Condition monitoring of an electro-magnetic brake using an artificial neural network

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Abstract. This paper presents a data-driven approach to Condition Monitoring of Electromagnetic brakes without use of additional sensors. For safe and efficient operation of electric motor a regular evaluation and replacement of the friction surface of the brake is required. One such evaluation method consists of direct or indirect sensing of the air-gap between pressure plate and magnet. A larger gap is generally indicative of worn surface(s). Traditionally this has been accomplished by the use of additional sensors - making existing systems complex, cost-sensitive and difficult to maintain. In this work a feed-forward Artificial Neural Network (ANN) is learned with the electrical data of the brake by supervised learning method to estimate the air-gap. The ANN model is optimized on the training set and validated using the test set. The experimental results of estimated air-gap with accuracy of over 95% demonstrate the validity of the proposed approach.

1. Introduction

The goal of Condition Monitoring (CM) of electric machines is to acquire a “health” indication in real-time; in order to identify possible faults and failure in advance – thus avoiding costly and unscheduled down time, upholding accurate servicing schedules [1]. An ideal CM method should be non-destructive and should depend on easily measurable parameters [2]. In contrast to sensor-based techniques, data-driven condition monitoring methods are interesting because they do not require any knowledge about the machine parameters and models; instead they only require a database of both healthy and faulty conditions of the machine for eventual feature extraction and classification [3].

Conventional methods of fault diagnosis and condition monitoring are based on well-tested mathematical models incorporating various machine faults. Generally, heavy and time-consuming computational tasks must be performed due to the complexity of the applied analytical models and the large number of required parameters [2]. The authors of [4] and [5] showed analytical methods of estimating the air-gap of a magnetic field for different electromagnetic systems. In [6] and [7] analytical methods of estimating the air-gap of a brake are shown based on the derivation of the characteristic current progression of the coil during movement of the pressure plate. A continuous method to determine the air gap using a pulsating voltage and evaluation of the resulting current is demonstrated in [8]. In industrial solutions, different sensors are also available to monitor the air-gap. One existing industrial solution is the application of eddy current sensors that can monitor the functional status of the brake [9], but it requires additional wiring. Another industrial solution is the use of recoiling micro-switch in closed contact or in open contact depending on task [10]. Unfortunately, this increases complexity in the entire construction. Adjusting the micro-switches for
very low air-gap is also a difficult task. This paper presents an application of data-driven approaches to non-destructive condition monitoring of a Magnetic brake.

2. Magnetic Brakes
Magnetic brakes are an important part of electric motors requiring a regular servicing schedule. The brake considered in this paper is an electromagnetic brake with a DC coil that releases electrically and brakes using a spring force (Figure 1). The principal parts of the brake system are brake coils (acceleration coil and holding coil) comprising the brake, coil body (Magnet) with an encapsulating winding and a tap, moving pressure plate, brake springs, brake disk, brake end shield, carbon-based friction surface between pressure plate and brake carrier. The two-coil system (acceleration coil and holding coil) ensure fast braking and releasing. The acceleration coil is switched on first. The high acceleration current of the acceleration coil results in a very short response time without reaching saturation limit, and then followed by the holding coil (entire coil). The pressure plate is forced against the brake disk by the springs when the electromagnet is de-energized. When the brake coil is connected to the corresponding DC voltage, the force of the springs is overcome by the magnetic force thus bringing the pressure plate into contact with the magnet and the brake disk moves clear and the rotor can turn.

![Figure 1. Principal parts of the Brake [11].](image)

The friction caused by the sliding action eventually causes wear of carbon-based brake-discs. For high cycle rates therefore, a frequent replacement of brake-disks and/or the frictional surface is necessary. A too large air-gap between the dampening plate and stationary disk (caused by worn brake-disks) can result in a dysfunctional magnetic force; leading ultimately to a failure of the brake [11, 12].

3. Current and flux linkage analysis
The response of a brake at different air-gaps and operating conditions can be determined from the coil current ($I_{\text{coil}}$). Figure 2 shows one example for a coil current which contains four characteristics points representing the brake responses. The top points p1, p2 - represent the require current to move the brake and brake response time and bottom points d1, d2- represent the current and time when the brake hits the magnet (coil body). For an ideal case there should only be two points (p1 and d1), but the gap between pressure plate and coil body was adjusted manually, thus the air-gap was not equal throughout the surface which made the brake moved twice. These characteristic points are considered to estimate the air-gap using a machine learning algorithm, which will be described in section 4.3.
The four points (p1, p2, d1, d2) on current curve represent the brake’s response properties.

Figure 3. Coil Current (only for switch-on or brake release part) for different air-gaps.

Figure 4. Flux linkage [Vs] for different air-gaps.

The measurement of magnetic properties of electromechanical systems is conventionally based on voltage, induced voltage and electromagnetic flux linkage [13]. Gadyuchko et al. in [13] presented a magnetic testing method which is considered here for electromechanical error detection. In their work, the magnetic characteristics $\Psi(i, \delta)$ are analyzed and utilized as testing/verification function of an electromagnet, where $\psi$ represents magnetic flux linkage, $i$ the current and $\delta$ the air-gap. The relationship between voltage ($u$) and magnetic flux linkage ($\psi$) is shown in Eq. (1)

$$u = iR + \frac{d\Psi(i, \delta)}{dt}$$

(1)

where $\psi = \int (u - iR) dt$  

(2)

Gadyuchko et al. [13] showed that different conditions (or faults) of the electromagnetic brake i.e. short circuit between turns of the coil, broken leg of the membrane spring, wear from endurance testing with several million cycles etc. can be accurately evaluated from the $\Psi(i, \delta)$ character. Figure 4 shows $\Psi$ for different $\delta$ in relation to $i$. This paper also considers this magnetic characteristics to be determined from electrical parameters $(i,u)$ of the brake, in order to estimate the air-gap using a machine learning algorithm.
4. Data driven approach

Different Artificial Intelligence techniques have been widely developed in recent years in the field of machine condition monitoring. However, they are not extensively used in the industry [3]. In this work, a supervised multi-layer Artificial Neural Network (ANN) is used to determine the air-gap from the electrical parameters \((i, u)\) measured from the brake. Figure 5 shows the different steps involved to estimate the air-gap using ANN. The steps are described in the following sub-sections and the output is discussed in section 5.

![Figure 5. steps involved in the proposed data-driven approach.](image)

4.1. Data Collection

A large number of data is recorded to learn the ANN from minimum air-gap of the brake to the maximum allowable air-gap. To achieve robust ANN solution for estimating air-gap, currents were recorded at three different operating voltages. For supervised learning purpose each recorded data was labelled for corresponding air-gap and voltage (Figure 6). The air-gap between the pressure plate and brake was adjusted by loosening or tightening the nuts as needed to achieve the necessary air-gap. Simplified diagram of data collection setup using oscilloscope as data acquisition are shown in Figure 7 and 8.

![Figure 6. Example of recorded raw data for different air-gaps (sample rate 125kHz). The top figure shows coil currents during releasing and engaging of the brake and the bottom figure shows the corresponding voltages.](image)
4.2. Pre-process
This step involves de-sampling and filtering of the data. Two filter algorithms are used to smooth the data to eliminate the noise within the data:

- **Moving average filter:**
  \[
  y_s(i) = \frac{1}{2N+1} (y(i + N) + y(i + N - 1) + \cdots + y(i - N))
  \]
  where, \( y_s(i) \) is the smoothed value for the \( i \)th data point, \( N \) is number of neighbouring data points on either side of \( y_s(i) \) and \( 2N+1 \) is the span.

- **Savitzky-Golay Filter:**
  \[
  Y_j = \sum_{i=\frac{m-1}{2}}^{\frac{m+1}{2}} C_i y_{j+i}, \quad \frac{m+1}{2} \leq j \leq n - \frac{m-1}{2}
  \]
  where, data is a set of \( n \) \( \{x_j, y_j\} \) points \( (j = 1, \ldots, n) \), \( x \) is independent variable, \( y_j \) is an observed value and they are treated with a set of \( m \) convolution coefficients \( C_i \).

4.3. Feature Extraction
A huge number of data directly to patter recognition algorithm may not be computationally feasible, require longer computational time and also too many parameters increases the complexity of network (ANN). In machine learning algorithm, the aim is to find useful features from data, where pattern recognition is hope to be easier. We calculated the characteristic points or the brake moving points described in Section 3 as the features as the learned input. We determined these points by the peak-detection algorithm based on second derivative approach (Figure 9). In one way of peak detection of signal processing is to find the downward-going zero-crossing of the first derivative of the data. But due to random noise in the experimental data zero-crossing give false peaks. Instead we calculated the second derivative of the original data and choose the maxima and minima points to locate the desired points on the original data.
4.4. Learning input

Here, the input matrix used to learn the ANN is called the learning input. To achieve a robust ANN and to obtain optimize results, in this work we tested different learning conditions to train the ANN. ANN performance is compared between learning the ANN with $I_{\text{coil}}$ data, which means no feature was extracted from the data and with the ANN learned with calculated feature data.

Different combination of input matrix depending on following parameters (training conditions):

- **Training dimension**: learning input ($I_{\text{coil}}$) contains all three or two or one voltage data set
- **Training $t$ or $t_{\text{max}}$**: learning input ($I_{\text{coil}}$) contains time ($t$) data/not or only time ($t$) at maximum current ($t_{\text{max}}$)

4.5. Target output

As the network was trained by supervised learning method, the corresponding target output for the input data is given as learning output matrix. Size of Target output or ANN output depends on learning dimension (Table 2), which means learning both air-gap and voltage or learning only air-gap.

4.6. Network Parameter

Network parameters are determined from the learning input and output matrix size.

| Number of learned gap: 0.25: 0.05:0.9mm | $g = 14$
| Number of measurements for each gap | $m = 10$
| Number of data for each measurement or number of neurons in input layer | $N = 150$ (with $I_{\text{coil}}$) $\times$ 2 (with $t$) + 1 (with $t_{\text{max}}$) and 8 to 1 (with feature)
| Number of learned voltage | $V = 3, 2, 1$
| Number of observation (neurons in input layer) | $g \times m$
| Learning output | 2 or 1
| Number of hidden layer | 2 or 1
| Number of neurons at hidden layer-1 | $g$
| Number of neurons at hidden layer-2 (if exists) | $V$
4.7. ANN model
A supervised ANN is a general Function Approximator which can synthesize relationships between different variables constituting the input vectors and the output variable(s) [3]. The number of hidden layers depends on number of learning output described in Table 1. Figure 10 shows the proposed network structure of this work when considering learning dimension of 2.

![Figure 10](image)

Figure 10. For learning two outputs (air-gap and voltage) the proposed structure of ANN consists two hidden layers.

5. Results and discussion
Performance of the ANN for different training conditions is evaluated by calculating the Mean-Square-Error (MSE). Considering training dimension (1 to 3), learning dimension (1 to 2), Training t (0 or 1) and Training t_{max} (0 or 1) total 18 combinations of training conditions were tested. Figure 11 shows the MSE (mm) of learned air-gap by ANN trained with \( I_{\text{coil}} \) for all 18 conditions. Table 2 shows comparison of different training conditions by comparing the learning performances of ANN trained with \( I_{\text{coil}} \). Compared learning performances are: Number iterations required to estimated air-gap closest to target air-gap, required training time and average accuracy (%) of learned air-gap and MSE (mm) of learned air-gap. Table 2 shows also the average accuracy of estimated air-gap for Test data.

| Training dimension | 3 | 3 | 2 | 2 | 1 | 1 |
|--------------------|---|---|---|---|---|---|
| Learning dimension | 2 | 1 | 2 | 1 | 1 | 1 |
| Training, t        | 0 | 0 | 0 | 0 | 0 | 1 |
| Training, t_{max}  | 1 | 1 | 1 | 1 | 0 | 0 |
| Num. of iteration   | 50 | 11 | 23 | 8 | 6 | 6 |
| Training time(s)    | 30,185 | 4,96 | 12,303 | 2,517 | 1,807 | 6,133 |
| Learning accuracy (%) | 98,3 | 98,4 | 97,9 | 96,1 | 97,5 | 98,1 |
| MSE (mm)            | 3E-04 | 3E-04 | 2E-04 | 1E-03 | 3E-04 | 5E-04 |
| Estimation acc. Test data | 93,1 | 92,1 | 91,3 | 94,0 | 87,1 | 83,1 |
The learned model was tested with newly recorded data (test data). For testing the robustness of the ANN, we recorded the data of the brake operated in different voltage source. The result shows the feature points describe best the mathematical relation between air-gap and the feature points, which the ANN can successfully learn from the training. In case of training the ANN with $I_{coil}$, the learning accuracy is very high but ANN does not show robustness for estimating air-gap for different voltage test data. The following figures 12 and 13 show the estimated air-gap for the test data by the leaned ANN model. The points are plotted as expected value (measured gap) versus predicted value (estimated gap). To visualize the error the heavy black line (ideal gap) is plotted in the figures showing how far or close the estimated values.

The presented ANN model with coil current ($I_{coil}$) and feature data ($p_1, p_2, d_1, d_2$) as learning parameter have MSE between 1E-05 to 1E-04 mm; but output for test data of ANN learned with
feature data give improved results. Figures 12 and 13 show the comparison of estimated air-gap by ANN trained with coil current and feature data or brake response properties (p1, p2, d1, d2).

6. Conclusions
Different Artificial Intelligence (AI) based machine condition monitoring is discussed in [1-3] which are generally classification of different faults. In this work we showed estimation of a physical parameter (air-gap) of electromagnetic system by using ANN regression model. By estimating the air-gap from coil current information, it is possible to determine the amount of wear of the friction surface more precisely and hence possible to make maintenance decision. The wear detection method shown in [8] also considered determining the peaks and time from coil current (similar as feature points described in section 3 and 4) to compare with stored data to generate warning message of wear. A method and device is proposed in [7] where mean of coil current is considered to determine the threshold value to monitor operating state for variety of brakes. The proposed approach in this work shows ANN learned with the feature points able to estimate air-gaps with high accuracy even the operating voltages of the test data are different than the learned data.

In conclusion, in this work, it is shown that condition monitoring of a complex electromechanical system can be performed without detailed analytical modeling or use of additional sensors. Through a discriminative learning of state of the art ANN models, the required mathematical function of condition monitoring of an electromagnetic brake through air-gap detection was successfully estimated. The work presented herein represents an interesting potential application in the area of condition monitoring for industrial usage; where handling and maintenance requirements of the machine can be substantially improved through data-driven methods.

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