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Early Fault Detection in Paper Machine Motors Using Machine Learning

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Abstract: This research addresses the application of a neural network as a tool for early fault detection in the motors of a paper machine under a simulated environment. It proposes the analysis of variables from a torque control loop. The data for training and validating the model is obtained through the simulation of Direct Torque Control (DTC) of an AC motor in Simscape within Simulink. Both normal and faulty operating modes are considered. Under these two scenarios, various speed setpoints are configured, and the necessary data for training the developed model is collected.

Keywords Machine Learning · Predictive Maintenance · Paper Machine · DTC · Simscape

1 Introduction

In the industrial sector, especially in areas like paper manufacturing where operational efficiency and process continuity are paramount, equipment maintenance plays a crucial role in the success and profitability of operations. Maintenance management is sometimes conducted traditionally with manual records and data entry in spreadsheets, methodologies that have yielded good results for industrial production [1]. However, this approach involves several issues, such as human errors in data collection and record entry, the frequency of maintenance plan execution, among others. Therefore, the ability to effectively prevent unexpected motor failures remains a significant challenge [2][3].

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Moreover, artificial intelligence has seen broad evolution across diverse fields, including service sectors, healthcare [4], robotics [5], and the industrial domain. In this context, predictive maintenance, supported by advances in technologies such as machine learning, could emerge as a strategy to ensure the availability and reliability of industrial assets and processes [6][7]. For instance, [8] shows the application of neural network classifiers is proposed for detecting anomalies such as specks and various types of diffraction in a laser beam. The research achieves an accuracy of around 99% with very short processing times, aiming to reduce reliance on an expert for beam evaluation. Moreover, a review of ML technologies related to predictive maintenance of conveyor belts is conducted in [9], summarizing the results and challenges of various methodologies used in these systems. In addition, [10] shows a multihead neural network developed under the variability of individual machine degradations to derive machine-level prognostics. This network learns degradation features and updates remaining useful lifetime (RUL) distributions from diverse distribution ensembles. Even though these articles are closely related to the paper manufacturing sector, a comprehensive analysis using artificial intelligence to extend the useful life of engines might still be unresolved.

In this work, a machine learning algorithm is incorporated into the predictive maintenance of the drive motors of a paper machine. The aim is to provide a tool that facilitates the early diagnosis of anomalies in motor operation, thereby preventing mechanical damage to couplings, crosses, and cardan shafts in the system. With the incorporation of this tool, the information from operating variables such as speed reference, speed feedback, motor current, torque reference, and motor torque (calculated based on motor voltage and current) is analyzed. This analysis helps determine whether the machine's operation is adequate or if there is a need to plan activities to address out-of-standard conditions, thereby avoiding unplanned production stoppages [11][12]. The document presents the result of a direct torque

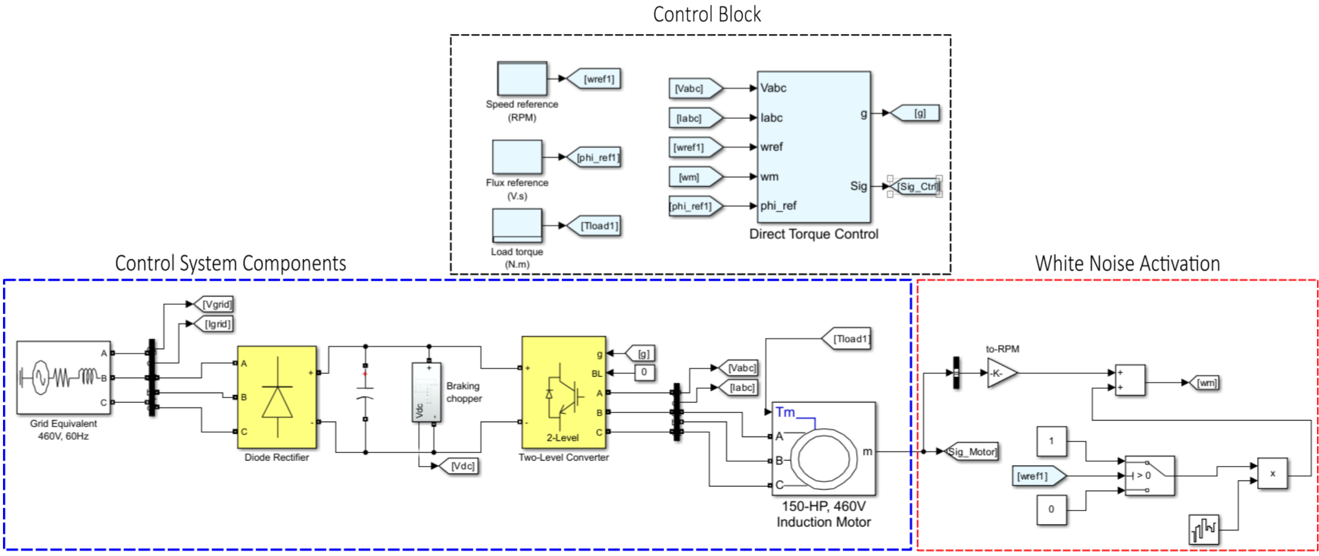

Fig. 1 Direct Torque Control (DTC) system.

control (DTC) simulation of a three-phase motor using Simscape in MATLAB [13], from which the parameters for training the neural network are obtained [14]. The main contribution of this work is the incorporation of a neural network for anomaly detection in motors in the paper industry. By validating the contribution of this neural network, it is possible to integrate the algorithm into a real production environment and connect it to the SCADA system via an OPC server, simplifying signal interpretation and contributing to industrial maintenance management.

2 Neural Network Configuration and Training

2.1 Simulation Scenario Setup

For the implementation of the simulation environment, Simscape Electrical blocks are used, starting with one of the direct torque control (DTC) exercises available on the official MathWorks website [15]. The main blocks within the simulated environment are: the direct torque controller, the noise signal activation, and the elements that emulate the physical system: power supply, rectifier block, inverter, and motor. Fig. 1 shows the cited setup and its connections.

2.2 Data Generation for Training

As described in Table 1, during the model simulations, different combinations of speed and torque are applied by using step signals at specific time intervals at the controller inputs, see Figure 2.

Once the controller's operation has been verified, a simulation is run with the same speed and torque setpoints, incorporating random noise in the system feedback to emulate abnormal system behavior. The results shown in Figure 3 indicate that the controller exhibits highly oscillatory behavior.
The simulation behavior aligns with mechanical issues encountered in a real system, as shown in Figure 4. The figure displays the torque of four motors: motors a and b are operating normally, while motors c and d exhibit signals from systems with mechanical problems.
The data for the analysis are obtained from several simulations, which include different scenarios such as acceleration, deceleration, and steady state. The training of the algorithm is based on identifying the behavior of the torque control loop variables. For this purpose, 6 variables are considered, from which a total of 533310 samples are obtained. The analyzed variables are:

- Set Point or speed reference in RPM.
- Motor speed feedback.
- Set point or torque reference.
- Torque control signal (controller output).
- Motor torque.
- Motor current.

2.3 Neural Network Training

The process is divided into several trials to define the best parameters for the neural network, with the configurations shown in Table 2. After the training process, the model's performance is evaluated using confusion matrices for each trial, allowing us to visualize the model's ability to correctly classify normal and

Table 1 Example of applied speed and torque combinations.

step	Operation State	Torque Ref	Torque Motor	Speed Ref
T1	Null	Null	Null	Null
T2	Acceleration	Null	Over Reference	0 to 1200 RPM
T3	Stable	600 and 100 Nm	According with reference	1200 RPM
T4	Deceleration	100 Nm	Under refernce	1200 to 500 RPM
T5	Stable	100 Nm	According with reference	500 RPM
T6	Acceleration & Stable	100 Nm	Over and according with reference	500 to 700 RPM

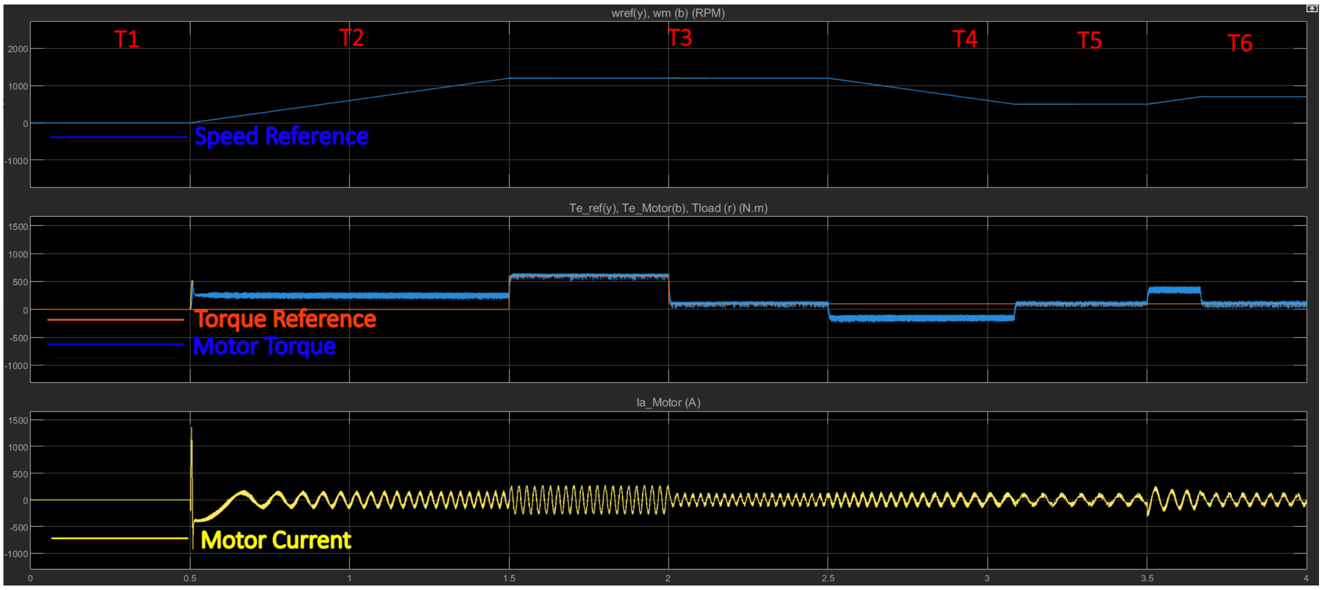

Fig. 2 Direct Torque Control loop response, normal operating conditions.

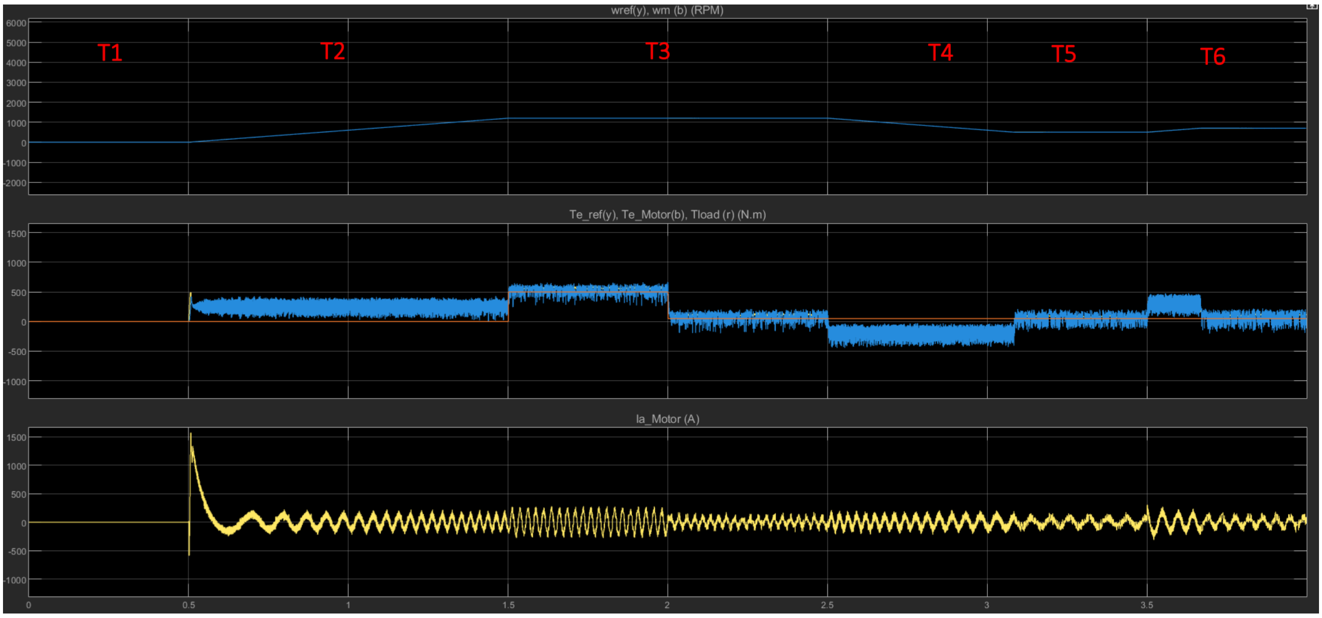

Fig. 3 Direct Torque Control loop response, operating conditions with noise.

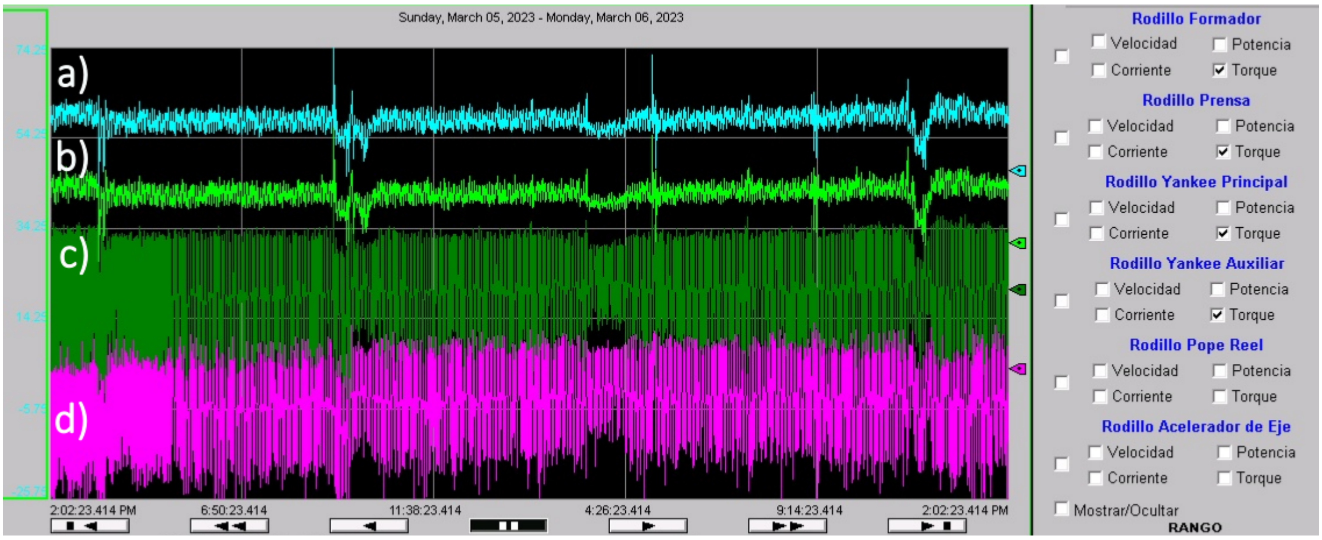

Fig. 4 Torque trends of 4 motors: a) and b) normal operation, c) and d) with mechanical issues.

faulty operating states of the system. The results of each trial conducted are presented below: In the first trial, the confusion matrix (Figure 5) shows that the model achieved a 70.3% accuracy. In the second trial, whose results are presented in the confusion matrix in Figure 6, the model's consistency was confirmed, and a 72.7% accuracy was achieved. Subsequently, in Trial 3, an increase in the input data was made, and three previous samples were considered for analysis. That is, to determine the system's performance at time t_0, the values corresponding to t_{-3}, t_{-2}, t_{-1}, and t_0 were taken into account. Therefore, if the same variables are considered for each moment in time, the number of neurons in the input layer will be 24. With the changes considered, a 73.9% accuracy was achieved, and the model's ability to distinguish between normal and faulty states improved (Figure 7). In Trial 4, the algorithm's robustness and its ability to generalize from the training data were demonstrated, achieving the best performance (Figure 8). For Trial 5, an adjustment was made to the data allocation as follows: 70% for training and 30% for testing, in order to evaluate whether the algorithm maintains its performance and to rule out overfitting of the network (Figure 9).

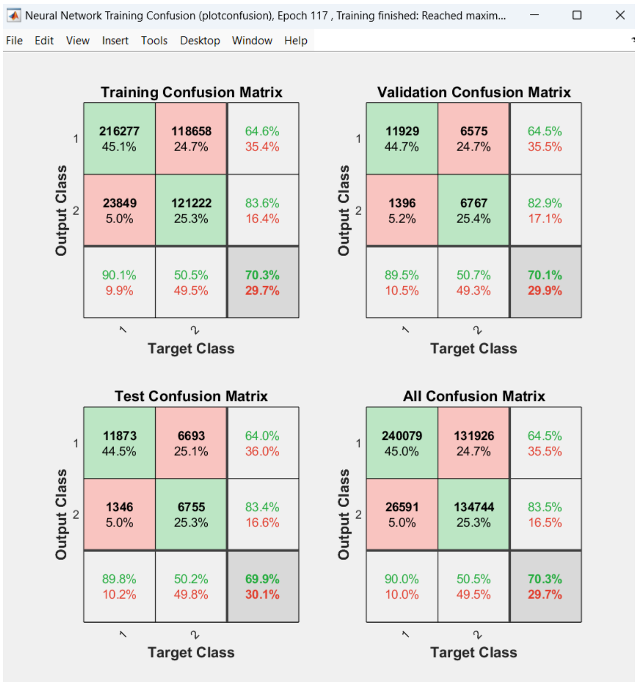

Fig. 5 Confusion matrix, Trial 1

3 Metrics Calculation

Based on the developed trials, precision, accuracy, and recall are calculated, considering the values of true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) shown in each of the confusion matrices from the previous section. Accuracy indicates the proportion of correct predictions and is defined as (1):

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision shows the proportion of correct positive predictions. (2):

$$precision = \frac{TP}{TP + FP} \tag{2}$$

Recall indicates the proportion of actual positives that have been correctly predicted. (3):

Table 2 Configuration of the conducted trials.

Trial	Input layer size	Hidden layer size	Output layer size	Training-validation sample split
Trial 1	6	2	2	90 - 10
Trial 2	6	5	2	90 - 10
Trial 3	24	1	2	90 - 10
Trial 4	24	3	2	90 - 10
Trial 5	24	3	2	70 - 30

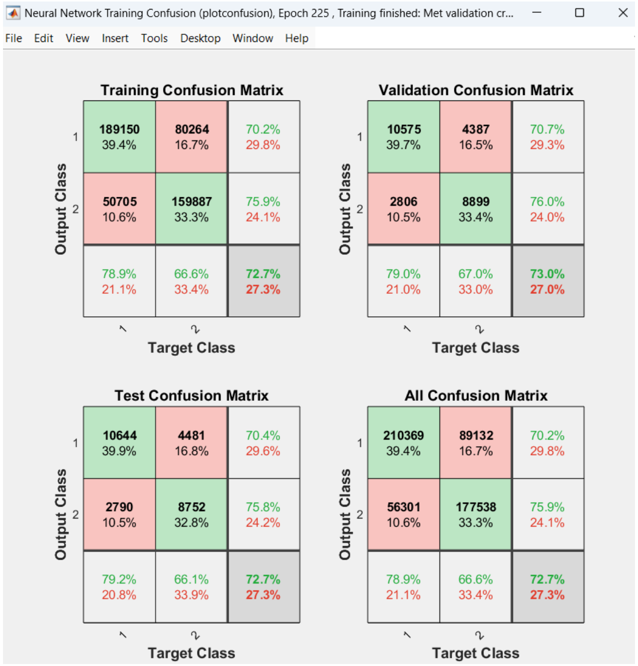

Fig. 6 Confusion matrix, Trial 2.

Fig. 7 Confusion matrix, Trial 3.

Fig. 8 Confusion matrix, Trial 4.

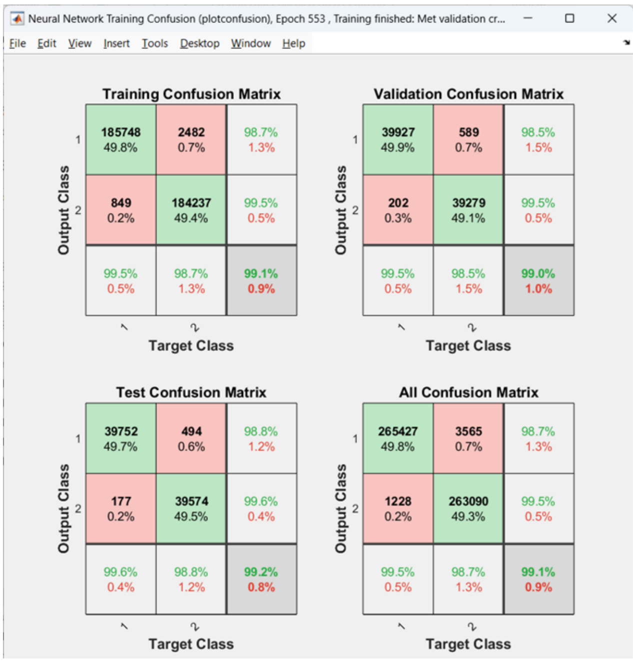

Fig. 9 Confusion matrix, Trial 5.

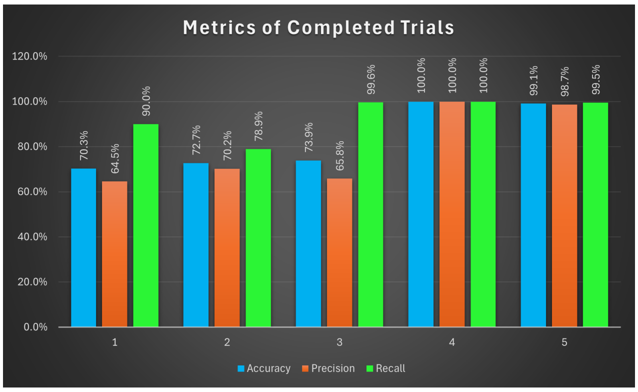

Fig. 10 Metrics calculated for each trial conducted.

$$recall = \frac{TP}{TP + FN} \tag{3}$$

Using the values obtained in (see Sect. 2.3) and according to (1), (2), and (3), the metrics for each of the trials are obtained (Fig. 10). The best performance of the neural network is achieved with the structure proposed in Trial 4. Finally, in Trial 5, this structure is maintained, but the percentage of samples assigned for training is set to 70% and for validation to 30%. Under these conditions, precision reaches 98.7%, accuracy 99.1%, and recall 99.5%, indicating that the algorithm performs well under the proposed scenario and conditions

4 Conclusions

The main contribution of this work is the application of a neural network for the early detection of faults based on the analysis of variables from a direct torque control (DTC) system. Using Simscape in MATLAB, the simulation environment was configured, and the necessary data for model training was generated. It has been demonstrated that the developed system can satisfactorily identify normal and fault conditions with an accuracy exceeding 99%, confirming the effectiveness of the adopted approach and highlighting the potential of machine learning to enhance predictive maintenance in industrial environments.

As shown in the development of this proposal, it is possible to design a machine learning algorithm that continuously analyzes motor operation variables without interfering with daily production activities, providing a basis for future research and practical applications related to optimizing control systems and reducing operational costs through early fault detection.

Conflict of interest

The authors declare that they have no conflict of interest.

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