad (4)$$

With the simplification of a rigid rotor, the conclusion is: one blade is enough to raise the vibration level to  $160 \mu\text{m}$  (peak-to-peak) minimum on the (1X) component; but with 4 blades, the  $500 \mu\text{m}$  (peak-to-peak) limit is reached on the closest bearing. And this does not even include yet the weight of gone off shrouds in the calculation. The threshold  $254 \mu\text{m}_{\text{Pk-Pk}}$  (as configured in Figure 3) is reached at least for two de-rooted blades. The conclusion would not be significantly different considering a flexible rotor, which it actually is, at 3000 RPM.

The hypothesis for this scenario would have been as follows:

- one blade detached from its shroud, or the reverse, and this caused the blade to be de-rooted from the shaft,
- large unbalance generated by this event then created vibrations that triggered other blades to detach very quickly, causing yet other vibration increases up to more than the maximum at  $500 \mu\text{m}$  Peak-to-Peak, and obviously to the threshold at  $254 \mu\text{m}$  Peak-to-Peak,
- The lost blades or shrouds “flew” into the turbine body, and generated erratic vibrations at fractional ratios of  $1/3X$ ,  $2/3X$ , etc. for a while before being blocked somewhere in the LP turbine shell.
- Due to the protection, no part reached the condenser.

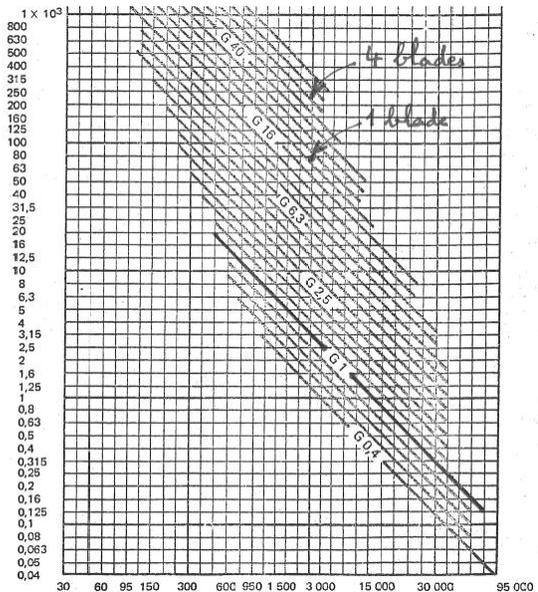


Figure 16. Static Unbalance calculation with removal of 1 blade, then 4 blades, on x-axis: speed in RPM (on graphic from ISO 1940-1)

In terms of balancing standards, the initial turbine could be specified G2.5, was actually G6.3, and the loss of 4 blades moves it to G63, which is a considerable value of unbalance to consider at this nominal speed (3000 RPM).

**4. AUTOMATIC DIAGNOSTIC METHODS**

The further question is how to, not only protect the machine (like it was achieved), but also provide automatic diagnostics, and possibly a prognostic indication of the event. However, at this stage, a blade loss is known to be more or less impossible to predict. Nonetheless, providing an automatic diagnostic tool with the CMS was required for this facility for other types of defects. It was required because the site is remote. Availability of experts is scarce there and travelling to the site is long and costly.

**4.1. Rule-based expert system**

The CMS provided was completed by an expert system running a set of rules to detect 6 types of defects. A summary is provided in Table 2. For each defect, and after a check on the machine condition, there are 2 successive criteria applied:

First is an “Existence” criteria, by which the presence of a typical signature in the spectra is not in error and of sufficient significance.

Second is a “Dominance” criteria, by which the component in the spectra, by combination, or association with others, is recognized as being the “highlight” of what is happening, in real time.

Table 2. Defects detected by the Diagnostic Rule Box.

Fault	Criteria	Bands ratio	Tunable parameter	Qualifier
Unbalance	Level	1X>Alert	Alert	
	Dominance	1X/OVR	93%	Probable
Misalignment	Level	2Xor3X >Alert	Alert	
	Dominance	(2X + 3X) /1X	100%	Probable
Bearing stiffness	ratio	"abs"/OVR	< 33 %	
	Meaning:	AbsCasing /RelShaft	> 66%	Probability
Oil Whirl	Existence	SUB	> 10 um	
	Dominance	SUB/OVR	55%	
	Dominance	0,5X/SUB	80%	Probability
Steam Instability	Existence	SUB	> 10 um	
	Dominance	SUB/OVR	55%	Possibility
	Dominance	0,5X/SUB	< 80%	-
Rub	Existence	HI	> 10 um	
	Dominance	HI/OVR	30%	Possibility

The object under scrutiny are “ratios” being just a particular band or a combination (that can be a ratio) of them. The tunable parameter is the threshold beyond which the rule is considered as true. A qualifier aims then at indicating the quality of the decision that is being made.

The “Probable” is almost sure, and “Probability” is stronger than a “Possibility”. Using other parameters than vibrations can alter the qualifier. For example, higher metal temperature on a bearing would raise a misalignment defect from “Possibility” to “Probability” in this “kind-of” ranking method. An example of rule is shown graphically below in Figure 17. This rule combines the SUB, 1/2X, 1X bands of both sensors X and Y in the intent to detect:

- fluid dynamic instability of steam, whose signature is a strong sub-synchronous, but rarely restricted to 0.5X only,
- oil whirl in the journal bearing, indeed a quite different defect, always located between 0.43X and 0.48X, so that all its energy, using the FFT configured resolution, is located in the 0.5X band.

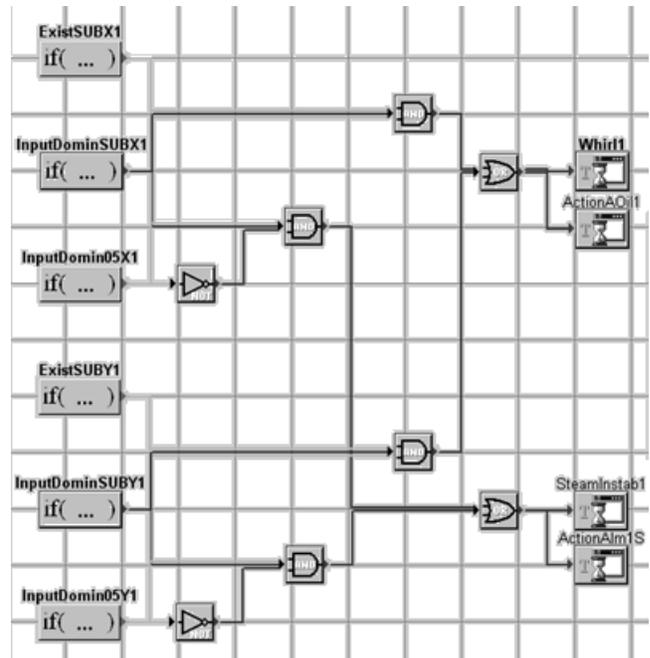


Figure 17. Example of rule for Oil-whirl and Steam instability with tests (at left), operations (in middle) and actions (at right).

Together with the rules, the quadratic sum of the vibration at 1X is computed in real time, in the same way as the computation of the residual unbalance index. Similarly, an index of residual misalignment is computed by the quadratic sum of harmonics 2X and 3X assuming that misalignment depends on these harmonics. This is a novelty and is called “General misalignment index”. Only experience will tell

whether this indicator would give valuable information in future.

Maintenance operators will display both indexes (as in Figure 2), trend them against time, and provide feedback.

In this machine, we had an exception to the rules concerning the “Bearing stiffness” defect. This is because the absolute bearing vibration is affected by the transmission path through the pedestal between bearing 5 and bearing 6 (across the generator). We then had to alter the rule by including a certain amount (45%) of bearing 5 vibration in the rule for bearing 6, and the same for bearing 5 from bearing 6 location. We had included this in the calculation, instead of an “independent” per bearing calculation:

$$\frac{AbsVib(brg5) - 0.45AbsVib(brg6)}{RelativeVib(brg5)} \quad (5)$$

for bearing 5, and:

$$\frac{AbsVib(brg6) - 0.45AbsVib(brg5)}{RelativeVib(brg6)} \quad (6)$$

for bearing 6.

Eventually on this machine with 7 bearings and 6 rules each; only 42 rules give an idea of main vibration features, if not a precise diagnostic which is, after all, impossible to give with just an expert system without the vector information on synchronous harmonics, and without built-in additional knowledge specific to each particular machine.

These rules are generic, quite basic, and not sophisticated, but are robust and prove to give good results in most cases. However, they cannot detect subtle changes in the vibration behavior, like we will see with other methods (§ 4.2). This type of expert system is installed on 11 large Steam Turbines totaling 2.4 GigaWatt installed capacity in India. Unfortunately, the automatic rule-based expert system was tuned, in this plant, for preventive detection/classification, but not for sudden events diagnostics. To that goal, it executed the rules (including also the calculations):

- Only when speed is close to the nominal, in the interval [2800 .. 3200 RPM],
- Every 15 seconds under this condition.

The rules did not give any message in this context, despite the importance of the event. It would have been a “good luck” if the rule ran just during the event was occurring. The probability of this to happen depends on the 3 seconds event duration over 15 seconds between the rules: the probability was then: 1/5.

The rule-box ran last time a few second before the event. The next run 15 seconds later would have happened only while the machine speed already dropped below 2800 RPM. Had it run, it would have probably detected unbalance all over the places, and potentially also a “Steam instability” which it wasn’t, but only a strong sub-synchronous signature just after the trip (due to the 1/3 harmonics and multiples). The expert system missed the event then.

As a conclusion, an expert system based on a set of rules provides valuable diagnostics, but in this example, it failed to provide information:

- beforehand, as a predictive tool, because not fine-tuned enough to detect subtle changes,
- during the trip when this was precisely useful, because not executed often enough,
- after the trip because it did not consider interharmonics during rundown.

#### 4.2. AANN Post-processing

Auto-Associative Neural Networks (AANN), also known as Replicator Neural Networks or Auto-encoders, are families of Neural Networks which are trained to reproduce their input at the output (Kramer, 1992).

At first sight, this replication task could seem trivial; however, the network structure has a “bottleneck” as the hidden layer has fewer neurons than the input and output layers as it can be observed in Figure 18.

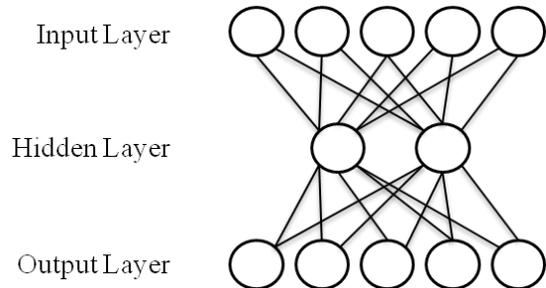


Figure 18. A simple Auto-Associative Neural Network.

This means that within the hidden layer(s) a compression process of the input data takes place. This forces the network to learn the significant features of the input data. Once trained with healthy data, the AANN is capable to replicate unseen nominal data with good accuracy. However faulty data are expected to possess information content which is structured differently from the healthy ones and that cannot be efficiently compressed in the hidden layers. As a consequence the reconstruction result will be inaccurate.

Once a new sample is processed by the AANN, the measure of the difference between output and input, the Reconstruction Error (RE) is computed as:

$$RE(X) = \|X-Out_X\| \quad (7)$$

where  $X$  is the input vector  $Out_X$  is the output of the AANN and  $\|$  symbol stands for any p- norm.

The RE measures how accurately a new sample can be replicated by the network. A small RE indicates that there is no new information content in the data under test, hence no novelty or anomalies are present. A thresholding logic can then be applied to establish if the data belongs to the same class used during training which is, usually the healthy class.

The threshold value can be determined using the information contained in the statistical distribution of the RE computed over the training set (for instance average and standard deviation).

In recent times, AANN methodology has been increasingly proposed for machine condition monitoring purposes (Worden, 1997) (Sanz, Perera, & Huerta, 2007) (Chandola, Banerjee, & Kumar, 2009) (Lu, C., Hsu, & Zhang, 2000).

As a consequence after the trip event it has been decided to analyze the data recorded approximately ten hours before the incident with AANN to understand if such methodology could have been helpful to detect symptoms in advance with respect to our traditional strategy.

Therefore an AANN has been trained using data recorded the day before the incident. Network input is represented by 12 features computed on vibration data acquired by accelerometers on bearings 3, 4 and 5.

The AANN is a single hidden layer network with 12x4x12 topology; the training set size is 880 samples.

Once training has been completed data acquired during the last ten hours before the incident has been processed by the network. For each sample the reconstruction error using  $L^2$  norm has been computed. The results, plotted in linear and log10 scale, are shown in Figure 20

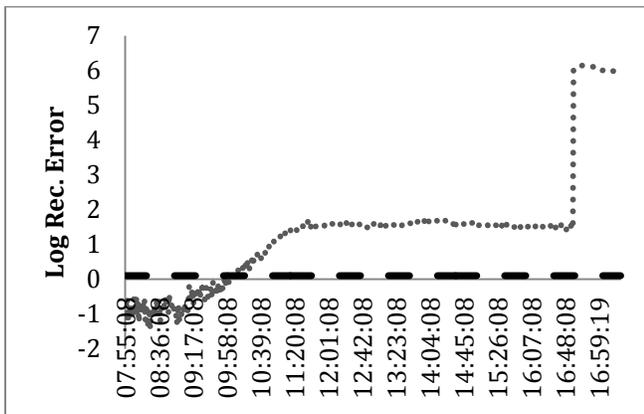


Figure 19. Reconstruction error in Log10 scale. Dashed line represents the threshold level, dotted line the Log10 of RE.

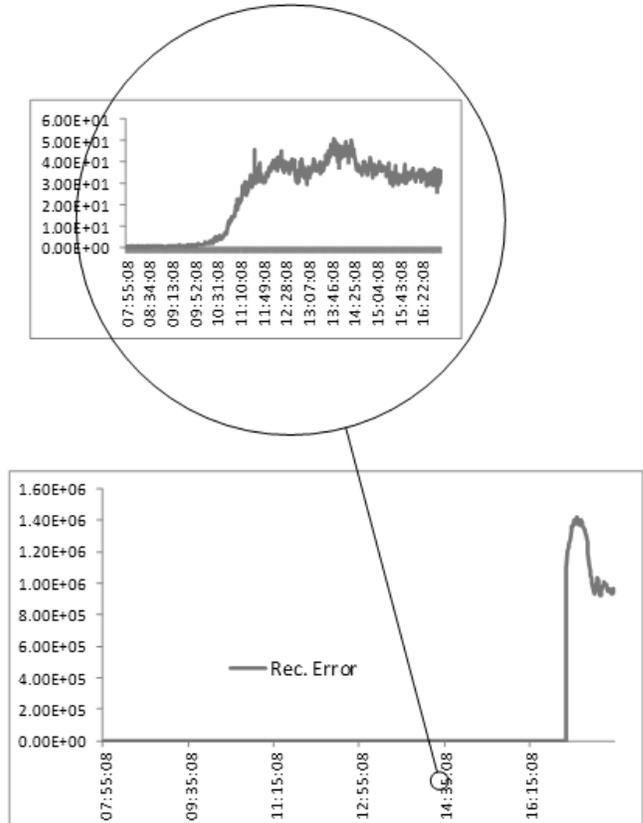


Figure 20. Reconstruction error in linear scale, on top the zoom of the period before the incident

It is fairly visible from both plots that RE starts increasing just before 10 am. On the logarithmic plot our statistical threshold level (dashed line) is crossed before 10 am. Then a plateau is reached just after 11 am and this level is maintained until the trip event.

### 5. CONCLUSIONS

This case study shows the benefit of protection against high vibration, with properly configured systems able to trip a unit quickly enough but with no false alarm. An on-line Condition monitoring System is then quite useful to analyze the signature of before and during the trip and understand the events sequence. The automatic diagnostic using a set of rules failed in this case because it was configured to run in steady-state, not often enough, and with too basic rules.

Data reprocessed and analyzed by means of an AANN shows that precursors of the trip event would have been identified well in advance with respect to the methods currently configured and implemented. As a consequence the AANN methodology is very well suggested for next generation of online monitoring systems aside more fine-tuned rule-based expert systems.

The results of these methods are particularly important for remote power plants with no expertise at site. This incident

represented a consequence of the shortage of power event in the summer 2012 in Northern India (Singh & Katakey, 2012).

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## BIOGRAPHIES

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