Feasibility study for the application of a neural network for operating condition detection of a centrifugal pump

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Abstract. Artificial intelligence (AI) technology is successfully used in many fields. Originally, AI was developed for image and voice recognition and has been spread out on other fields like detecting deceases, behaviour, traffic movement etc. AI is also applied in fluidmachinery, for example in order to detect defaults in pumps, fans, compressors and turbines. This work verifies the feasibility for the application of a neuronal network (NN) for operation point detection of an impeller pump by vibration signals. Once the NN is trained with the vibration signal, it can recognize the operating point by the vibration signal of the impeller pump. In order to test whether the neural network method is feasible, a pump loop system was built up, which contains a radial centrifugal pump with a replaceable impeller. The vibration signal of the impeller pump is taken for different operating points and used for training a NN. In the first step a simple self-programmed NN in C++ is applied in order to find out a convenient NN-topology for operating point detection. The congruence rate of this simple NN method already reaches about 90%. The research results in this paper show that an operating point can be detected by the application of a simple NN. It is carried out how large the influence of the topology of a NN is in regard to the congruence rate (CR). By further application of AI like convolutional layers, batch normalization etc. a better CR seems to be very likely. From this point of view this contribution reports about a starting point of operating point detection of impeller pumps by the application of a NN.

Keywords: radial centrifugal pump, operating condition detection, neural network, vibration signal

1. Introduction

Artificial intelligence (AI) technology has been used increasingly in mechanical engineering in recent years. From the term “artificial intelligence” first coined by John McCarthy in 1956, it has been nearly 70 years. Machine learning has played a vital role in the rapid development of AI over the last 20 years. With the reinvigoration of neural network (NN) in the 2000s, deep learning has become an extremely active area of research that is paving the way for modern machine learning [1]. In the last ten years many famous deep learning frameworks such as TensorFlow, PyTorch, Caffe are published. TensorFlow is based on C++ and developed by Google in 2015, which can be applied in almost every field. PyTorch is based on Python and developed by the Torch7 team in 2017. Caffe is developed in 2013 by Jia Yangqing of the University of California, which is support for convolutional NN. These highly developed deep learning frameworks are successfully applicable to many cases about pumps, fans, compressors and turbines. Based on large number
of real-time data of electric pump wells in offshore oilfields, Yuan has built a neural network model based on TensorFlow to predict wellhead production of electric pump wells and detect abnormal operation conditions[2]. Khan used a new hybrid approach of principal component analysis (PCA) and deep learning with a TensorFlow framework to uncover the hidden patterns from wind data and to forecast accurate wind power for large scale wind turbine[3]. But all these successful cases are based on a complex NN which contains conventional layer, recurrent layer or long short-term memory (LSTM) layer and so on [4]. These NN requires a long training time and complex parameter adjustment.

In this paper, the applicability of a simple NN for operating condition detection by vibration signals of a centrifugal pump was investigated. In the first step a simple self-programmed NN in C++ is applied in order to find out a convenient NN-topology [5]. The NN consists of one input layer, several hidden layers and one output layer. The number of hidden layers and nodes of each layer can be defined according to the needs of the application. By changing these parameters, the influence of the topology of a NN is detected and the best NN-topology in accordance with the congruence rate (CR) is investigated.

In order to obtain the training and test data for the NN, a pump loop system was built up. The vibration signal of different operating conditions of the impeller pump is taken from a simple acceleration sensor ADXL345 (Analog Devices), which is glued on the pump casing. The time domain vibration signal was converted into the frequency domain by Fast Fourier transform (FFT) before it was classified by a sorting algorithm and used as training or test data sets of the NN. The vibration signals of 92 operating conditions were measured in present work. The CR of over 80% confirmed the applicability of the simple NN method.

2. The Pump Loop System

In order to obtain the training and test data for the NN, a pump loop system was built up at the Institute for Interdisciplinary Research at Jianghan University (JHU). It contains a centrifugal pump with a replaceable impeller, which is designed and manufactured by the Institute of Fluid Mechanics and Fluid Machinery (SAM) at Technical University Kaiserslautern (TUK). The specific speed of the pump \( n_q = 39 \), head \( H = 30 \text{m} \), volume flow rate \( V = 100 \text{m}^3/\text{h} \), rated rotation speed = 3000 rpm. The pump has 6 blades, blade_exit_angle (hub) = 22.8°, blade_exit_angle (middle) = 24.4°, blade_exit_angle (shroud) = 25.9°. The medium in the pump is water and the rated head of the pump is 30m. Figure 1 shows the pump loop system. The pump is driven by an asynchronous motor with a rated rotation speed of 2950 rpm. The rotation speed of the motor can be controlled by a frequency converter. Between the pump and the motor is a torque meter, which measures the number of revolutions of the motor \( n \) and the torque of the motor \( M \).

![Figure 1. Depiction flow the pump loop system](image-url)
The blue arrows indicate the flow direction. On the left of the pump loop system a 4000L water tank is installed. Two cut-off valves are next to the tank, which can cut off the tank from the pipe loop. A control valve is next to the cut-off valve 2 in order to regulate the flow volume $Q$ in the loop. The flow volume can be measured by the flow meter below the control valve. A pressure sensor is located on the suction and discharge side of the test pump in order to measure the static pressure increase ($\Delta P_{\text{static}} = P_{\text{stat,d}} - P_{\text{stat,s}}$) over the pump.

![Figure 2. Measuring box](image)

A self-designed measuring box is used for the pump loop system to communicate with a computer (Figure 2). The kernel of the measurement system is an Arduino-microcontroller-board Mega 2560 [6] which controls the electrical valves and motor automatically. Form the Analog IO port of the board, the data of the pressure sensors, the flow meter and the torque meter can be collected. With MATLAB Support Package for Arduino Hardware, a software based on the board was programmed. With the software the operating condition of the pump can be detected by traditional method based on equation (1)

$$H = \frac{\Delta P_{\text{static}}}{\rho g} + \frac{1}{2g} \left( \frac{Q}{A_d} \right)^2 - \left( \frac{Q}{A_s} \right)^2 + h$$  \hspace{1cm} (1)

with density of the fluid $\rho$, gravitational acceleration $g$, the static pressure increase $\Delta P_{\text{static}}$, flow volume in the pump loop $Q$, pipe cross-sectional area of the discharge side $A_d$, pipe cross-sectional area of the suction side $A_s$ and the height difference between the pressure sensors on the suction and discharge side $h$.

3. Experimental Method

3.1. Collection and processing of the vibration signal

The experimental procedure is shown in Figure 3. For the automatic measurement, the rotation speed of the motor $n$, decrement $x$ of the control valve opening, the minimum of the control valve opening $O_{\text{min}}$ and the sampling size of the vibration signal for each operating condition $s$ was set up in the software.
After the settings, the automatic measurement started. Under each operating condition, in addition to the collection of the vibration signal, the flow volume \( Q \) was measured ten times and the average was recorded as the mark of this operation condition. After the measurement of each operating condition, the control valve closed by \( x \) automatically. Then the control valve opening was measured, if it was not less than \( O_{\text{min}} \), the measurement of the next operating condition started. Otherwise, the motor will turn off and the automatic measurement was finished.

**Figure 3.** Experimental Procedure

**Figure 4.** Three-axis accelerometer ADXL345
As shown in Figure 4, the vibration signal was taken from the three-axis accelerometer ADXL345 (Analog Devices), which is glued on the transparent casing of the pump. The ADXL345 is a three-axis accelerometer which measures the static acceleration of gravity in tilt-sensing applications, as well as dynamic acceleration resulting from motion or shock [7]. The accelerometer was connected to the Arduino board through the I²C digital interface. During each measurement, the digital output data of the accelerometer was converted from 16-bit two's complement to binary values by the driver application and stored in the computer as the time domain vibration signal under each operating condition. In this paper only the vibration signal on z-axis which is perpendicular to the ground was used. The signals of the other two axials will also be integrated to the training- and test data for the research work in the future.

![Diagram showing time domain and frequency domain analysis](image)

**Figure 5.** Vibration signal at $Q = 57\frac{m^3}{h}$, $n = 2500$rpm

The time domain vibration signal under operating condition $Q = 57\frac{m^3}{h}$, $n = 2500$rpm is shown in Figure 5. It was converted into a frequency domain signal by Fast Fourier transform, and then with the mark of the operating condition combined to become a part of a training or test data set of the NN. To obtain the FFT coefficients, the MATLAB command `fft()` was used. After the FFT, the absolute values of the resulting complex Fourier coefficients which represent the amplitudes are formed by means of the `abs()` command. A total of 276 vibration signals under 92 operating conditions with a sampling frequency of 160Hz were measured in present work. The 92 operating conditions were recorded at four different speeds (1000 rpm, 1500 rpm, 2000 rpm, 2500 rpm). By each rotation speed, the opening of the control valve was varied at a constant speed starting from 40% valve opening in steps from 2.5% to 95% valve opening. As a result, signals were recorded in a volume flow range from $16.5\frac{m^3}{h}$ to $107\frac{m^3}{h}$. Under each operating condition the vibration was measured 1000 times by the accelerometer, it takes approximately 6.25s. For each operating condition, the measurement was repeated 3 times.
3.2. Structure of the Neural network

The applicability of a simple NN for operating condition detection by vibration signals of a centrifugal pump was investigated. A self-programmed NN based on C++ is applied in order to find out a convenient NN-topology for operating point detection of the pump [5].

![Structure of the NN](image1.png)

**Figure 6. Structure of the NN**

As shown in Figure 6, the structure of the NN is classic, it consists of one input layer, several hidden layers and one output layer. The number of hidden layers and nodes of each layer can be defined according to the needs of the application. The nodes are connected by weights, each node modifies the output values by the SIGMOID-function

\[
y = \frac{1}{1+\exp(-\sum_{j=0}^{n-1} z_j)}.
\]

(2)

\(y\) and \(z\) stand for the output value and the input value of each node.

The benchmark of the NN-topology is the congruence rate (CR) which is defined by

\[
CR = 1 - \frac{1}{n_{test}} \cdot \sum_{i=0}^{n_{test}-1} \left| \frac{f_{NN}(i) - f_{exact}(i)}{f_{exact}(i)} \right|
\]

(3)

\(f_{NN}(i)\) and \(f_{exact}(i)\) stand for the function value, which is calculated by the NN, and the exact function value of the test data, respectively.

Figure 7 shows the structure of the training and test data. The mark of the operating condition of the pump is divided into seven flow volume classes, therefore the red target value on the first column in the data can be any number between 1 and 7. The rest grey columns are the value of the frequency domain vibration signal. The size of the training or test set was defined by the number of the rows \(m\) of the data.

4. Result

4.1. Influence of the iterations and training data size on the CR

Figure 8 shows the result, when the test data size \(n_{test}=14\). The training data size training, were 35, 70, 105 and 140 respectively. The training data and the test data were selected from the total data randomly. The number of the hidden layers \(n_{\text{hidden}}=1\), the number of the first hidden layer nodes \(n_{\text{nodes}}=10\) and the learning rate \(\alpha=0.3\). As shown, the CR was increased with the increasing of \(n_{\text{iteration}}\). But more than 800 iterations
didn’t improve the CR any more. And when training, was increased, no matter how large the \( n_{\text{iteration}} \) was, a higher CR was achieved.

**Figure 8.** CR versus training, \((\text{test},=14, n_{\text{hidden}}=1, n_{\text{nodes}}=10\) and \( \alpha=0.3 \))

4.2. *Influence of the hidden layer on the CR*

Figure 9 and Figure 10 show the influence of the \( n_{\text{nodes}} \) on the CR. Figure 9 depict the result, when \( n_{\text{hidden}}=1, \) training, =140, test, =28 and \( \alpha=0.3 \). The CR of the NN with less hidden layer nodes was larger and converged faster than the CR of the NN with more hidden layer nodes.

**Figure 9.** CR versus \( n_{\text{iteration}} \) \((n_{\text{hidden}}=1, \) training, =140, test, =28 and \( \alpha=0.3 \))
Figure 10. CR versus number of nodes of the hidden layer \((n_{\text{hidden}}=1, \text{test}_s=28, \alpha=0,3)\)

Figure 10 shows the result, when the test was fixed at 28, \(n_{\text{hidden}}=1\), \(\alpha=0,3\) and the variation range of the \(n_{\text{nodes}}\) was between 2 and 40. For all combinations of the training and \(n_{\text{iteration}}\), the maximum of the CR was achieved invariably, when the \(n_{\text{nodes}}\) was about 10. In principle more than 10 hidden layer nodes didn’t improve the CR anymore and even brought a decline of the CR.

Figure 11. CR versus two hidden layers \((n_{1\text{nodes}}=10, \text{training}_s=140, \text{test}_s=28 \text{ and } \alpha=0,3)\)
Figure 1 compares the results of using one hidden layer and two hidden layers, respectively. The \( n_{\text{nodes}} = 10 \), testing = 140, test = 28 and \( \alpha = 0.3 \). The best CR of 92.86\% of all the testing appears, when only one hidden layer was used. A variation of the number of the second hidden layer nodes \( n_{2\text{nodes}} \) between 5 and 10 showed no effect on the CR. In this condition, the using of a second hidden layer leaded to even worse CRs.

### 4.3. Influence of the learning rate on the CR

![Influence of the learning rate](image)

Figure 12 shows the influence of the learning rate \( \alpha \), which regulates the adjustment of the weights during training. Only one hidden layer was used, the \( n_{1\text{nodes}} = 10 \), \( n_{\text{iteration}} = 750 \). Under the three training and test data combinations, the highest CR appears at \( \alpha = 0.3 \). And the best hit rates of the self-designed C++ program are also reached, when the learning rate is close to \( \alpha = 0.3 \) [5]. Therefore, the learning rate of all topologies in the results of chapter 4.1 and 4.2 was chosen to be 0.3.

### 5. Conclusion

In the current work, the applicability of a simple NN for operating condition detection by vibration signals of a centrifugal pump was studied. First of all, a pump loop system was built up and a measuring box based on Arduino for the system was developed with MATLAB. Subsequently, a total of 276 vibration signals were collected under 92 different operating conditions with a simple acceleration sensor and converted from time domain signals to frequency domain by FFT. The database of the NN consists of these signals. The highest achievable CR of all the tests was 92.86\%. Therefore, the realization of such a high CR confirms the applicability of NN for operating condition detection based on the measured vibration signal of the pump. In summary, the results of this work can be used to further explore the possible uses of NNs in the identification of operating condition. The research work of the NN in the future should be: 1. Analyse of the influence on CR of the input layer nodes and the output layer nodes; 2. The addition of vibration signals in the other two coordinates; 3. The expansion of the database and so on. Furthermore, the method which can increase the achievable CR, such
as genetic algorithm, fuzzy control method or convolutional layer should also be account into the future research of this work.

6. References

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