Detection of cavitating states (swirls) in a Francis test pump-turbine using ultrasonic and transient pressure measurements

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Abstract

Operators of hydro machinery want to use their plants as efficient as possible and in a wide range of operating points. This gives them the capability to fulfil the different process demands they are exposed to. The operation in certain operating points can however cause cavitation problems. During part load operation of a pump-turbine in turbine mode swirling flow in the draft tube can occur. The low pressure in the draft tube and frequency components of the swirl or vortex can lead to situations where the unsteady fluctuations may lead to cavitation and other damage of turbine and hydraulic equipment. Conventional methods of the detection of the unsteady conditions occurring in the draft tube at part load turbine operation are not yet reliable enough in order to distinguish between dangerous and non-dangerous operating points. If a vortex related to the swirling flow in the draft tube can be detected and its frequency can be estimated, an important indicator for dangerous operating situations of the turbine can be provided

This paper describes the detection of different cavitating swirl states, normal operating states (pure water states) and water/air bubble states. Often cavitation detection is not reliable enough to allow the operators to use their machines in a cavitation endangered region. This work deals therefore with the classification of specific potentially dangerous cavitation states using ultrasound and pressure signals in combination with operating point information. The method has been applied to a small Francis test pump-turbine in a laboratory environment.

1. Introduction

In order to integrate renewable energy sources like wind power and photovoltaic into to the energy grid, hyd-ropower stations are used to store this intermittent and non-constantly produced energy Due to the flexible operating possibilities, hydropower is also used to dampen frequency deviations of the power grid. In both cases the hydraulic machines such as pump-turbines have to operate in pump and turbine modes and under various part load operating conditions as well as overload condition.

The flow instability in the draft tube of a hydraulic turbine, frequently called as "draft tube surging" results from the swirling flow (vortex rope) associated with part-load or overload operation of the hydraulic turbine, in our case of the pump-turbine. Draft tube surging is the source of additional noise, severe vibrations, and eventual excessive bearing wear in the generator. When the frequency of swirling flow (vortex rope) coincides with a natural system frequency, the draft tube surges can produce big power swings, destructive structural resonance, or uncontrollable penstock pressure changes. Therefore, it is very important to determine the frequency of the swirling flow or vortex rope in the draft tube during the part load operation.

If a turbine is operated far from the nominal load condition, complex flow phenomena can occur. In these conditions the flow in the draft tube of the turbine does not only have a component in direction of the water flow but also a circumferen-tial component at the exit of the impeller. This can especially in Francis turbines (because of single regulation) lead to a swirl or vortex in the draft tube. The swirling flow has a frequency which lies in the range of the resonance frequency of the hydraulic system as mentioned above. If both frequencies are too close to each another high pressure variations might occur. These variations can lead among others to cavitation effects. Cavitation is the result of the generation and collapse of evaporation bubbles, because of low pressure in the flow. While collapsing, the bubbles can locally generate large transient pressure waves, which can damage parts of the turbine. Therefore, it is desirable to find a measurement method, which can detect the existence and the frequency of the swirl. Transient pressure sensors at the impeller exit can be used for such a detection but its installation is difficult and the mechanical stress is high due to the exposure. Here an alterna-tive ultrasonic measurement method has been used which is nonintrusive. Before the swirl frequency can be estimated, it is however important to detect and distinguish the existence of a vortex from other flow conditions (water states) of the turbine operation. The detection is split into the following two subsequent steps:

1) Different flow conditions are therefore classified first via decision tree methods by exploiting a number of measured physical quantities and their characteristics. The way of how the signals are selected and the procedure how to find the classification trees will be explained in this paper. The method applied here follows the works of ([1], [2], [3], [4], [5]) and uses pure statistical signal processing without temporal information.

2) In a second step the frequency of a swirl is identified after this condition has been detected by using temporal information of the signal characteristics. Results of this step have been reported in [6] and are not presented in this paper.

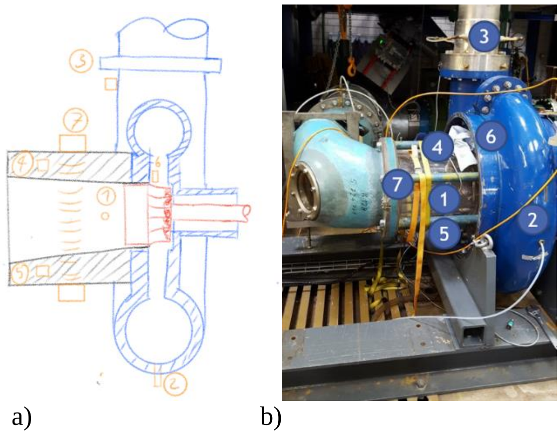
2. Experimental Setup

In the hydro laboratory of the Lucerne University of Applied Science and Architecture, experiments were carried out with a model test pump turbine (PT) in turbine mode. The pump turbine is equipped with a large number of sensors such that a variety of tests and experiments can be performed. The larger number of measured quantities are used for operating point information and are thus averaged, stationary values. A smaller number of measurements are used for transient measurements. Both types of measurement quantities are listed in Table 1. All data points were acquired by a Labview software environment with the exception of the ultrasonic measurement which were recorded by an oscilloscope.

Table 1: All data acquisition points and physical quantities of the model test pump turbine

Operating point, averaged quantities	**Transient measured quantities**	
Rotational speed N [1/s]	Pressure at draft tube	(1=position)
Torque	Pressure at spiral case	(2)
Angle guide vane (LA)	Pressure at pressure side	(3)
Pressure difference Δp across the turbine [Pa]	Pressure entrance to impeller (runner) (7x)	(6)
Relative pressure of pressure side to ambient pressure	accelerometer draft tube (2x)	(4,5)
Volume flow of turbine $\dot{V}$ [m^3/s]	Ultrasonic sensors	(7)
Water temperature		
Ambient temperature, pressure and humidity		
Quadrant		
Flows of various hydraulic supply pipes		
Rotational speeds of various supply pumps		

A schematic drawing and a picture of the test machine is shown in Fig.1a & 1b. The averaged quantities are steady state measurements of a turbine, while the transient measurements contain information of time dependency, frequency content and statistical parameter of the recorded signals. The draft tube consists of a cone of 300mm inlet diameter made out of plexiglass.



a) b)

Fig.1. a) schematic drawing of turbine with transient measurement positions **b)** photo of the pump turbine test rig

3. Operating point information for classification of water condition

After an extensive analysis of all acquired operating point information the following two dimensionless parameters Φ (PHI) and Ψ (PSI), used for the characterization of the operation of turbines, have been selected for the classification:

$$\Phi = \frac{\dot{V}}{N * D * \pi * D^2 * \frac{\pi}{4}} = \frac{\dot{V}}{N * D^3 * \frac{\pi^2}{4}}$$

D: Impeller outer diameter [m]
ρ: density [kg/ m^3]

$$\Psi = \frac{\frac{\Delta p}{\rho * g}}{\frac{(N * D * \pi)^2}{2 * g}} = \frac{\frac{\Delta p}{\rho}}{\frac{(N * D * \pi)^2}{2}} = \frac{\Delta p}{N^2 * D^2 * \rho * \frac{\pi^2}{2}}$$

Φ is linear in $\dot{V}$ and inverse dependent on N, Ψ is linear in Δp and inverse dependent on the square of N, that means on flow, rotational speed and pressure difference. More than 20 operating points are also indicated in the diagram. These operating points were classified into 4 water condition states: clear water, water and gas, pulsating swirl, stable periodic swirl.

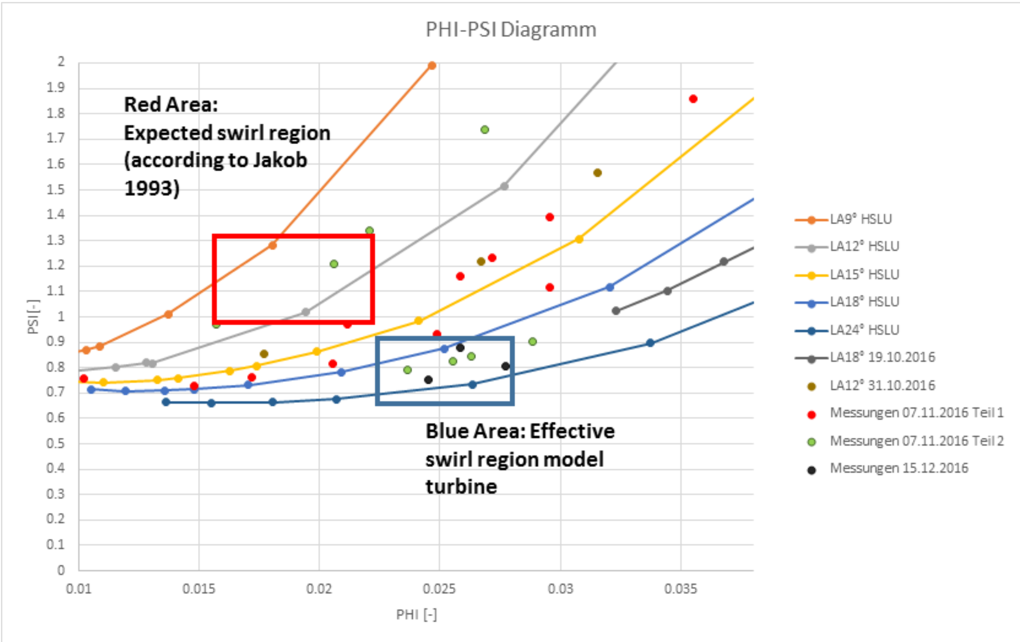


Fig. 2: Characteristic curves for constant guide vane (LA) opening in the Φ-Ψ-plane and the operating points for the measurement campaigns, measurement points indicated by single colored dots, red area swirl region from [7]

The interesting and usable states of the machine in this measurement campaign have been identified as:

- clean water	operating points OP1-11,17,18	total 44 data sets
- water and gas (air bubbles)	operating points OP13,23	total 8 data sets
- stable swirl in the draft tube	operating points OP19-22	total 16 data sets
- pulsating swirl in the draft tube	operating points OP14-16	total 12 data sets
Total number of training data sets		**80 data sets**

Each operating point OP consists of 4 signal sets of 50 signals

4. Transient measurement points for classification

4.1 Pressure signals

Of the transient pressure and acceleration measurements, the most useful ones were the pressure measurements at the impeller inlet. From this transient signals the intensity $I_{impeller,f1}$ of the first harmonic in the frequency domain was used as a classification parameter. With the use of Φ, Ψ, and $I_{impeller,f1}$ the training of decision trees by the Tree Bagger method (see section 5) was possible.

Figure 3 shows the spectrum of the pressure signal for operating point 3 (clean water) and 20 (stable swirl). The large change of the 7Hz amplitude (normalized 1st harmonic of a pump-turbine with 7 blades) is clearly visible.

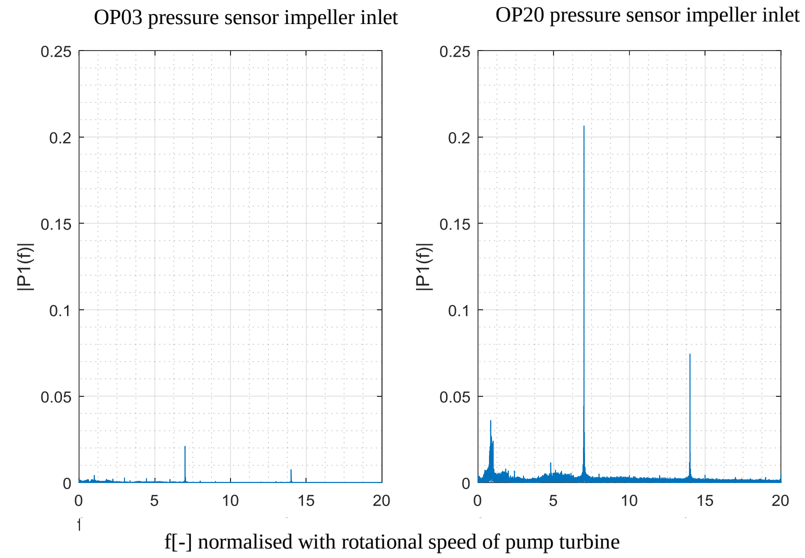


Fig 3: Frequency spectrum of transient pressure sensor (impeller inlet) without (left) and with (right) swirl

As the implementation of the pressure sensor is difficult to achieve in a real machine, additionally ultrasonic signals of the draft tube were investigated for possible substitutes of the transient pressure measurements at the impeller.

2.2 Ultrasonic signals

As can be seen from Fig.1 the 500kHz ultrasonic transducers provided by Rittmeyer Ltd are mounted from the outside in a clamp on fashion to the transparent draft tube. This involves a minimum effort in installation time and the sensors are not directly exposed to the pressure variations. This is in contrast to the different transient pressure measurement transducers at the impeller (runner) inlet. The ultrasonic signals are of a pulse shape (wavelet) and are periodically sent through the water with a repetition rate of up to 100Hz, where water can be disturbed by for instance a swirl or by cavitation bubbles. If the pulses are sent through undisturbed (clean) water (no air bubbles, particles, cavitation bubbles, swirl, etc.) the variation of individual recorded signals is small. Figure 4 shows 200 recorded signals over time for clean water conditions. From Figure 5 it is clearly visible that under disturbed water conditions (e.g. cavitation), the shape of the receiving pulses change from one recording time to the next one. If these variations are analysed in the time, frequency and correlation domains in a statistical way, the transient pressure measurement analysis can be replaced by some characteristic parameters of this analysis. It can even surpass the results obtained by the former choice. A similar approach had been investigated by [8].

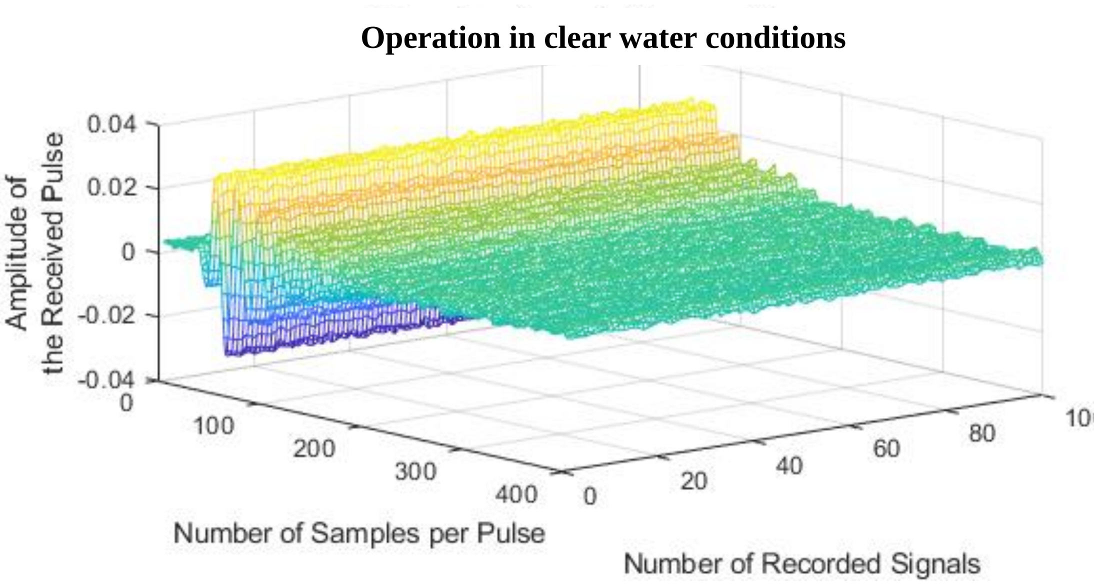


Fig. 4: Ensemble of signal shape (amplitude) of the recorded ultrasonic pulses over time for clean water conditions

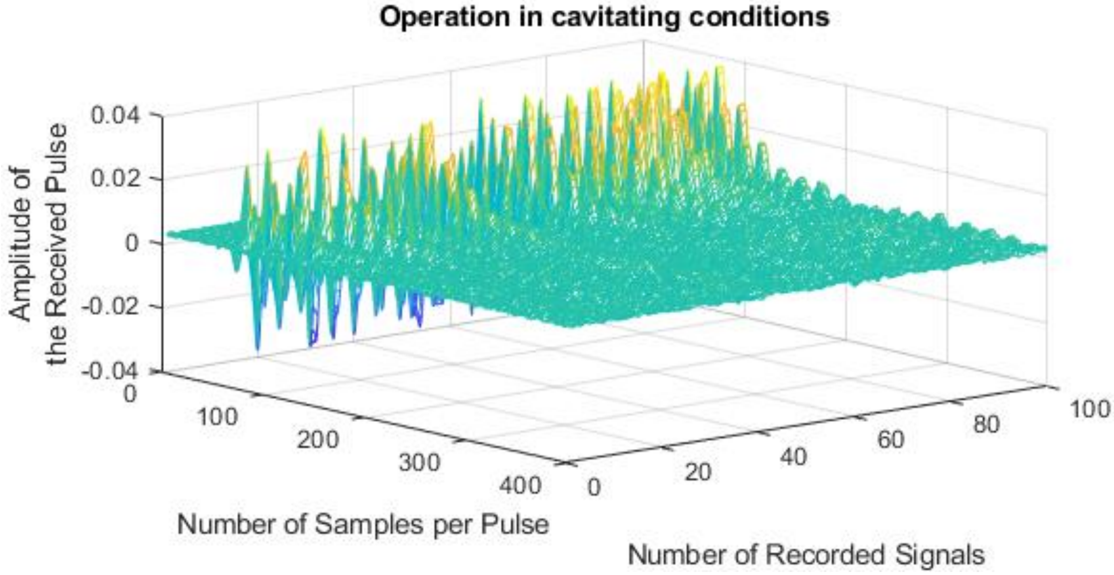
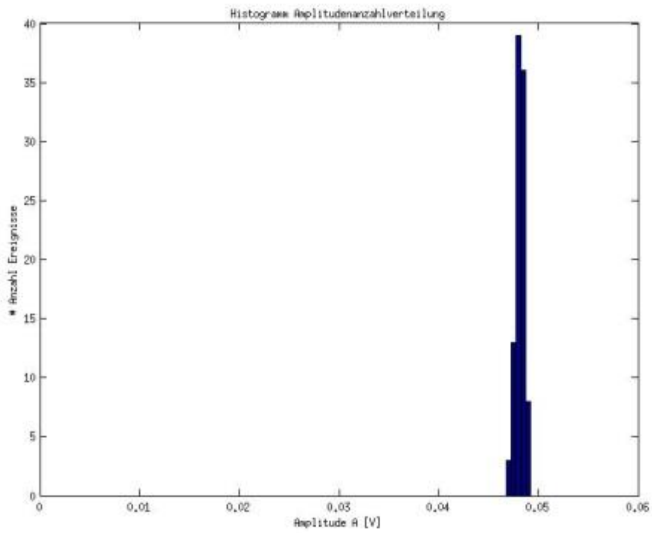


Fig. 5: Ensemble of signal shape (amplitude) of the recorded ultrasonic pulses over time under cavitating conditions

5. Extraction of statistical ultrasonic signal parameters (characteristics)

5.1 Statistical signal parameters for raw signal

For each operating point in each test series hundreds of signals (500kHz pulses) have been recorded. If they are disturbed by not ideal water conditions, various quantities of the signal change: amplitude (signal maximum), time of arrival of signal maximum, frequency content and power. As the distortions do not occur continuously in time, the signals recorded sequentially experience different levels of random distortions for the different water states. Statistical signal processing is therefore a good way to analyze the behavior. Histograms of various quantities are the first step for the investigation. Figure 6 shows histograms of groups of 100 signals. All the signals were preprocessed to remove outliers and signals with very low signal level. For clean water conditions the maximal amplitude is mainly centered around 0.048Volt while for the disturbed case the distribution is broader and the values much smaller (0.006Volt to 0.011Volt). In the Appendix a sample signal (Figure A1) is shown and 15 statistical signal parameters defined and listed in Table A1.



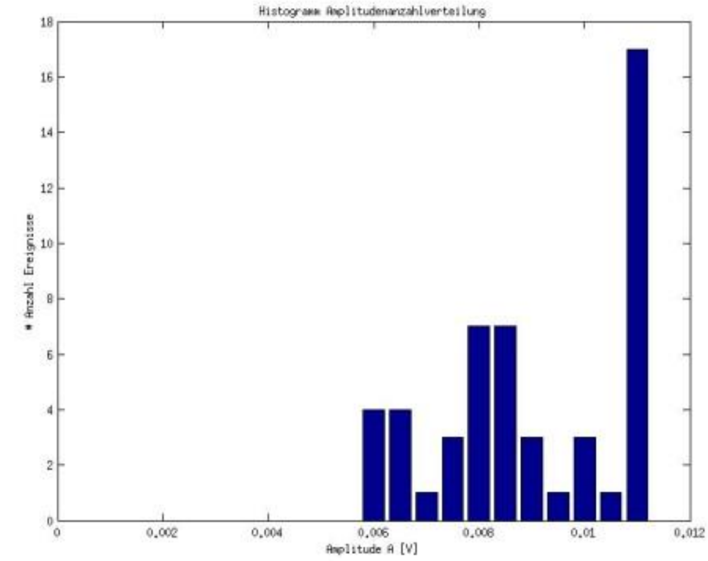


Fig. 6: Histogram of 100 measurements of amplitude: upper: undisturbed, lower: disturbed (draft tube swirl)

5.2 Statistical signal parameters for correlation function

An interesting function to examine is next to the individual ultrasonic signals, the correlation of each incoming signal with a reference signal that corresponds to a signal obtained under undisturbed conditions. In contrast to the signal analysis of the previous section, characteristic parameters of two signals are evaluated and compared to one another, if correlation is applied. Figure 7 shows some examples of computed correlation function for undisturbed and disturbed signals. As for the individual signals a sample correlation function (Figure A2) is shown and 23 statistical signal parameters defined and listed in Table A1 of the Appendix.

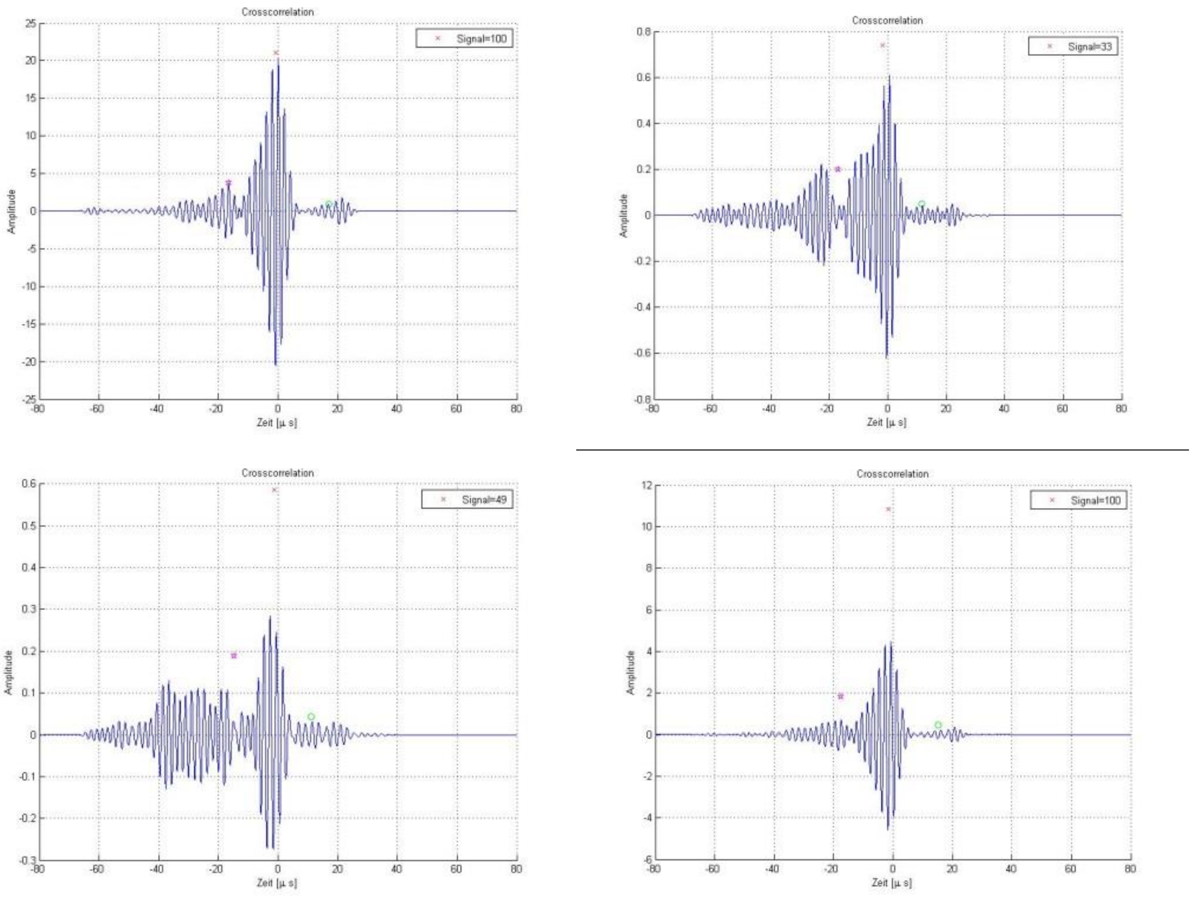


Fig 7: samples of correlation functions: upper left undisturbed signal, other signals: different degree of disturbance

6. Classification by decision trees

There exists a variety of classification methods like nearest neighbours method, case based methods, neural networks or rule based methods (Etterlin [1], Lerch [3], Gruber [4], Duda [9], Theodoridis [10], Hand [11]). In this study binary decision tree methods were used. Decision trees are a hierarchical structure of rules that have to be trained and validated. The training results in trees with a certain complexity and structure. Each nod of a binary decision tree contains a binary decision formulated as a condition with a threshold for a selected statistical or operating point parameter (see section 4.1 and 5.1 / 5.2).

6.1 Single tree versus Bagged-Tree model

The main requirement for a decision tree model is to predict correctly the state of the monitored plant if the model is fed with statistical and operating point parameters obtained from measurement data of the plant. In order to achieve a high probability of a correct prediction, the tree model has to be trained with representative training data. In real applications, the training data measurements might vary considerably. Therefore, a certain robustness of the tree model is required. If a single tree model is used, the robustness is limited due to the limitations of the training data and/or overfitting. In the ideal case that the training data are complete, that means for every possible situation the outcome is known, a single tree could be trained. As this situation is not fulfilled in most real applications, an extension of the single tree method has been developed by L. Breiman [12] that can cope better with uncertainty by enhancing robustness and predictability. This method is called Bagged-Tree model. The prize to be paid is an augmented complexity in terms of training and implementation. In the works of Frei [1] and Agner [5] both approaches have been applied to the cavitation detection problem.

6.2 Bagging

Bagging is an abbreviation for Bootstrap Aggregation. Bootstrapping is a method used in statistics. It works as follows: For a given set of N data sets, m new subsets are built. Each of these subsets contains N' data sets of the original N data sets. The picking of the individual data sets for each of the m subsets is done randomly. After each pick, the selected data set is put back in the original data set. That means, that a specific data set can be picked several times for a given subset. Figure 8 shows in example a realization how $m=4$ subsets containing each $N'=5$ data set of the original $N=8$ data sets are built. The subsets are called ‘bootstraps’, the total model containing all trees ‘ensemble’ or ‘Bagged-Trees’. For the cavitation detection problem each data set corresponds to one of the 80 training data sets (section 2) [13, 14].

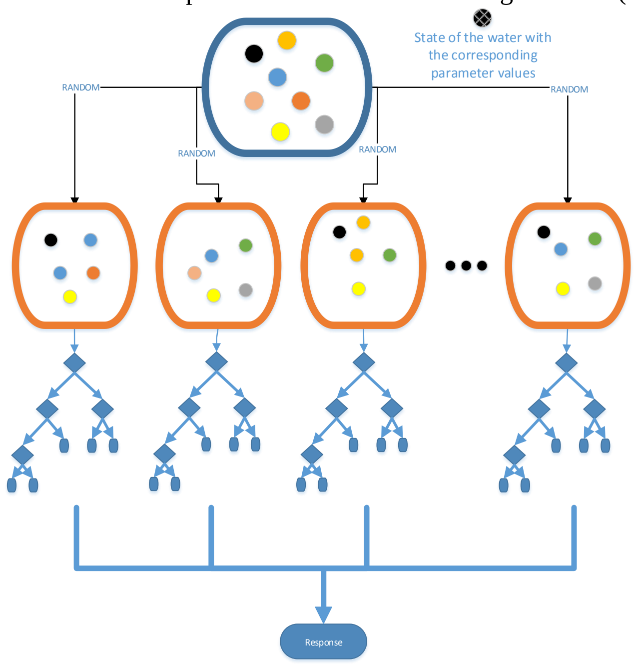


Fig. 8: Ensemble of Decision-Trees of a Tree-Bagger Model

For each subset, a single decision tree is trained. Additionally to the randomness of the selected sub-sets, the number of training parameters is also restricted for each split of a tree. The number of randomly chosen parameters for one tree is the nearest integer to the geometric mean between 1 and the total number of parameters taken into account (pump-turbine example: total number of parameters is 41, therefore the number of randomly chosen parameters is at most $\sqrt{41} = 6.4$). The training of the Bagged-Tree model is done by the command *TreeBagger()* of Matlab [8]. After the training of all m trees, this ensemble of parallel classifiers is applied to new incoming data in the following way: Each tree is fed with the required input parameters and produces a resulting detected class. The final result or response of the ensemble classifier is the class that has been identified by the relative majority of the individual trees.

6.2.1 Out of Bag Error und parameter importance
An important measure for the reliability of a Bagged-Tree model is the Out of Bag Error (OOBError). As data sets of the basic set are picked randomly for the subsets, it will be most unlikely, that all data sets will be used a tree. The left out data sets are the so called Out Of Bag (OOB) samples or sets. They can be used for validation of the trained tree model. The outcome of the validation is a measure of the robustness of the model to unknown new data.
Another important measure obtained from the OOB samples is the importance of the input parameters. If a single decision tree is used, it is easy to find out the importance of the parameters: the parameters used in the final tree are the important ones. If an ensemble of 50 or more trees is used, the evaluation of the importance of the parameters is not evident. Matlab offers for both cases the possibility of an importance measure by computing the 'OOB Permuted Predictor Delta Error'. Imagine that you take a single parameter, and you randomly reorder (*permute*) all of its values in the OOB samples, while keeping the rest of the dataset in the same order. The error across the ensemble of subtrees of the classifier is computed by averaging.
If parameter values can be interchanged in between the OOB Samples without an increase of the classification error, this parameter is of low importance. If however the error increases significantly by the permutation, the importance of this parameter is high. Figure 12 is an example of such an evaluation. To be absolutely sure that a parameter has no influence, one has to train a model without using this parameter and checking the outcome of the classifier.

6.2.2.Overfitting
Overfitting refers to a model that models the training data too well [15]. It happens when a model learns the detail and noise in the training data to the extent that it has a negative impact on the performance of the model to new data. This means, that the noise or random fluctuations in the training data are picked up and learned as features of the model. The problem is that these overtrained models do not apply to new data and negatively influences the models ability to generalize. Overfitting is more likely with nonparametric and nonlinear models that have more flexibility when learning a target function. As such, many nonparametric machine learning algorithms also include parameters or techniques to limit and constrain how much detail the model learns. For example, decision trees are a nonparametric ma-chine learning method that is very flexible and is subject to overfitting training data. This problem can be addressed by pruning a tree after training in order to remove some of the picked up details. Therefore, the chance of overfitting of a single tree is high. In contrary, Breiman [12] has shown that even a high number of subtrees in a Bagged-Tree model does not lead to overfitting due to randomization. Figure 9 shows how the OOBError is changing with the number of trained subtrees for ultrasonic data from another experiment [2]. 9 Bagged-Tree models from 30 up to 230 subtrees have been trained. It is easily visible that the OOBError converges to a small constant value. 50 trees seem to be good enough.

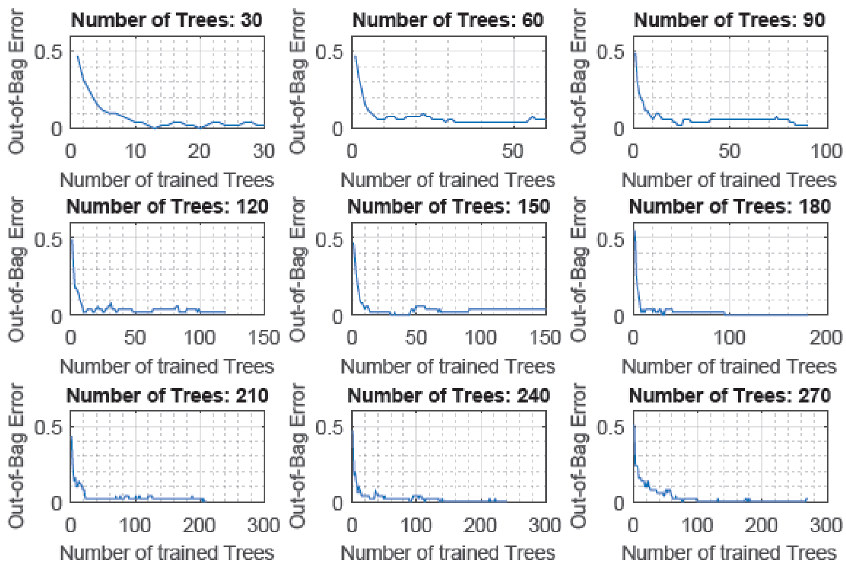


Fig. 9: Out of Bag Error (OOBError) and overfitting versus number of subtrees (complexity of the classifier)

6.3 Validation of measurement data
As mentioned before, the reliability of a classifier must be validated by OOB samples or separate validation sets. In the following, the validation is done by the so called 'Holdout'. The total available data set is split into two sets: 1) a validation set, that means data 'holdout' from training (fraction given in % from 10% up to 80%) and 2) a training set with the remaining data sets. After the training is completed, OOB samples might be present in the training set. These are not used for the validation of the trained classifier. The result of the classifier fed with the validation set is then compared with the

correct class. A ‘Holdout’ of 10% means that 90% of the data are used for training, while 80% ‘Holdout’ means only 20% training data. Figure 10 explains the splitting procedure.

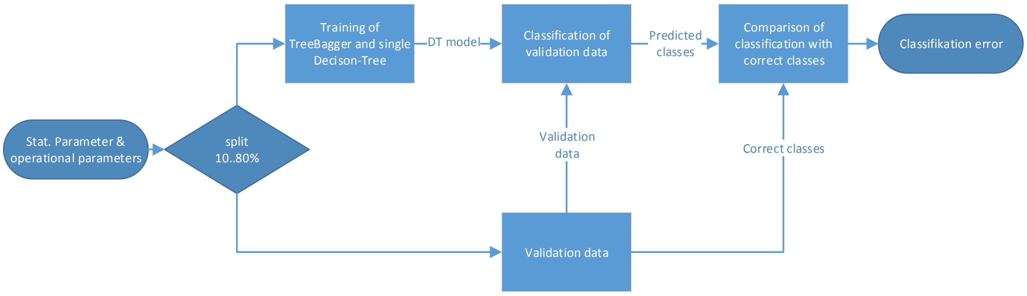


Fig. 10: Data split for training and validation

In the following example, a single tree classifier and a Bagged-Tree classifier are compared if the ‘Holdout’ percentage is steadily increased. The Tree-Bagger model was trained with 50 trees, and the training has been repeated 200 times and then averaged in order to obtain a statistical significant error result. As can be seen from Figure 11, the error rate increases faster as a function of the ‘Hold-out’ rate if only a single tree is used in comparison to a Bagged-Tree model. The increase of reliability for the Bagged-Tree model must be paid by an increase in training time, a larger software code and a higher classification time.

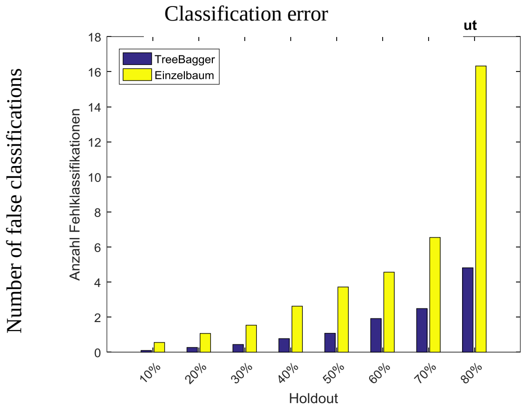


Fig. 11: classification error as function of Holdout percentage

The classification time of a Bagged-Tree model in Matlab is substantially higher as can be seen in Table 2 for a classification of 100 data sets.

	time
single DecisionTree	1.4ms
Tree-Bagger	86.5ms

Table 2: execution time for classification

The difference is large, but for hydropower application not of importance. The data acquisition and storage of e.g. 50 transient signals uses more time than the classification.

7. Classification of the pump-turbine measurements

Single decision tree models and Tree-Bagging Tree models were trained and validated with the following features:

- Out of the total 80 data sets (see section 3), 70% (56) are used for training and 30% (24) for validation.
  4 water states (clean water (W), water & gas (G), stable swirl (WZ), pulsating swirl (PZ))
- The total number of parameters per data set is 41:
  38 ultrasonic parameters, 1 pressure parameter (transient measurements)
  2 operating point parameters (static measurements)
- The Bagged-Tree model has 50 trees
- The training and validation is repeated 500 times
- Single and Tree-Bagged tree models have been trained for the following parameter sets
  1) 2 static operating parameters Φ, Ψ and 1 transient pressure parameter I_FFT_p_Impeller
  2) Only 38 ultrasonic statistical parameters

3) 38 ultrasonic statistical parameters and transient pressure parameter I_FFT_p_Impeller
4) 38 ultrasonic statistical parameters and 2 static operating parameters Φ, Ψ
5) all 41 parameters

- For each parameter set the importance of the individual parameters are evaluated ('OOB Permuted Predictor Delta Error')
- For each parameter set a normalized confusion matrix which visualizes the performance of the classification is build. For a perfect classifier the matrix corresponds to the identity matrix as shown in Table 3.

		actual class			
		W	WZ	PZ	G
Pred. class	W	1.00	0.00	0.00	0.00
	WZ	0.00	1.00	0.00	0.00
	PZ	0.00	0.00	1.00	0.00
	G	0.00	0.00	0.00	1.00
		1.00	1.00	1.00	1.00

Table 3: Confusion matrix for perfect classification

In the next section, case 2) and case 4) are presented in detail. The other cases do all include the measurement of the transient pressure at the impeller inlet, which is difficult to install and to maintain. Therefore, they are not presented here although the results for these experiments were comparable to the two considered cases.

7. 1 Classification with Ultrasonic signals (US) only
First parameter choice was the use of ultrasonic (US) signal parameters only. Figure 12 shows the importance graph for all 38 statistical parameters of the ultrasonic signal. It is clearly visible, that the majority (~23) of the parameters are of small importance (value are smaller than 0.25). 10 are larger than 0.35 and the remaining 5 are in between. The most important parameters are:

1	*Laufzeitmittelwert mean_time*	signal parameter, time domain
2	*mean_Area_r_div_mean_Area_l*	correlation parameter, time domain
3	*mean_dt_1_pks*	correlation parameter, time domain
4	*std_dt_1_pks*	correlation parameter, time domain
5	std_mean_A_FT_sigma_s_1	signal parameter, frequency domain
6	*std_A_abs*	signal parameter, time domain
7	*mean_dt_2_pks*	correlation parameter, time domain
8	*mad_A*	signal parameter, time domain
9	mean_s_r	correlation parameter, time domain
10	mean_skew_corr	correlation parameter, time domain

Table 4: parameter ranking for US Bagged-Tree

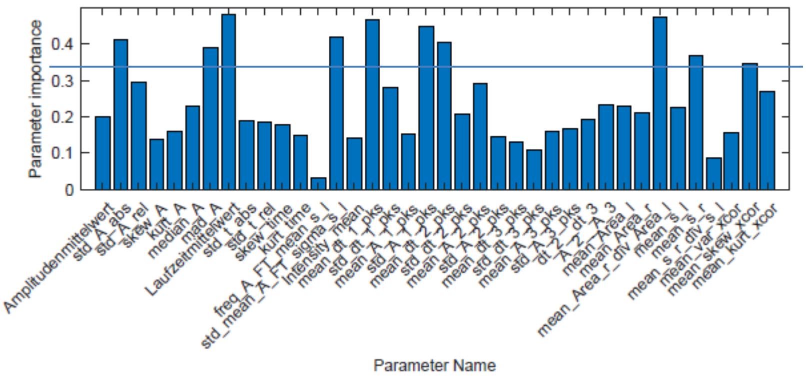


Fig. 12: Parameter importance for US only Bagged-Tree model

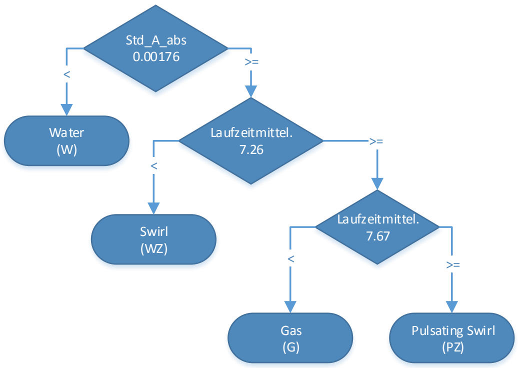


Fig. 13: Example of a single tree; only two parameters are needed

		single tree US only			
		W	WZ	PZ	G
Predicted	W	0.9570	0.0000	0.1397	0.0000
	WZ	0.0133	0.9034	0.0450	0.1098
	PZ	0.0151	0.0009	0.7731	0.0008
	G	0.0145	0.0957	0.0422	0.8894

Table 4: Confusion matrix for single tree US only

		Bagged-Tree US only			
		W	WZ	PZ	G
Predicted	W	0.9982	0.0000	0.1157	0.0000
	WZ	0.0000	1.0000	0.0000	0.0016
	PZ	0.0006	0.0000	0.8723	0.0048
	G	0.0012	0.0000	0.0120	0.9935

Table 5: Confusion matrix for Bagged-Tree model US only

Figure 13 shows an example of a single trained tree of low complexity. Tables 4 & 5 show the performance of the two approaches, where the differences between one and the numbers in the diagonal multiplied by 100% give the error rate per water state.

7. 2 Classification with Ultrasonic signals (US) & Φ, Ψ

The most important parameters in this case are listed in Table 6 and their importance in Figure 14. An example of a decision tree is given in Figure 15. Figure 15 shows that in the case US & Φ, Ψ parameters, particular trees out of the 50 need US signals only, as is the case of the shown tree. Other trees are fed with important parameters of Table 6. Most trees have however a simple structure and need not more than 3 or 4 parameters. Table 7 and Table 8 show the confusion matrix for both cases.

1	*Laufzeitmittelwert mean_time*	signal parameter, time domain
2	*std_dt_1_pks*	correlation parameter, time domain
3	*mean_Area_r_div_mean_Area_l*	correlation parameter, time domain
4	*std_A_abs*	signal parameter, time domain
5	freq_A_FT_mean_s_1	signal parameter, frequency domain
6	*mean_dt_1_pks*	correlation parameter, time domain
7	**PSI**	Operating point parameter
8	*mean_dt_2_pks*	correlation parameter, time domain
9	*mad_A*	signal parameter, time domain
10	**PHI**	Operating point parameter

Table 6: parameter ranking for US & Φ, Ψ Bagged-Tree model

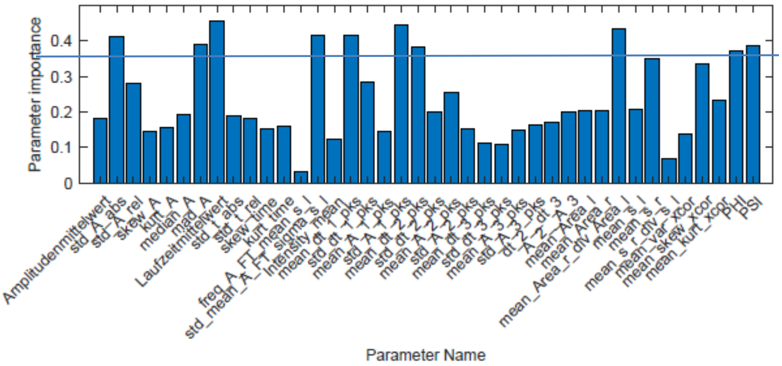


Fig. 14: Parameter importance for US & Φ, Ψ Bagged-Tree model

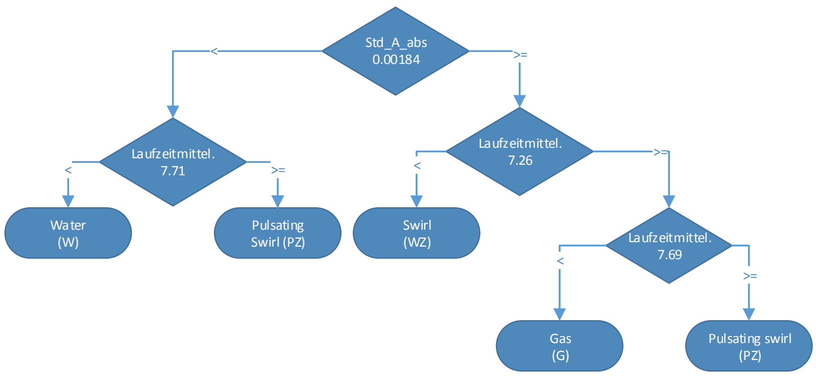


Fig. 15: Example of US and Φ, Ψ tree; only 2 parameters are needed

Single Tree US PHI PSI	W	WZ	PZ	G
Predicted W	0.9570	0.0000	0.1397	0.0000
Predicted WZ	0.0133	0.9034	0.0450	0.1098
Predicted PZ	0.0151	0.0009	0.7731	0.0008
Predicted G	0.0145	0.0957	0.0422	0.8894

Table 7: Confusion matrix for single tree US & Φ, Ψ

Bagged-Tree US PHI PSI	W	WZ	PZ	G
Predicted W	0.9996	0.0000	0.1203	0.0000
Predicted WZ	0.0000	1.0000	0.0000	0.0000
Predicted PZ	0.0004	0.0000	0.8694	0.0016
Predicted G	0.0000	0.0000	0.0103	0.9984

Table 8: Confusion tree for Bagged-Tree US & Φ, Ψ

7. 3 Comparison and Interpretation

The comparison of the performance reveals the following facts:

1) The single tree method is for both cases inferior to the Bagged-Tree method by margin of 5-10% depending on the detected state. The performance of the single tree method is the same for the US only and the US & Φ, Ψ configuration. The Bagged-Tree method works nearly fault free.
2) The performance of the US & Φ, Ψ configuration over all states is slightly better than the US only configuration (~0.35%). Only the detection of pulsating swirls (PZ) is slightly worse than the US only configuration (~0.29%).
3) The parameter ranking tables show some interesting observation:
   a) Seven out of the ten most important parameters, marked in italics, are for both considered configurations the same: 3 signal parameters in the time domain and one in the frequency domain, and 3 correlation parameters in the time domain.

b) The operating point parameters appear in the US & Φ, Ψ configuration case in the list of the ten most important parameters (position 7 and 10 in bold). So one can conclude that they contribute to the better performance of the US & Φ, Ψ configuration compared to the US only configuration. For the single tree method, no improvement could be found.
c) For the other three parameter choices mentioned above, similar conclusions can be drawn.
d) To analyse the number of parameters and their choice one would need to evaluate all configurations in a systematic way. This has however not been done. From the obtained results, a good selection of parameters could be:
   1) One or two US signal parameters in the time domain (maybe one additionally in frequency domain)
   2) One or two US correlation parameters
   3) Φ and Ψ
   4) Transient pressure signal parameter in the frequency domain, if available

   So the number of parameters could be restricted to 4 up to 8.

It is to be noted, that the performance is dependent on the validation method. If the 'Holdout' is larger, clearly the Bagged-Tree models would perform worse. Additionally, the available number (80) of data set is rather small. A larger collection of data sets are therefore highly recommended.

8. Conclusions

The Bagged-Tree model for classifying seems to be a very promising method for monitoring the water states in a pump-turbine. At least in the case of the test pump-turbine at the HSLU hydraulic laboratory good results were obtained. The ultrasonic measurements mounted in a clamp-on fashion to the draft tube are able to capture important information about cavitation and gas bubble states of the water that operating point information cannot deliver. The installation of such a measurement set up is in contrast with the mounting of transient pressure sensors at the inlet of the impeller, easy. If additionally other measurements are available (accelerometer, hydrophones, vibrations, noise,..), they can be added to the classifier scheme without difficulties. Further investigations with a turbine, pump or pump-turbine in the field are high on the agenda.

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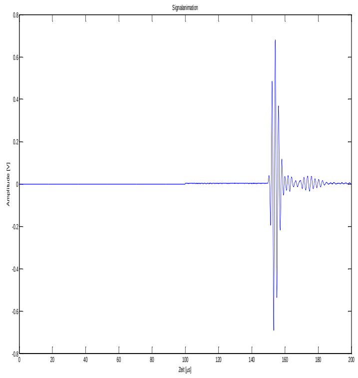
Appendix

Definition of all 41 input parameters for Classifier:



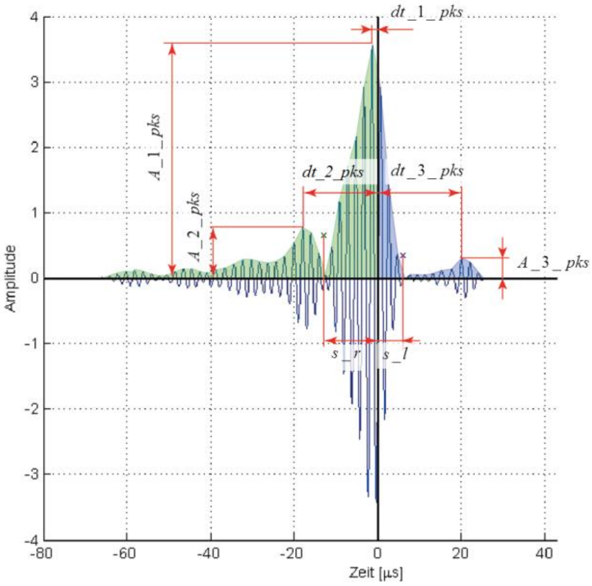


Fig. A1: typical ultrasonic signal

Fig. A2: correlation function with characteristic parameters

Statistical signal parameters

Signal parameters in the time domain (12)	
mean_A	Amplitudenmittelwert / mean of maximum of signal amplitude
std_A_abs	standard deviation of maximum of signal amplitude
std_A_rel	coefficient of variation
skew_A	skewness of maximum of signal amplitude
kurt_A	kurtosis of maximum of signal amplitude
median_A	median of maximum of signal amplitude
MAD_A	median of absolute deviations from the median_A
mean_time	Laufzeitmittelwert von Anfang Messfenster/ mean of arrival time of maximum of signal amplitude from time of recording in microsec
std_t_abs	standard deviation of arrival time of maximum of signal amplitude
std_t_rel	coefficient of variation of arrival time of maximum of signal amplitude
skew_time	skewness of arrival time of maximum of signal amplitude
kurt_time	kurtosis of arrival time of maximum of signal amplitude
Signal characteristics in the frequency domain (2)	
freq_A_FT_mean_s_1	frequency for which the mean of the contribution is maximal
std_mean_A_FT_sigma_s_1	mean of standard deviation of each frequency contribution
Signal characteristics in the time/frequency domain (1)	
Intensity_mean	signal intensity (power)
characteristics of correlation function (23)	
Main peak (1)	
mean_dt_1_pks	mean of time difference to middle position of main peak in seconds
std_dt_1_pks	standard deviation of time difference in seconds
mean_A_1_pks	mean of amplitude maximaum of main peak
std_A_1_pks	standard deviation amplitude maximum of main peak
peak (2)	
mean_dt_2_pks	

std_dt_2_pks mean_A_2_pks std_A_2_pks **peak (3)** mean_dt_3_pks std_dt_3_pks mean_A_3_pks std_A_3_pks	
dt_2/dt_3	mean_dt_2_pks / mean_dt_2_pks
A_2/A_3	mean_2_3_pks / mean_A_3_pks
mean_Area_l	mean of left side Integral of left absolute value of correlation
mean_Area_r	mean of right side Integral of left absolute value of correlation
mean_Area_r_div_mean_Area_l	
mean_s_l	mean of center of gravity of left side area
mean_s_r	mean of center of gravity of right side area
s_r/s_l	
mean_var_xcor	mean of variance of correlation function
mean_skew_xcor	mean of skewness of correlation function
mean_kurt_xcor	mean of kurtosis of correlation function
Transient pressure signal characteristic	
I_FFT_p_Impeller	mean of intensity of first harmonic

Operating point parameters: static measurements of flow, rotational speed and pressure difference

Φ (PHI)	linear in $\dot{V}$ and inverse dependent on N,
Ψ (PSI	linear in Δp and inverse dependent on the square of N,