Transactions of the Korean Nuclear Society Autumn Meeting
Goyang, Korea, October 24-25, 2019

Fault State Detection in Solenoid Operated Valve based on Convolutional Neural Network using Coil Current Signature

Utah Michael Ngbede, Adebena Oluwasegun, M.J. Choi, J.C. Jung*
KEPCO International Nuclear Graduate School (KINGS),
658-91 Haemaji-ro, Seosaeng-myeon, Ulju-gun, Ulsan, 45014 Republic of Korea.
Corresponding author: michaelutah91@gmail.com, jcjung@kings.ac.kr

1. Introduction

It has become imperative for the nuclear power plant (NPP) to further tilt the economic balance towards more sustainability while increasing safety and reliability. This is necessary if nuclear power is to remain a competitive and economically viable option in the new trend of global electricity market. One way to achieve this is to optimize plant maintenance strategy such that downtime is reduced, uptime is increased and resources are efficiently allocated. Maintenance optimization has the effect of improving the overall plant safety, reliability and availability. An aspect of the plant processes that can benefit considerably from maintenance optimization is the monitoring and maintenance of solenoid operated valve (SOV).

Many SOVs are commonly utilized for process control in nuclear power plants. Under the framework of reliability centered maintenance (RCM), the maintenance activities that are typically performed on these SOVs include service, overhaul, repair and replacement of parts [1]. These actions are generally carried out under corrective or preventive maintenance strategy. A simple corrective maintenance strategy, also called run-to-failure, involves invoking maintenance actions only after a failure has occurred. This incurs high cost for repairs and spare management, and lost revenue due to unavailability [2]. Likewise, traditional preventive maintenance strategy is described by scheduled periodic maintenance actions according to prescribed criteria regardless of the component health condition. Although it generally improves plant's reliability, it adds significant burden on plant economics. Hence, to strike a balance between reliability and economics, consideration must be given to condition monitoring and health assessment of components. This is known as condition based maintenance (CBM).

CBM forms the basis for predictive maintenance (PdM) since the future state of the component can be predicted quiet well based on the current state of the component and a maintenance action can be planned in advance of the actual fault occurrence.

The starting point of any maintenance action is the timely and accurate determination of component faulty state. An early detection of fault condition which could lead to eventual failure is critical to the development of effective predictive maintenance programme. This paper is therefore focused on the detection of fault state of a solenoid operated valve using artificial intelligent techniques to process the coil current signature. This project is focused on the use of convolutional neural network (CNN) for classifying the state based on extracted features from the coil current signature. The project is part of the methodology that is being developed to optimize the predictive maintenance of solenoid operated valve.

2. Theory

The tasks performed during predictive maintenance are divided into three parts: detect incipient failures of equipment, determine the maintenance actions required and restore the equipment to its operable condition. The data driven approach will use data gotten from the monitored conditions of the SOV. Correlations in the collected data can be revealed with artificial intelligence which can be used to detect incipient faults.

Data driven methods require sufficient historical data for model training and it does not depend on prior knowledge of the system and is widely used in real industries [3]. The main challenge in data-driven method is the extraction of useful features from the raw collected data [3], [4]. Data analysis techniques are mainly divided into analysis methods, expert systems and plant view [5]. Analysis methods consist of the following but not limited to trend analysis, pattern recognition, correlation, test against limits or ranges, relative comparison and statistical process analysis. The expert systems makes use of artificial intelligence to perform diagnostics and predictions. There are a variety of expert systems whose capabilities depend on pattern recognition, neural networks, Bayesian belief networks and so on [5].

For this paper, a Convolution Neural Network (CNN) which is a deep learning method was used to classify fault state of the SOV.

There have been some research done on the classification and detection of fault on the SOV using different approaches. O.Moseler et al. [6] performed a model based method for fault detection which is able to measure the solenoid's armature stroke based on measured current and voltage. Atia.A [7] performed fault detection of the SOV by analyzing the current signature. Chuan Y.T et al. [8] proposed a fault classification algorithm for the SOV using an artificial neural network (ANN) with three layers, one hidden, one input and one output layer. This paper proposes a deep learning approach to classifying faulty SOVs.

The deep learning based approach has a number of advantages over the traditional machine learning based approaches such as best-in-class performer, automatic feature extraction and transferability [9]. The deep learning is characterized by the deep network architecture where multiple layers are stacked in the network to fully capture the representative information from raw input data [10].

The convolutional neural network used was fed with scalograms that were obtained from the wavelet transformation of the input data. A wavelet transform is an effective method to analyze non-periodic and non-stationary signals which are promising on improving the fault detection results [3]. The wavelet transform is one of the methods of performing time-frequency analysis of signals. The time-frequency analysis was chosen as opposed to the very popular time domain and frequency domain analysis because the features obtained usually have stationary variation tendency until severe fault occurs [11]. Experiments were performed on a solenoid operated valve test rig to obtain data. The data obtained was used for the analysis in this paper.

2.1. Wavelet transform

A wavelet is a 'small wave' which has its energy concentrated in time to give a tool for the analysis of transient, non-stationary or time varying phenomena [12]. With the oscillating characteristics of the wave, it still has the ability to allow both time and frequency analysis of a signal with flexible mathematical foundation [12]. The wavelet unlike the very common fourier transform has varying frequencies, limited duration and zero average value. Wavelet transformation was implemented to transform the data into a form that is accepted by the CNN. The output that was generated from this transformation was a scalogram that was fed into the CNN. Wavelet transform is classified into two: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). For this paper, a CWT was implemented because it can be used to obtain simultaneous time-frequency analysis of a signal which offers a good time frequency oscillations while the DWT is more suited for de-noising images. The CWT is represented in equation below. The equation shows a basic function *f(t)* is decomposed into a set of basis

$$\gamma(s,\tau) = \int f(t)\,\Psi^{*}{}_{s,\tau} t dt \qquad (1)$$

functions $\Psi_{s,\tau}(t)$, called wavelets where * denotes complex conjugation, s and τ are the new dimensions, scale and translation (space) and $\Psi_{s,\tau}$ is called the mother wavelet. The mother wavelet is also represented by the equation below

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\,\Psi\left(\frac{t-\tau}{s}\right) \qquad (2)$$

Fig 1 and Fig 2 show the wavelet transformation of two different signals that represent the state of the SOV which was implemented using Python. Fig *1* shows the wavelet transformation of an SOV that is working within the normal operating conditions while Fig *2* shows the wavelet transform of an SOV that is operating in an abnormal condition.

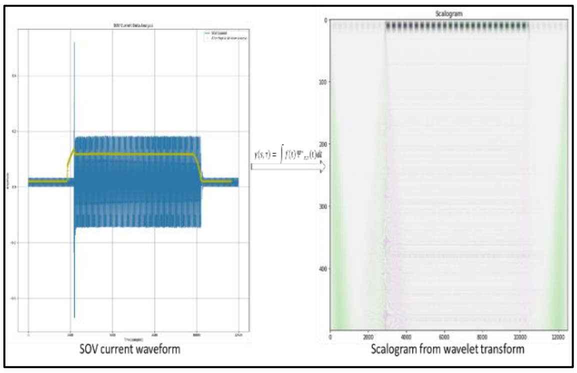

Fig 1: Wavelet transform of a good SOV current signal

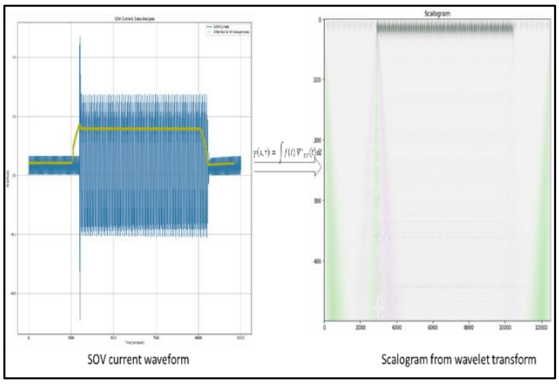

Fig 2: Wavelet transform of a bad SOV current signal

2.2. Convolutional Neural Networks (CNN)

CNN is a type of deep learning model and is sometimes called ConvNet. CNNs are widely used for deep learning with images, audio, speech recognition and videos. CNNs perform automatic feature extraction which eliminates the need for manual feature extraction. This is done in the convolution layers and the pooling layers as shown in Fig 3. The CNN shown in Fig 3 consist of a neural network that performs the feature extraction (feature maps) and another neural network that classifies the feature image.

The convolutional layers convolve multiple filters with raw input data and generate features, and the pooling layer extracts the most significant feature afterwards [3] which forms the feature extraction layers. One other function of the pooling layer is to decrease computational power required to process the data. There are different types of pooling, some of which are max pooling and average pooing. For the sake of this paper, the max pooling was applied, which computes the maximum value from the neighboring elements [3]. The classification layers consist of fully connected layers that gives an output in the dimensions based on the number of classes to be classified. The softmax function provides the actual classification of the output. This is based on probabilities.

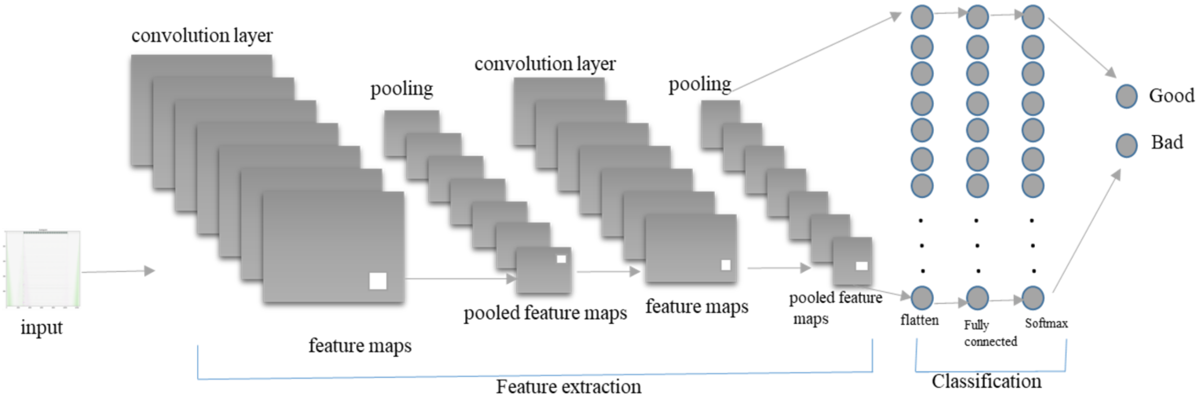

Fig 3: Typical Convolutional neural network

3. Proposed Method

Fig 4 shows the proposed method for this paper. SOV current dataset was obtained in a comma separated value (csv) format. A csv file had 12500 samples taken over 5 seconds at a sampling frequency of 2.5 kHz. The dataset was passed into a wavelet transform algorithm to obtain the time-frequency domain transformation. These images were split into training, testing and validation dataset that will be used to train and test the neural network. Performance metrics of accuracy, precision were applied to measure the performance of the network.

3.1. Proposed network architecture

The proposed network architecture follows what is shown in Fig 3. The input images from the wavelet transformation were rescaled to fit the input parameters of the CNN. The images were in a 2-dimensional (2D) format, they were in the red, green and blue (RGB) colour scale and an input scale that matches that of the convolution layers.

The filter size for the network was 3 x 3 and 4 filters were used in the network. Max pooling was used to extract the most significant features from the neighboring elements. The size of the max pooling filters was 2 x 2 and 4 of them were used for the model. Also, zero padding was implemented throughout the network. Zero padding ensures that the output size of the neighboring elements remains the same as the input size. There are two categories of zero padding; valid and same. The same zero padding was used to ensure that the dimensions stay the same.

Dropout which is a technique used to avoid over fitting when training a neural network and also to avoid poor performance of the test data [13] was also applied to the network. Dropouts of 0.25, 0.25, 0.4, 0.5 and 0.5 were applied to the feature extraction and classification layers. The activation function adopted in this paper was the leaky rectified linear unit (leaky ReLU). The leaky ReLU is a type or rectified unit. The leaky ReLU do not suffer from gradient vanishing [3].

The classification layer consist of the flatten layer that transforms the image into a column vector and makes it easier for the CNN to work with. The output from the flatten layer is fed into the fully connected layer where the classification of the images is done. The softmax assigns probabilities to the output of the fully connected layer. The total probabilities must sum up to 1.0. Training of the network was done over 20 epochs, 1000 steps per epoch, validation steps of 500, learning rate of 0.0001, metrics of accuracy, and RMSprop optimizer.

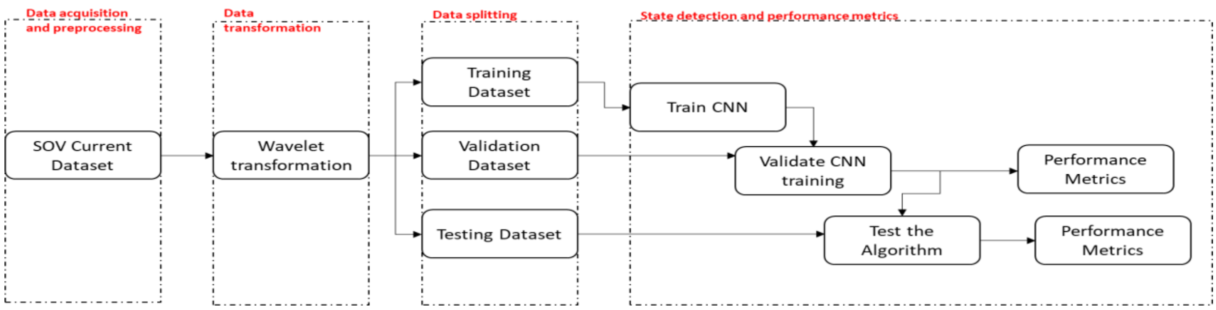

Fig 4: Proposed work flow

4. Results

Fig 5 and Fig 6 show the result of the CNN training. The network had a training accuracy of 0.9860 and a validation accuracy of 1.0000, also the network had a loss of 0.0479 at the end of the training phase.

The model was tested with new data and the performance is shown in Fig 7. Here, the model was able to accurately classify between a SOV that is operating normally and operating abnormally.

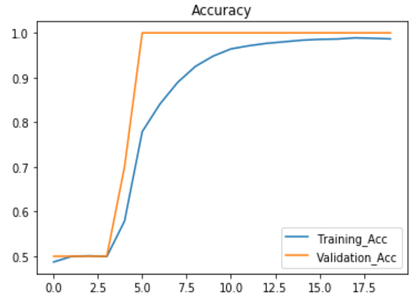

Fig 5: Training accuracy

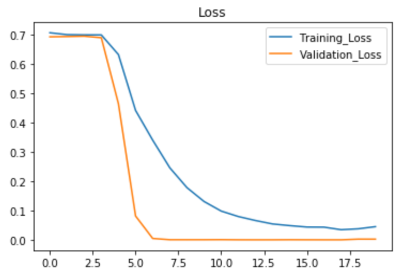

Fig 6: Training loss

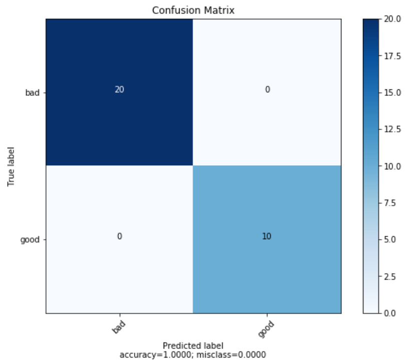

Fig 7: Confusion matrix

5. Conclusions

The proposed network was able to efficiently classify between good and faulty SOV which involves two classes. The paper introduces wavelet transforms and its application to CNN. For future work, more classes will be added to cover the different failure modes of the SOV and also to be able to perform prognostics on the SOV.

Acknowledgement

This research was supported by the 2019 Research Fund of the KEPCO international Nuclear Graduate School (KINGS), the Republic of Korea.

REFERENCES

[1] I. A. E. Agency, Maintenance optimization programme for nuclear power plants / International Atomic Energy Agency, Vienna: IAEA, 2018.

[2] R. K. Mobley, An introduction to predictive maintenance: 2nd ed, USA: Elsevier Science, 2002.

[3] W. Z. Q. D. Xiang Li, "Deep learning-based remaining useful life estimation of bearings using multi-scale feature extraction," *Reliability Engineering and System Safety,* vol. 182, pp. 208-218, 2019.

[4] W. Ahmad, S. A. Khan, M. M. M. Islam and J.-M. Kim, "A reliable technique for remaining useful life estimation of rolling element bearings using dynamic regression models," *Reliability Engineering and Safety System,* vol. 184, pp. 67-76, 2019.

[5] J. Sharkey, "Predictive Maintenance Primer: Revision to NP-7205," EPRI, Palo Alto, CA, 2003.

[6] O. Moseler and H. Straky, "Fault detection od a solenoid valve for hydraulic systems in vehicles," *IFAC Proceedings Volumes,* vol. 33, no. 11, pp. 119-124, 2000.

[7] A. Adrees, "Fault detection of solenoid valve using current signature analysis," Sheffield, 2009.

[8] C.-Y. Tseng and C.-F. Lin, "Solenoid valve failure detection for electronic diesel fuel injection control systems," IFAC, Pingtung, 2005.

[9] S. Zhang, S. Zhang, B. Wang and T. G. Habetler, "Machine Learning and Deep Learning Algorithms for Bearing Fault Diagnostics – A Comprehensive Review," *arXiv,* vol. 1901, no. 08247v1, 2019.

[10] X. Li, Q. Ding and J.-Q. Sun, "Remaining useful life estimation in prognostics using deep convolution neural networks," *Reliability Engineering and System Safety,* vol. 172, pp. 1-11, 2018.

[11] M. Zhao, B. Tang and Q. Tan, "Bearing remaining useful life estimation based on time–frequency representation and supervised dimensionality reduction," *Measurement,* vol. 86, pp. 41-55, 2016.

[12] C. S. Burrus, R. A. Gopinath and H. Guo, Introduction to Wavelets and Wavelet Transforms, New Jersey: Prentice-Hall, Inc, 1998.

[13] W. Sun, S. Shao, R. Zhao, R. Yan, X. Zhang and XuefengChen, "A sparse auto-encoder-based deep neural network approach for induction motor faults classification," *Measurement,* vol. 89, pp. 171-178, 2016.