Increasing the operating range and energy production in Francis turbines by an early detection of the overload instability

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ARTICLE INFO

Keywords:
Francis turbine
Overload instability
Data-driven method
PCA
SOM

ABSTRACT

With the increasing entrance of wind and solar power for the generation of electricity, more flexibility is demanded to hydropower plants. More flexibility means that hydro turbines have to increase the operating range between minimum and maximum power. In Francis turbines the maximum power is limited by the appearance of a strong hydraulic excitation called overload instability. When the turbine operates at loads higher than design, the cavitating vortex rope that is generated in the draft tube may become unstable, producing huge pressure fluctuations, vibrations and power swing. Turbines are not allowed to operate under these conditions in order to avoid the destruction of the unit. The overload instability emerges abruptly, even when the machine is operating in a smooth condition. No visible transition can be detected by the monitoring system, so turbine operators have no margin to react. To avoid this phenomenon, operators limit the maximum power much before reaching this condition. By doing that, the maximum power is limited as well as the regulation capacity of the unit. In this paper, the feasibility of detecting the onset of this phenomenon is analyzed. Data-driven methods and artificial intelligence techniques, including principal component analysis, self-organizing map and artificial neural networks, are applied to the data available from experimental tests in a Francis turbine. The signals of vibration, pressure fluctuations and other parameters are combined and studied. The possibilities of a premature detection of the instability before it occurs are discussed. The method could be implemented in the monitoring system of the unit so that the operating range could be safely increased.

1. Introduction

Because of their flexible output power and fast response, hydraulic turbines have been widely used in the last decades to match the generation of energy with the demand of the electricity grid. This task has become more challenging with the massive entrance of new renewable energies, such as wind and solar energies, because of their intermittent and unpredictable nature. For hydraulic turbines, which have to balance this complicated behavior of the electricity grid, this implies working in a wide operating range; far away from its best efficiency point (BEP) and with multiple start and stops. The most common type is the Francis turbine due to its versatility in terms of design head. Francis turbines have been used for more than one century, but due to the relatively new requirements of the electricity market, more dynamic problems and damage have been reported recently. For example, fatigue damage [1,2], resonance problems [3,4] and power swing [5,6] have been reported in the last decade. Minimizing the adverse effects of these phenomena and running the unit safely in an extended operating range is one of the main concerns of turbine operators, manufacturers and researchers.

Regarding Francis turbines, the overload instability is a problem that might be dangerous and hence not part of the operating range of a properly designed runner. This phenomenon was firstly documented in 1940 [7] but it is still one of the main concerns in current operating units [8]. It is known that such phenomenon starts with a stable cavitating vortex rope in the draft tube. Such rope is generally a vertical cavitation column centered in the runner cone [9]. In Fig. 1, the physical parameters’ fluctuation of a Francis turbine operating at 96.43% (475 MW) and 98.36% (477 MW) has been represented. The consequences of this vortex rope on the pressure pulsations, vibrations, torque on the shaft and power swing are almost negligible as it can be seen in Fig. 1 left. For certain conditions, which according to the present knowledge are

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https://doi.org/10.1016/j.measurement.2021.109580
Received 6 December 2020; Received in revised form 27 April 2021; Accepted 7 May 2021
Available online 18 May 2021
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measurement 181 (2021) 109580

Fig. 1. Example of a Francis turbine with a stable cavitating vortex rope and with an unstable vortex rope. Effects on the fluctuation of the mechanical, hydraulic and electrical system. Vortex rope pictures are taken from [12] and [13].

Fig. 2. Actual operating range based on real monitoring data. Estimated possible increased range below the overload instability area.

partially unclear [10], this smooth cavitating column turns suddenly into an important and aggressive cavitating system with huge oscillations of the cavitating volume (Fig. 1 right). Note from the figure, that only a small change in the regulating system (wicket gate opening), and therefore in the output power, triggers this instability. Such instability produces huge pressure oscillations in the hydraulic circuit, torque oscillation in the rotating shaft and finally power swing [8,9,11]. These pressure pulsations can cause damage on the mechanical parts in contact with hydraulic circuits, including pipes, and they compromise the safety of the power station itself [9]. Furthermore, the power swing produced is unacceptable for the stability of the electricity grid.

An early detection of the instability can be a complicated task as the unit normally runs in a stable manner and without any clear symptom before its onset. Nevertheless, the transition to the instability, which entails large pressure, torque and power oscillations, is short [11]. In order to avoid this dangerous situation, some operators choose to work far away from these high loads during the normal operation of the unit [14]. This increases the safety of the system as the risk of instability is decreased but it has the main drawback that the effective operating range of the unit and the amount of energy produced (capacity factor of the unit) is greatly reduced. Real operating data of the analyzed operating unit can be seen in Fig. 2. During approximately half a year, the head of the machine was high and the overload instability may have occurred for full power. Although the unit was able to produce around 490 MW (wicket gate opening of the regulation system at 100%) the operators limited the power of the machine to approximately 440 MW in order to reduce the risk of an overload instability. As seen in Fig. 1 left, the machine could smoothly operate quite close to the instability (around 475 MW), so it can be concluded that with an appropriate monitoring system, the operating range of the machine could be safely increased. In fact, it is roughly estimated that the amount of energy contained in this increased range area (energy that could have been produced with an extended range) is 160 GWh per year.

Therefore, in order to extend the operating range and increase the production of such units in a safe manner, it is of paramount importance to accurately determine the safety operating areas and to quantify the risk or proximity of the instability, even when the machine is running in a smooth condition.

For such purpose, accurate continuous monitoring of the unit is necessary. Condition monitoring systems have been widely used in hydraulic turbines, [14–17] showing relatively good performance in detecting abnormal phenomena and incipient damage. Regarding the overload instability, Presas et al. [18] show that piezoresistive pressure sensors installed on the draft tube and spiral case, which are robust and typically used in monitoring systems, may be the most correlated and sensitive sensors to detect the overload instability phenomenon. Particularly, following the spectral band associated to the frequency of the vortex rope for both sensors, the instability can be easily detected. Nevertheless, that study mainly focuses on the detection of the phenomenon once it has started, leaving a small margin to correct the instability before it is amplified. Therefore, if the objective is an early detection of the instability several seconds before its onset, more refined and advanced data analysis techniques may be necessary.

With the rapid development of computer technology, data driven techniques and artificial intelligence (AI) have attracted considerable attention from researchers all over the world and shown a promising way in machinery condition monitoring applications [19–23]. AI algorithms have been widely applied in condition monitoring, fault diagnosis, prognostics, etc. Generally, an AI diagnosis procedure consists of two steps: feature extraction (data processing) and pattern recognition [24]. During feature extraction, raw data is processed by traditional signal processing methods such as time average, Fourier transform, wavelets and so on. Then the feature matrices are input into AI models for pattern recognition. The aim of pattern recognition is to project the information in feature space into a new recognition space, which involves numerous mathematical tools including mathematical optimization, convex optimization, classification, and probability-based methods [25]. Among them, statistical learning methods and classifiers are the most widely used in machinery engineering applications, including support vector machine (SVM) [26], k-nearest neighbor algorithm (k-NN) [22] and artificial neural network (ANN) [27]. In recent years, deep-learning algorithms like convolutional neural networks (CNN) have also been introduced into fault detection [28,29].

In this paper, we use advanced data driven techniques and AI algorithms to analyze the complex problem of the overload instability in an existing Francis turbine prototype. The main goal is to develop a methodology that is capable of predicting the onset of the instability prematurity. For this purpose, experimental data obtained when the
turbine was having strong oscillations at high load have been used. Several signal indicators carefully selected with the accumulated experience analyzing this turbine have been used as inputs of data driven techniques (principal component analysis) and AI algorithms (self-organizing map, artificial neural networks). It has been shown that when such methods are conveniently applied they are perfectly capable of classifying dangerous stable conditions that will lead to instability and to anticipate the onset of the instability several seconds before it occurs. Such methods could be implemented in future advanced monitoring systems.

2. Overload instability in the analyzed unit

2.1. Problem description

The analyzed turbine unit is a large medium-head Francis turbine located in a hydro power plant in Canada, with a rated power of 444 MW. It has a specific speed ($n_s$) of 46. Other basic parameters are listed in Table 1.

The unit analyzed in this paper presents a clear part load instability and under some circumstances an overload instability with high power fluctuations. These were first analyzed and confirmed by Mueller et al. [9] in a reduced scale model. Later, some works measured and confirmed the existence of power swing in the real prototype [5,11,30,31]. In [5] it was confirmed that the interaction between the planar wave travelling from the draft tube to the penstock and vice versa is able to deform the runner axially and torsionally, producing a fluctuation of the mechanical torque on the shaft which leads to an oscillation in the mechanical and electrical power.

The part load instability can be explained by the precession of the part load vortex rope. The part load vortex rope, which appear always under the Best Efficiency Point (BEP) has a clear precession motion with a frequency of about 0.25-0.35 times the rotating speed of the runner ($f$). When the pressure fluctuations generated by this precession motion coincide with one of the acoustic natural frequencies of the hydraulic circuit, a resonance occurs and the pressure, torque and electrical power fluctuations are greatly amplified. A detailed study of the part load instability occurring in this machine can be found in [32].

The overload instability is a much more complex phenomenon, whose causes are not clearly understood at present [10]. Recent studies performed in a reduced scale model [9] point out that such phenomenon can be described as self-excited hydro-mechanical system with positive feedback. Compared to the part load instability, the consequences of the overload instability on the hydraulic, mechanical and electrical system are much more serious due to the self-excited oscillation behavior and because the output power is much larger [33].

In [11] the complexity of an early detection of the overload instability was clearly shown. As it can be observed in Fig. 3, for the part load instability the oscillation amplitude of the power swing increases in a smooth way until the maximum power swing occurs. Therefore, some actions to avoid this operating point can be performed beforehand. For the overload instability, this increase is much more abrupt, showing that this phenomenon cannot be easily detected beforehand and hence it is more dangerous.

This dangerous behavior, when the unit approaches its maximum power, is considered in the general operation of this machine. As shown in Fig. 2, this unit never works with an output power larger than 440 MW in regular operation, even if these conditions are generally stable (band 440 MW-470 MW). Therefore, limiting the output power of the machine reduces the risk of developing the overload instability but the output power and energy produced (capacity factor) by the unit is highly reduced and also the operating range available is narrowed.

2.2. Tests on the overload instability

In the HYPERBOLE project [34], several measurement campaigns were performed in order to measure stresses, vibrations, pressure fluctuations, torque fluctuations and power fluctuations. The data acquired was used to analyze the present unit but also to calibrate numerical, computational and experimental models.

In the present paper we focus on the overload instability and therefore we will analyze the conditions where the wicket gate opening (WGO) was higher than 94% and the output power was close to its maximum for the given net head. In a normal operation, such situation is generally avoided in order to prevent the overload instability. Nevertheless, during the tests such conditions were reached in a safe way, where the output power was manually adjusted. In this way, if the operators thought that the existing power fluctuation and pressure

### Table 1

<table>
<thead>
<tr>
<th>Item</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated output $P$</td>
<td>444 MW</td>
</tr>
<tr>
<td>Rotation speed $n$</td>
<td>128.4 rpm (2.14 Hz)</td>
</tr>
<tr>
<td>Number of runner blades $n_b$</td>
<td>16</td>
</tr>
<tr>
<td>Number of wicket gates</td>
<td>20</td>
</tr>
<tr>
<td>Runner diameter $D$</td>
<td>5.4 m</td>
</tr>
<tr>
<td>Rated net head $H_n$</td>
<td>161.9 m</td>
</tr>
</tbody>
</table>

![Fig. 3. Relative power fluctuation while entering part load and overload instability](image)

![Fig. 4. Sketch of the sensors used](image)
fluctuation was too high, the power of the unit was slightly reduced by closing the wicket gates and the machine turned back to a stable condition.

The sensors and signals used for the present study are schematized in Fig. 4: two pressure sensors on the draft tube (PDT) and spiral case (PSC) respectively, an axial (AGA) and radial accelerometer (AT) on the generator and turbine bearing respectively, a displacement sensor on the shaft (DT) and the SCADA operating signals of the WGO and Power (POW). The sampling frequency of the acquisition system was set at 4096 Hz. All the signals were simultaneously acquired by a B&K LAN XI module. More details on the experimental set-up can be found in [11]. The selected sensors for this study are robust and have also been used for long term condition monitoring [14] and therefore their signals can be used in advanced monitoring systems that could continuously control the risk of instability.

Five situations where the WGO reached a value higher than 94%: S-S1, S-S2, S-U1, S-U2 and S-U3 have been chosen. S-S represents a stable condition that remains stable when the maximum possible WGO is reached, while S-U refers to the stable condition leading to an overload instability. Table 2 shows the main operating parameters during these operating conditions. In S-U1 and S-U2, the head was relatively high and the instability appeared as seen in Fig. 5b and Fig. 5c. It can be appreciated that the overload instability appears suddenly and the power oscillation increases fast from 3 MW to 4 MW to approximately 30 MW-50 MW. Nevertheless, in a similar operating condition S-S1 (Fig. 5a), the instability was not developed even though the output power (mean value) was less than 1% lower than in S-U1 and S-U2. Comparing S-S1, S-U1 and S-U2, one could think that a larger WGO is the main cause for the instability development but in S-S2 (Fig. 5d) no instability appeared even with 100% of WGO. In this situation the head was low and the output power was also lower than in the other conditions. In S-U3 (Fig. 5e) the instability also appeared with a WGO around 100% but with less head and output power than for the stable condition S-S1. For the conditions tested, no clear relationship was observed with the submergence level of the runner.

Regarding the time scale in Fig. 5, for S-U conditions $t = 0$ s is defined for the inflection point where the power fluctuation starts to increase. For S-S conditions, where no instability has been developed, we consider $t = 0$ s as the operating point where the maximum WGO is achieved.

Two things can be concluded from this preliminary analysis. First, power oscillations produced by the overload instability are unacceptable for the safety of the electrical grid. These can also be dangerous for the power station itself. As a reference, IEC 60041 defines a stable condition when the oscillation of the power (peak-peak) is less than 3% and in this

<table>
<thead>
<tr>
<th>Overload test</th>
<th>Net head (m)</th>
<th>WGO (%)</th>
<th>Power (MW)</th>
<th>Peak to peak value of power (MW)</th>
<th>Instability</th>
</tr>
</thead>
<tbody>
<tr>
<td>S-U1</td>
<td>176.0</td>
<td>98.2</td>
<td>477.8</td>
<td>42.0</td>
<td>Yes</td>
</tr>
<tr>
<td>S-U2</td>
<td>175.8</td>
<td>99.0</td>
<td>477.1</td>
<td>47.0</td>
<td>Yes</td>
</tr>
<tr>
<td>S-U3</td>
<td>173.5</td>
<td>102.6</td>
<td>465.1</td>
<td>35.1</td>
<td>Yes</td>
</tr>
<tr>
<td>S-S1</td>
<td>178.7</td>
<td>94.0</td>
<td>474.1</td>
<td>3.0</td>
<td>No</td>
</tr>
<tr>
<td>S-S2</td>
<td>162.9</td>
<td>99.4</td>
<td>400.2</td>
<td>2.4</td>
<td>No</td>
</tr>
</tbody>
</table>

Fig. 5. Variation of power, WGO and peak to peak value of power during the overload instability tests (Instabilities are marked with red background).
5

Table 3
Condition indicator definition.

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS</td>
<td>Root mean square value of the time signal</td>
</tr>
<tr>
<td>P2P</td>
<td>Peak to peak value of the time signal</td>
</tr>
<tr>
<td>P2P/RMS</td>
<td>P2P to RMS ratio</td>
</tr>
<tr>
<td>MEAN</td>
<td>Mean value of the time signal</td>
</tr>
<tr>
<td>( f_v )</td>
<td>Vortex rope band value of the envelope curve</td>
</tr>
<tr>
<td>( f_{vr} )</td>
<td>RMS value of the vortex rope band</td>
</tr>
<tr>
<td>( f_b )</td>
<td>RMS value of the blade passing frequency band</td>
</tr>
</tbody>
</table>

Table 4
Used indicators.

<table>
<thead>
<tr>
<th></th>
<th>PSC10</th>
<th>PDT10</th>
<th>AGA12</th>
<th>AT9</th>
<th>DT9</th>
<th>POW</th>
<th>WGO</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS</td>
<td>1</td>
<td>8</td>
<td>15</td>
<td>21</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P2P</td>
<td>2</td>
<td>9</td>
<td>16</td>
<td>22</td>
<td>27</td>
<td>31</td>
<td></td>
</tr>
<tr>
<td>P2P/RMS</td>
<td>3</td>
<td>10</td>
<td>17</td>
<td>23</td>
<td></td>
<td></td>
<td>32</td>
</tr>
<tr>
<td>MEAN</td>
<td>4</td>
<td>11</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( f_v )</td>
<td>5</td>
<td>12</td>
<td>18</td>
<td>24</td>
<td>28</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( f_{vr} )</td>
<td>6</td>
<td>13</td>
<td>19</td>
<td>25</td>
<td>29</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( f_b )</td>
<td>7</td>
<td>14</td>
<td>20</td>
<td>26</td>
<td>30</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The final list of selected indicators is shown in Table 4 (32 indicators). Some indicators are not considered as they don’t have a physical meaning due to the sensor characteristics. For example, the mean value for an IEPE accelerometer is always filtered. For the displacement sensor the mean value is arbitrary depending on the distance sensor-shaft.

These indicators, which are obtained every 0.25 s for the five conditions tested in Fig. 5, is the whole dataset used in this paper. Depending on the analysis performed, different timeframes of the data will be used. For convenience of the readers, Fig. 6 includes the timeframes used for every method.

3. Analysis of the data during the stable condition

The early detection of the overload instability of a Francis turbine is necessary if the unit has to work close to this condition. In classical condition monitoring, signal indicators conveniently selected are trended and compared with reference values in order to detect abnormal phenomena. In this section, besides this method, we also use PCA (Principal Component Analysis) and SOM (Self-Organizing Map) as alternative methods to detect changes in the high dimension data that could indicate the onset of the instability.

3.1. Data analysis by single indicators

By means of statistical tests (Independent two sample t-Student test) the data from –50 s to –25 s (S1 in Fig. 6) is compared with the data from –25 s to 0 s (S2 in Fig. 6). Both datasets have 100 samples (4 samples per second for 25 s). As both datasets (S1 and S2) have the same number of samples and assuming equal population variance for both groups, the t statistic can be calculated as [35]:

\[
t = \frac{X_{n1} - X_{n2}}{\sqrt{\frac{1}{n_{1}} + \frac{1}{n_{2}}}}
\]

(1)

With

\[
t_p = \sqrt{\frac{(n_{n1} - 1)s_{n1}^2 + (n_{n2} - 1)s_{n2}^2}{n_{n1} + n_{n2} - 2}}
\]

(2)

Where, \( \bar{X}_{ni}, s_{ni}, n_i \) are the sample mean, sample variance and number of samples for each group. The \( p \)-value is obtained according to the corresponding t-Student distribution (two-tail test) and compared with a
significance level \( \alpha = 0.05 \) [35]. If the obtained \( p \)-value is less than the significance level it may be concluded that there is a statistical difference between both groups.

A robust indicator for an early detection of the instability should have a statistical change for \( S-U \) conditions (\( p \)-value < \( \alpha \)) and no significant statistical change for \( S-S \) conditions (\( p \)-value \( \geq \alpha \)). A first list of potential indicators is obtained by comparing the condition \( S-S1 \) and the condition \( S-U1 \). Table 5 shows the results of the decision tests for the indicators analyzed. For the stable condition \( S-S1 \), \( \checkmark \) means that the indicator has not a significant change (\( p \)-value \( \geq \alpha \)) while \( \times \) means that there is statistical difference between them (\( p \)-value < \( \alpha \)). For the stable condition that leads to instability \( S-U1 \), the meaning of \( \checkmark \) and \( \times \) is the opposite as we should expect a significant change in the indicator, when the instability is about to appear.

Only a few indicators have the desired behavior for both situations, which are marked in bold font. Nevertheless, when using the rest of analyzed unstable and stable conditions available, there is no indicator which behaves as desired (Table 6). From this section, we conclude that for an early detection of the instability, the trend of a single indicator is not significant enough and that more refined techniques are necessary.

### Table 6

Selected indicators for all the conditions tested.

<table>
<thead>
<tr>
<th>Stable conditions</th>
<th>Unstable conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S-S )</td>
<td>( S-S1 )</td>
</tr>
<tr>
<td>PSC-RMS</td>
<td>( \checkmark )</td>
</tr>
<tr>
<td>PSC-MEAN</td>
<td>( \checkmark )</td>
</tr>
<tr>
<td>AGA - ( f_s )</td>
<td>( \checkmark )</td>
</tr>
<tr>
<td>PSC - ( f_s )</td>
<td>( \checkmark )</td>
</tr>
<tr>
<td>DT9-P2P</td>
<td>( \checkmark )</td>
</tr>
<tr>
<td>DT9- ( f_v )</td>
<td>( \checkmark )</td>
</tr>
</tbody>
</table>

3.2. Data clustering by PCA (3-dimensional space)

Principal component analysis (PCA) is a widely used method for multivariable data processing [36]. By the decomposition of the correlation or covariance matrix, this method can transform the original multidimensional data to a new space which has less dimensions than the original one, while preserving most of its information [37]. Assume the feature pattern \( X_{m \times n} \) is a matrix with \( n \) indicators and \( m \) samples. The feature matrix can be projected to a new space by a transform matrix \( T \):

\[
Y = TX
\]

(3)

The transform matrix \( T \) can be obtained by either eigen decomposition (ED) or singular vector decomposition (SVD), but SVD is preferred for large scale data since SVD requires less operations [38]:

\[
XX^T = U\Lambda U^T
\]

(4)

As \( XX^T \) is a symmetric matrix, according to SVD, \( U \) is an orthogonal matrix with all the vectors orthogonal with each other. The singular values \( \{v_1, v_2, \ldots, v_p\} \) are sorted from smallest to largest on the diagonal of matrix \( \Lambda \). \( T \) is built by the first \( d \) columns of \( U \). The number \( d \) can be determined by the eigenvalues:

\[
\sum_{i=1}^{d} v_i \times 100\% > p\%\#\]

(5)

Therefore, the first \( d \) principal components (PCs) contain more than \( p \% \) of the information of \( X \).

From the original set of indicators, we don’t use the mean value of the power as it can differ a lot between different conditions. For example, the maximum power is 400 MW and 490 MW in \( S-S2 \) and \( S-U \) respectively while both situations could potentially develop overload instability. As a consequence, two sets of data with different mean power would appear in two separated clusters, hiding relevant information.

The measured signals before the instability in each condition are used as the feature pattern, which is a 500 \( \times \) 32 matrix. As the samples are obtained every 0.25 s, this means that for all the conditions the corresponding data is taken from \(-125 \) s to \( 0 \) s according to Fig. 6. The matrix is processed by Equation (4) and the eigenvalues and loading matrix are obtained. To decide which of the eigenvectors gives maximum variance in the data, a score test is carried out in Fig. 7 (scree plot). It can be seen that except the first three values, the others are much lower than 1.0. Therefore, according to Kaiser’s principle [38], the first 3 dimensions of the projection space are sufficient for retaining most of the original data.

The score tests for the rest of analyzed conditions have been carried out and the intrinsic dimensionality is also 3 and therefore the data is generally well described in the three-dimensional space. The representation of the data on the different operating conditions in its first three principal components (PCs) is shown in Fig. 8.

It can be seen in the figure that the data related to \( S-U \) conditions are close to each other (Fig. 9b) while the \( S-S \) clusters are well separated. This clustering by PCA allows a much clearer view than the analysis performed in the previous section. It has to be noticed again that all this data corresponds to stable conditions (with almost no power swing), from which some finally developed into unstable conditions (\( S-U1 \), \( S-U2 \) and \( S-U3 \)). The interpretation of this figure may be summarized as follows: when the unit works in a stable condition and the PCA components of the indicators selected fall inside the critical area, the overload instability will soon appear. These borders can be further refined with more measured data for the machine working in mid heads. In terms of physical interpretation of the operation of the unit, this figure can be interpreted as follows: when increasing the WGO of the machine, the cluster of the data moves in the vertical direction (PC3) into a more unstable condition. This condition is reached earlier when the mean power (also net head) is large. For low head conditions (\( S-S2 \)), even when working at the maximum design opening (100% of WGO), the cluster does not fall inside the unstable area. Therefore, the instability does not occur.

Although this method could be used to separate and classify both types of stable conditions (\( S-S \) and \( S-U \)) a further analysis of the cluster does not show or explain the proximity of the onset of the instability. This is shown in Fig. 9, PCA analysis is applied to the data shown in Fig. 9a, corresponding to \( S-U1 \) condition. Fig. 9b shows that the stable and unstable parts have formed well separated clusters with a very short transition from one cluster to the other. A detailed analysis of the stable part cluster (Fig. 9c) shows that there is not a clear trend of the points of the cluster when the instability is about to occur, i.e., red colored points are randomly located in the cluster. This might be because the information neglected in the other components are critical for the evolution of the signal before the instabilities. It could be possible to visualize a trend on the data considering the components neglected in a higher dimension space. Nevertheless, this cannot be visualized directly.
To summarize, PCA is able to classify and separate both types of stable conditions (S-S and S-U). Nevertheless, during this stable phase there is no clear trend of the cluster moving towards the instability and the distance between the two clusters is not reduced, when considering the three-dimensional space of PC1, PC2 and PC3. In order to see if it is possible to detect some trends of the data during the stable part, further clustering methods are explored.

3.3. Data clustering by SOM (higher dimensional space)

The self-organizing map (SOM) is an algorithm that implements a characteristic nonlinear projection from the high-dimensional space of data onto a low-dimensional array of clusters [39]. Being firstly proposed in 1990 [40], it has been proven useful in many applications [41]. As shown in Fig. 10, a SOM network is composed of 2 layers: input layer and competitive layer (output layer). A typical training process of SOM is shown below:

Initialization. A typical self-organizing map is a two-dimensional array of neurons as shown in Equation (6), where \( p \) and \( q \) are the size of the output pattern. One neuron \( m_i \) is a vector called the codebook vector with the same dimension as the input vectors, as shown in Equation (7), where \( n \) is the dimension of the input pattern. During map initialization, random values are assigned to codebook vectors.

\[
M = \{m_1, m_2, \ldots, m_{p \times q}\} \tag{6}
\]

\[
m_i = \{m_{i1}, m_{i2}, \ldots, m_{in}\} \tag{7}
\]

Training. A similarity measure (e.g., Euclidean distance) is performed between the input vector and all the codebook vectors [42]. The codebook vector with greatest similarity with the input sample is chosen to be the best-matching unit (BMU) [43], noted as \( m_c \). After \( m_c \) is found,
Fig. 12. SOM neighbor distances for a) S-S1, b) S-U1, c) S-U2, d) S-U3 and e) S-S2. In S-S1 and S-S2 the instability did not occur, while in S-U1, S-U2 and S-U3 the instability appeared few seconds after.
the topological neighbors of \( m_c \) are modified in different degrees which is determined by a neighborhood function. The neighborhood function is usually a bubble function (Fig. 11) which is similar to Gaussian function but easier for the computer to calculate.

\[
\| x - m_c \| = \min_{i} \{ \| x - m_i \| \} 
\]  

(8)

**Visualization.** One of the most typical visualization methods of the training result of SOM is a unified distance matrix (U-matrix) [42]. A U-matrix visualizes the distances between the neurons, which are represented with different colors in a heatmap. Dark coloring between two neurons corresponds to a wide distance while light coloring implies the codebook vectors are close to each other, so that the light area can be regarded as a cluster center of the input pattern.

For a 2-D map space in the competitive layer, the visible nodes are arranged in regular hexagonal or rectangular grid and map units (or neurons) usually form a 2-D lattice, thus the high dimensional space can be mapped into a plane. The unsupervised learning algorithm allows SOM to cluster data without knowing the class memberships of the input data so that it can be used to detect features inherent problems. In our case, beyond the “stable” time signal before instabilities occurrence, the combination of the indicators may have changed in a higher dimension space which might be reflected by changes in SOM model.

In this case, the data used is the stable part used for PCA (Fig. 9 a) but only 17% data from the two ends SOM1 (from \(-125 \text{ s to } -104 \text{ s}\) and SOM2 (from \(-21 \text{ s to } 0 \text{ s}\) are extracted (see Fig. 6). For the data of S-S1, the start and end part of the signal include 84 samples respectively, so that the input pattern of S-S1 is a 168*32 matrix. Accordingly, the size of competition layer is set as \(10^4*10\) to visualize the map. The codebook values in the neurons are initialized randomly before training. The update range of bubble function is 3, which means the nearest 3 nodes of the winner will be updated.

The SOM neighbor distances of each condition are shown in Fig. 12. There are 100 nodes connected in hexagonal topology in each map. The color between two adjacent nodes represents the distance between them. Apparently, the distances map of S-S condition and S-U condition are quite different. Despite some dark colors on the edge, the colors in S-S1 map are uniform, indicating that the distances between different nodes are similar. This means it is difficult to find any clear trend among all of the samples in this data set. A similar result is generated by SOM model in the data of S-S2.

For the stable conditions that lead to an instability (S-U1, S-U2 and S-U3) the color distribution is completely different: a line of dark points splits the color map into two parts or clusters. In one cluster, all nodes are closely connected with the adjacent nodes (light color). The dark color in the maps, indicates that a long distance between the two clusters exists.

4. Early detection of the overload instability by artificial neural network

The objective of the previous section was to see if some trends or features of the data during the stable conditions could indicate the onset of the instability. As a conclusion, none of the single indicators was able to explain the difference between the stable condition that leads to instabilities (S-U conditions) from those which do not (S-S conditions). PCA could separate the S-S conditions and S-U conditions in a 3-dimensional space but it did not show a clear trend of the data towards the instability. With SOM, the data corresponding to the stable part was clearly separated in two groups for the S-U conditions and therefore a high risk of developing the instability when the data cluster “crossed” the dark line in Fig. 12. After having confirmed this, in this section we propose training an artificial neural network in order to quantify the proximity of the instability beforehand, which is the final goal of the paper.

In order to do that, an artificial unstable index (AUI) has been defined. According to the result obtained by SOM, a significant change between the data SOM1 and SOM2 (Fig. 6) was observed for the S-U conditions. As the dataset SOM1 ends at \( t = -104 \text{ s} \), the AUI is 0 until \( t = -100 \text{ s} \) (few seconds after SOM1 data ends) and increases linearly to 1 exactly at the critical point (\( t = 0 \text{ s}\) Fig. 13). For a stable condition outside this range this index is constantly set at 0. Although this definition is totally arbitrary, it has been proved to give good results for the rest of the conditions tested. If a similar methodology was applied in other Francis turbine, slightly different criteria for the definition of the AUI could be used depending on the behavior of the machine.

For the ANN (Fig. 14), the inputs are the 32 indicators and the output the AUI. The optimum number of neurons in the hidden layer is set as 30 after several trials in which the number of layers and perceptrons in the hidden layers were changed [44]. Levenberg-Marquardt (LM) backpropagation function is chosen as the training algorithm. This training method has a faster convergence speed on training process of middle-sized feedforward networks [45]. In present study, a conventional multilayer perceptron has been used, which has shown a good performance for the existing data. As the inputs have a time order, a time convolutional neural network could be used in future works [46].

The training conditions are the conditions S-U1, S-U2 and the totally stable condition S-S1. For validation, the condition S-U3 and condition S-S2 have been considered. Fig. 15 shows the results of the trained NN applied into the validation conditions. A moving average of 5 samples has been calculated in order to damp the oscillations of the data. The AUI for condition S-U3 (Fig. 15 a) increases from 0 to 1 in a relatively smooth way before the instability appears. It also shows the same trend as for the trained conditions, which have a linear variation. For the stable condition S-S2 (Fig. 15 b), the AUI shows a constant trend near zero. These results show that the trained ANN is capable of correctly
predicting the trend and classifying an S-U and S-S condition. With more training data, based on stable and unstable conditions, we expect having more precise trends around the defined AUI.

Finally, we can relate the AUI with the estimated time to instability (ETI) as it is a more intuitive parameter. A larger ETI means more margin to do some corrections in the unit before the instability really occurs. As shown in Fig. 16, for AUI equals to 1 ETI is 0 and for AUI equals to 0 ETI is set to 100 s, as defined in the training conditions. An AUI close to 0 is not significant and can correspond to any operating condition of the machine. Therefore, it is necessary to set an alarm threshold (for example AUI = 0.5 as shown in Fig. 16) which will correspond to the remaining time until instability. A suitable threshold can decrease false alarms significantly while keeping sufficient time margin for regulation.

To summarize, with the indicators selected and an appropriate definition of the AUI and by training the ANN during different overload instability tests (S-S and S-U conditions), it is shown that an early detection of the overload instability is possible. With more data available it is expected that the trend of the predicted AUI for new conditions would be closer to the ideal AUI.

5. Conclusions

The overload instability in a Francis turbine is a dangerous phenomenon that produces undesired power swings in the electrical grid and can also compromise the safety of the power station. This phenomenon is particularly challenging to detect and to anticipate, as the transition from a stable condition to an unstable condition happens in a short time. In order to avoid risks, some operators avoid using the machine at high loads. As a consequence, the capacity factors and operating ranges of such power plants are drastically reduced.

This paper explores the feasibility of using data-driven methods for an early detection of the overload instability in a Francis turbine prototype. It has been shown that with AI techniques the instability can be successfully predicted several seconds before it occurs. The implementation of these methods in advanced monitoring systems would be beneficial for the operators as the operating range and capacity factor of the power station could be safely extended. For the analyzed unit, implementing such method to the current monitoring strategy could safely increase the output power by 35 MW (8% of the rated power), which roughly represents 160 GWh every year.

The unit was monitored with many sensors during stable operating conditions finally leading to an overload instability. A set of signal indicators based on previous analyses of the machine and on the monitored data for more than one year have been obtained. These include time indicators and spectral bands.

A first analysis of the indicators during the stable conditions preceding the instabilities has led to the following conclusions. Statistical hypothesis testing of the indicators during the stable conditions preceding the instability have demonstrated that there is not a single indicator that can clearly predict the onset of the instability. With principal component analysis (PCA) the data of the stable conditions preceding the instability can be clearly clustered. The stable operating conditions that finally lead to an overload instability can be classified and separated from those which did not. The self-organizing map (SOM) has been used as an alternative method for clustering. It has been shown that SOM is able to detect changes in the data set before the instability occurs. Nevertheless, this method is not able to quantify the proximity of the instability onset.

Therefore, artificial neural networks (ANN) have been used to predict and to quantify the risk of overload instability before occurrence. An artificial unstable index (AUI), which increases when the instability is about to occur, has been used to train the neural network. It has been proved that the trained ANN is able to quantify the risk of instability several seconds beforehand and, therefore, that an early detection of the overload instability is possible.

CRediT authorship contribution statement


Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Acknowledgements

The authors want acknowledge the XFLEX HYDRO project (EU H2020 No. 857832). Weiqiang Zhao would like to acknowledge the Serra Hunter program of China Scholarship Council (CSC) for its grants. Alexandre Presas and David Valentin wants to acknowledge the Serra Hunter program of Generalitat de Catalunya.

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