# Linking Acoustic Emission signals to 2D-PIV results to monitor fluid flow in pipes

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**Extended Abstract**

With the step up towards Industry 4.0 and smart manufacturing, industry is demanding increasingly non-invasive and on-line process technologies. In particular demands on hygiene standards have increased over the last three decades, which includes the introduction of equipment design standards like EHEDG or on a legislative level the Machinery Directive 98/37/EC and the Council Directive 93/43/EEC [1,2]. With manufacturing lines often running 24/7 on high output volumes tools are required to keep process lines free from contamination and clean. This is achieved by microbiological swabbing to determine when the cleaning routine is required, or by the creation of rigid cleaning schedules, with COP or CIP cleaning being industrial standards [3,4]. However, microbial swabbing does not deliver instant results and can be costly. COP and CIP cleaning delivers good results, however the cleaning often makes use of corrosive chemicals or those hazardous to health. Hence, inflexible cleaning routines may introduce additional costs for unnecessary cleaning or increases equipment wear.

A solution to this problem may be provided by the use of acoustic emission sensors. There are two main types of such sensors which are determined by whether they rely on an emitter-receiver system (active acoustic emission sensors) or solely detect acoustic emissions generated by a process itself (passive acoustic emission sensors). Active acoustic emission sensors, with its most common set-up being ultrasound or Doppler velocimetry sensors, are proven to give reliable predictions on factors such as flow rate, degree of gassing or solid content. This technology works well for Newtonian and non-Newtonian fluids [5,6].

Passive acoustic emission sensors are used for leak detection in water pipes by employing in-pipe hydrophones [7] or by aiming to recognise acoustic patterns based on the signals of a series of sensors [8]. Other work on passive acoustic emission sensing has mainly focused on multiphase systems [9–11]. However, no work has been done so far on enclosed, fully flooded and single-phased systems.

The experimental setup consists of a water recirculation system powered by an I KA-5 132SSS1 centrifugal pump (Alfa Laval, Sweden). A total of 4 flow rates ranging from 1,300-6,350 $lh^{-1}$ are investigated. Additionally in-pipe obstructions of 4 different geometries are used, all being designed in AutoCad 2018 (Autodesk Inc., USA) and extruded by a FlashForge Dreamer 3D printer (Zhejiang Flashforge 3D Technology Co., Ltd., China).

The differences in flow pattern are visualised with the assistance of a TSI 2D Particle Image Velocimetry system (TSI Inc, USA) by using a Perspex box of same length (120mm) and inner diameter (1-inch) to the stainless steel pipe where the acoustic sensor will be placed on later. The system uses a green 532 nm Nd-Yag laser (Litron Nano PIV) pulsing at 7 Hz and is synchronised to a single TSI Power View 4 megapixels (2048 x 2048 pixels) 12-bit CCD

camera. The camera is connected to another synchroniser (TSI 610035) which is attached to a desktop PC. The PIV system is controlled by TSI Insight 4G software. Each experiment has been conducted on an image total of 500, afterwards combined and averaged in order to determine the flow field. The area is set to 32 x 32 pixels (Figure 1).

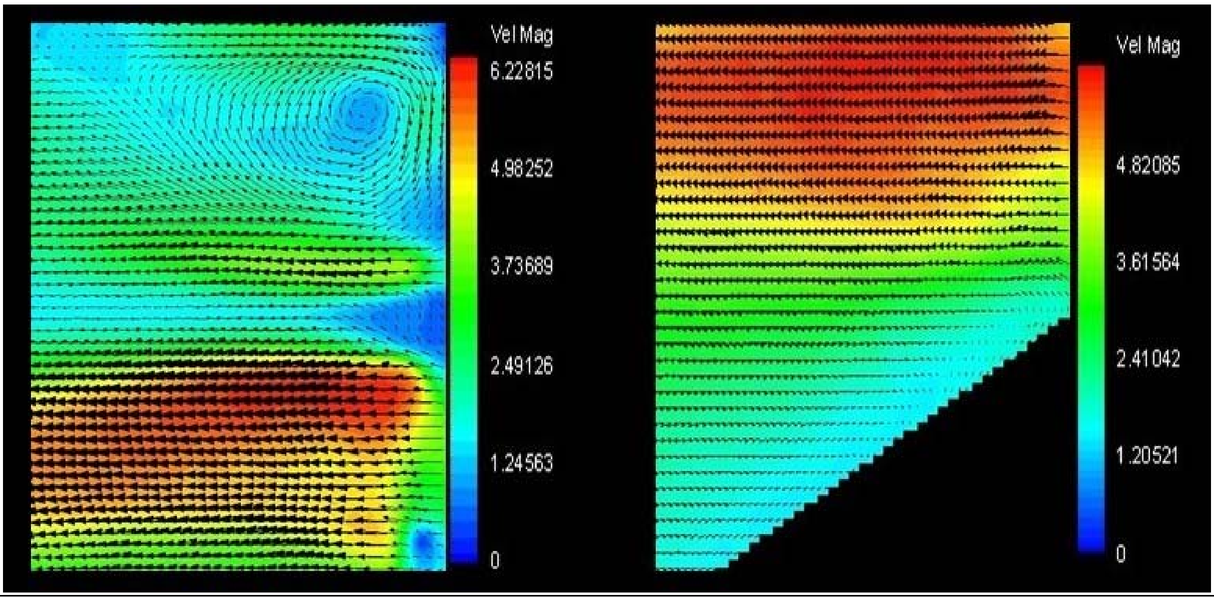


*Figure 1 Processed PIV images on a normalised scale for the obstacle types "cross" (left) and "cone" (right) at 6,350 lh$^{-1}$*

As expected, the PIV results show clearly that different types of obstacles lead to different flow regimes and increases in flow rate lead to increases in velocity magnitude.

The passive piezoelectric VS375-M acoustic emission sensor (Vallen Systeme GmbH, Germany) is linked to a 2.5 kHz to 2.4 MHz (10 Vpp) AEP5H preamplifier (Vallen Systeme GmbH, Germany) along with a DCPL2 filter unit (Vallen Systeme GmbH, Germany), a PicoScope 5000 Series oscilloscope (Pico Technology Ltd, UK) and a personal computer using PicoScope version 6.13.15 software is attached for data capture. 200 buffers, each of a length of 500ms, a resolution of 16-bit and an amplitude of maximum ±1 V is used. The sampling number is set to 600 kS.

The recorded acoustic emission are pre-processed, background noises of frequencies below 4 kHz are removed and the Fast Fourier Transform (FFT) spectrum is extracted. To reduce the total amount of data only those 5,000 FFT values with the largest relative variance are selected for further processing (Figure 2).

The selected frequencies are fed into the Matlab R2018a (MathWorks Inc, USA) Classification Learner Application (CLA) with enabled Principal Component Analysis (15 components). The dataset for the Machine Learning is further split into in a training (60%), optimisation (20%) and a test dataset (20%). The test dataset is supplied to supervised classifiers (e.g ANN, Decision Tree, SVM) whilst the second dataset is not fed into the CLA to evaluate the accuracy of the algorithms.

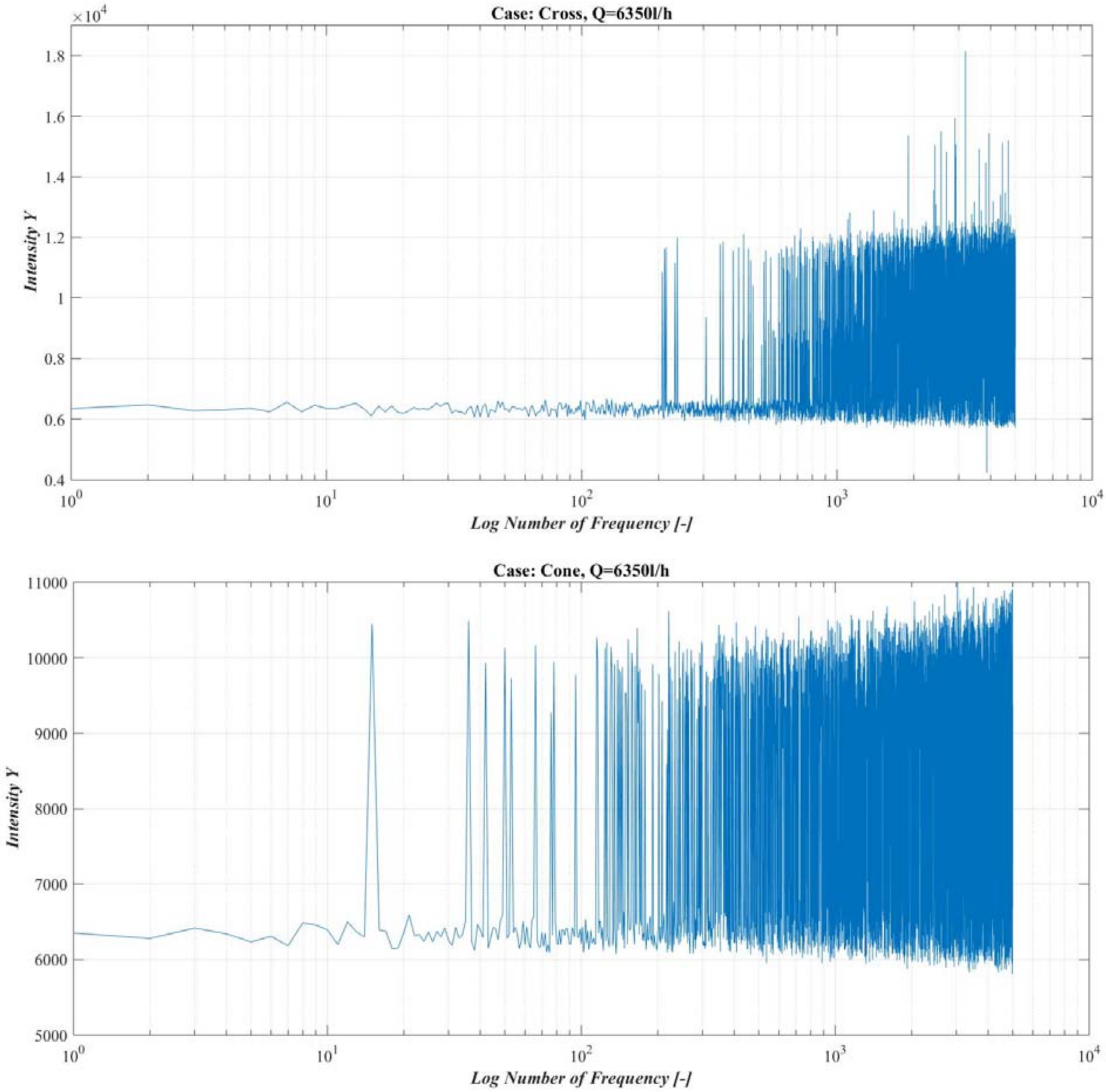


*Figure 2 FFT Spectrum of the 5,000 most prominent pre-processed frequencies for the obstacles Cross (top) and Cone (bottom) at 6350 $lh^{-1}$ in semi logarithmic scale.*

For the acoustic data higher flow rates lead to higher peak values and different pipe obstacles to different FFT spectra. Highest accurate predictions in supervised machine learning are attained by using quadratic SVM with accuracy levels being in the region of 95% or better for both cases; the identification of different flow rates and different obstacles.
This makes the use of a single passive acoustic emission sensor a viable option to be used for industrial applications and the prediction of pipe obstruction. Further, supervised machine learning has been proven useful to do predictions on limited computation power. However, as supervised machine learning is not a dynamic process the use of unsupervised machine learning neuronal networks could be subject for future research. Further the range of other types of in-pipe obstructions can be investigated.

Keywords: acoustic sensor, pipe flow, machine learning, smart manufacturing, Particle Image Velocimetry, Obstruction

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