Fault Prediction in Electrical Valves Using Temporal Kohonen Maps

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Abstract—This paper presents a proactive maintenance scheme for the prediction of faults in electrical valves. In our case study, these valves are used for controlling the oil flow in a distribution network. A system implements temporal self-organizing maps for the prediction of faults. These faults lead to deviations either on torque, on the valve end position or on opening/closing time. For fault prediction, one map is trained using data from a mathematical model devised for the electrical valve. The training is performed by fault injection based on three parameter deviations over this same mathematical model. The map learns the energies of the torque and the position that are computed using the wavelet packet transform. Once the map is trained, the system is ready for on-line monitoring of the valve. During the on-line testing phase, the system computes the Euclidean distance and the activation of data series. The biggest activation determines which is the winner neuron of the map for one data series. The obtained results demonstrate a new solution for prediction behavior of these valves.

***Index Terms*-Testability issues, electromechanical systems, self-organizing maps.**

I. Introduction

The prediction of certain phenomena, processes or failures (or time series prediction, also called as temporal sequences processing) is particularly interesting and useful and has been the subject of research in several areas (such as meteorology, economics, medicine and engineering, for example). Time series prediction could be applied to predict the probability of an earthquake or rain precipitation, changes in the stock market, thus saving lives or even reducing failures and increasing equipment reliability [10, 13, 14].

So, the main motivation for the time series prediction research is the need to predict the future conditions and to understand the underlying phenomena and processes of the system under study. Then, time series prediction focuses on building models of the system using the knowledge and information that is available. Then, the constructed model can be used first, to emulate the system behavior and second, to simulate the future events of this system.

Many methods for system prediction have been developed with very different approaches, either from statistics, such as AR (Autoregressive) and ARMA (Autoregressive Moving Average) models.

More recently, methods for system prediction have been developed from neural networks, such as MLP (Multi-Layer Perceptrons), RBF (Radial Basis Networks) or SOM (Self-Organizing Maps) for example [2, 8, 10, 18].

Usually, the statistics models (AR and ARMA) accomplish well the prediction on a rather short term, depending on the complexity level of the problem. However, their efficiency on a longer term is more questionable [3, 10]. This fact is due to the learning strategy used to fit the data into the model to whose goal is usually to optimize the performance at a given term, most often just the next time step.

The default neural network method accomplishes time series prediction through feed forward functions using particular neural network architecture, such as a standard MLP or SOM architecture [3, 13, 17].

Those neural networks approaches (MLP and RBF) are popularly used to estimate the future behavior. However, in the last years, local models, based on self-organizing maps, have been raising much interest because in many cases they give better results than global models.

The self-organizing map algorithms perform a vector quantization of data, leading to representatives in each portion of the space [8, 15]. The temporal models, built from self-organizing maps such as temporal Kohonen maps (TKM), Merge SOM, and recurrent self-organizing maps (RSOM), use a leaky integrator memory to preserve the temporal context of the input signals [2, 16].

The temporal Kohonen map is thus a self-organizing map based model that takes the temporal context of a pattern into account. In the temporal Kohonen map the outputs of the units (neurons) act as leaky integrators, adding up the temporal differences over a number of time steps.

These integrators (low pass) filter the unit activities over the sequence of inputs. It was shown that temporal Kohonen map learns the correct mapping from temporal sequences of simple synthetic data [15].

In this work, a proactive maintenance scheme is proposed for fault prediction in electrical valves. Temporal Kohonen map is used for the prediction of faults in these electrical valves. In our case study, the valves are used for controlling the flow in an oil distribution network.

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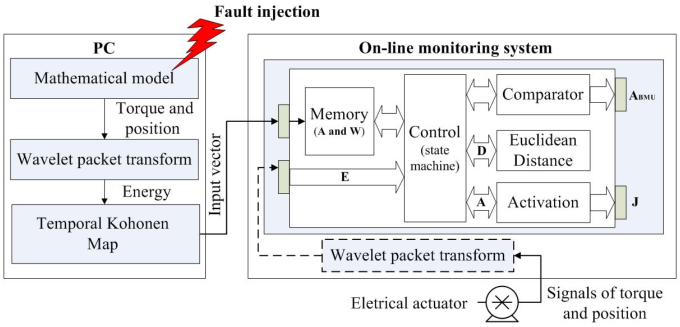

Figure 1. The proactive maintenance scheme.

The paper is organized as follows. In section 2 the proactive maintenance system is proposed. A mathematical model is devised for a particular valve and, considering this model, TKM is proposed for fault prediction. Fault injection is used for training the map. Section 3 presents experimental results, including fault prediction experiments that validate the proposed maintenance method. Concluding remarks are given in section 4.

II. Proactive Maintenance Scheme

Late advances in computing and electronics have made it interesting to automate and integrate proactive maintenance (also known as intelligent maintenance) tasks into systems. Traditional maintenance strategies (corrective, preventive or predictive) are based either on post-failure correction or on off-line periodic system checking.

The proactive maintenance, differently from the traditional strategies, is focused on fault prediction and diagnosis based on component lifetime and system on-line monitoring [5, 6, 13].

By using proactive maintenance it becomes possible to keep track of the equipment or the whole industrial plant, to quantify the performance degradation of the parts and thus to determine the remaining system lifetime. As a consequence, it turns feasible to schedule the replacement of degraded parts for idle or lower production periods of time, or automatically reconfigure the system for continuous (although degraded) operation till the faulty parts can be repaired. These systems require wide instrumentation for on-line monitoring, and distributed intelligence to accurately predict the parts that start deteriorating.

Within this context, some strategies for predictive and proactive maintenance have been proposed in the literature that are based on extensive signal processing, on statistical analysis, and often on artificial intelligence methods as well [7, 13].

Although the concepts exploited in this paper are quite general, the proactive maintenance system we are proposing here applies to a particular class of electrical valves. These valves have embedded sensors for torque and opening position measurement. Detectable faults in the valve are those that lead to measurable deviations either on torque, or on the opening position energies computed using the wavelet packet transform (WPT) [4, 9].

As a reference, the normal, degraded and faulty behaviors of the valve are learned by TKM that are on-line checked for fault prediction during the valve operation.

The TKM is built during a training phase using a mathematical model for the valve and is consulted on-line by computing the best matching between an acquired measure and the neurons of the trained reference map.

Fig. 1 shows the proposed system. The system is composed of three main blocks: a mathematical model that represents the actuator, the valve and the pipe behavior; the signal processing and characteristics extraction tool based on the WPT; and the artificial intelligence tool based on TKM, whose map is computed in a PC station and is later on stored in the on-line monitoring system.

A. Mathematical Model

Valves are devices used for flow control. They may be of different types (drawer, sphere or globe valves, for example) and each type fits better different kinds of applications. In our case study, an electrically actuated drawer valve is used for the control of the oil flow in a distribution pipe. In Fig. 2 the electrical actuator, the valve itself and the fluid pipe are shown.

The valve is modeled in order to evaluate its behavior in different operation conditions, including normal, degraded and faulty operation. As indicated in Fig. 2, this model takes into account a set of forces to analyze the gate valve opening and closing movements, when the actuating force is transmitted from the electrical engine (asynchronous machine) through the valve gears.

Differential and algebraic equations are devised and included in a system of non-linear equations to model the actuator behavior and the mechanical forces involved. Several physical constraints are considered in the modeling process in order to simplify the representation and, consequently, the computational effort required [1, 12]. A third-order model is chosen for the induction engine, because it can represent the permanent and transient conditions.

This mathematical model is given by the differential equations (1) to (3), where $V_d^{'}$ and $V_q^{'}$ are internal voltages, and s the slip of the asynchronous engine. The differential equations (4) and (5) complete the overall fifth-order mathematical model and relate the gear system and the pipe through the gate position (a), the speed (v_a) and the valve gate acceleration (a_a).

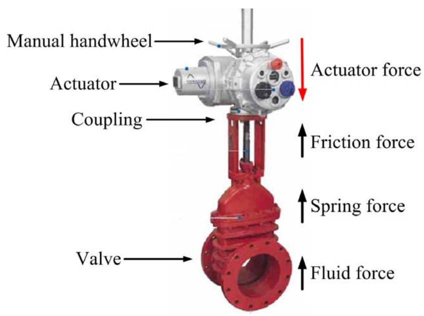

Figure 2. Electrical actuator valve and pipe.

Finally, the algebraic equations that describe the electrical torque of the asynchronous engine (T_e), the voltages of the asynchronous machine (V_{ds} e V_{qs}), the flow (F_f), friction (F_a) and spring force (F_m), as well as the gate shutter force (F_h) and gate shutter torque (T_h), are given by algebraic equations (6) to (12) for θ = 90º.

$$\dot{s} = \frac{1}{2H}\left(T_e - T_m\right), \tag{1}$$

$$\dot{V}'_d = \frac{-1}{T_0}\left[V'_d - I_{qs}\left(X_s - X'_s\right)\right] + s\omega_s V'_q, \tag{2}$$

$$\dot{V}'_q = \frac{-1}{T_0}\left[V'_q + I_{ds}\left(X_s - X'_s\right)\right] - s\omega_s V'_d, \tag{3}$$

$$\dot{a} = v_a, \tag{4}$$

$$\ddot{a} = a_a = \frac{1}{M_h}\left(F_h - F_f - F_a - F_m\right), \tag{5}$$

$$V_{ds} = V'_d - R_s I_{ds} + X'_s I_{qs}, \tag{6}$$

$$V_{qs} = V'_q - R_s I_{qs} - X'_s I_{ds}, \tag{7}$$

$$T_e = V'_d I_{ds} + V'_q I_{qs}, \tag{8}$$

$$F_h = \frac{T_h}{R_h \cos\theta} = \frac{-T_m K_R T_{mb}}{R_h \cos\theta}, \tag{9}$$

$$F_m = K_M a, \tag{10}$$

$$F_a = C_a v_a, \tag{11}$$

$$F_f = \frac{V_f^2 A_v}{\rho N_R^2 (100 - a)^2 C_v^2}. \tag{12}$$

The solution for the system of (1) to (12) is obtained in this work using the Newton-Raphson method. This mathematical model can be used to evaluate the normal behavior of the valve.

By deviating the nominal values of the parameters in the equations, fault injection can be performed in a simple manner and misbehaviors (degraded or faulty valve) may be observed in the torque and opening position curves. This mathematical model is implemented in a MatLab environment and runs in a PC station.

B. Signal Processing

Torque (T_e) and position (a) signals, (4) and (8), are generated by the mathematical model for normal, degraded and faulty operations. The wavelet packet transform is the signal processing tool used in this work for processing these two classes of signals.

Since the wavelet packet transform preserves timing and spectral information, it is a suitable tool for the analysis of non-stationary signals such as gears, bearings and actuators impulsive signals [9].

Additionally, the capability of decomposing the signal in frequency bands makes the WPT more attractive here than other signal processing tools such as the Fourier and the wavelet transforms.

The energy information (**E**) is extracted from the valve torque (T_e) and opening position (a) wavelet Packet transform. The spectral density is divided into N frequency bands, and the resulting information is used by the artificial intelligence tool for the construction of the temporal self-organizing map described next.

Similarly to the mathematical model, the wavelet packet transforms tool runs in a PC station during the system training phase. During on-line testing, the wavelet packet transform shall be part of the internal resources of the on-line monitoring system.

C. Temporal self-organizing maps

The self-organizing maps, or Kohonen maps, belong to a class of neural networks that apply the unsupervised learning paradigm based on competition, cooperation and adaptation techniques. Fig. 3 shows the basic self-organizing map structure.

Formally speaking, the ultimate goal of a self-organizing map is, after being trained, mapping any input data from an $\mathbf{R}^{\mathbf{n}}$ space representation into a two-dimensional, lattice-like matrix. This lattice builds over a competition layer, with J neurons on the net, where $J = C_m L_m$, as seen in Fig. 3.

The internal processing of self-organizing map algorithms can be simplified and divided in three different steps or stages: start up (when the synaptic weights are initialized), training (when knowledge is acquired by the map) and recovery (when data inputs are classified on the map).

For self-organizing maps (and temporal Kohonen maps) training, the synaptic weights $\mathbf{W} = [W_1, W_2, ..., W_N]^T$, of all network neurons are initially assigned as random values. Next, known input vectors representing the system behavior are mapped into the matrix. The input vectors, in our case, are energy values obtained from the WPT and defined as $\mathbf{E} = [E_1, E_2, ..., E_N]^T$.

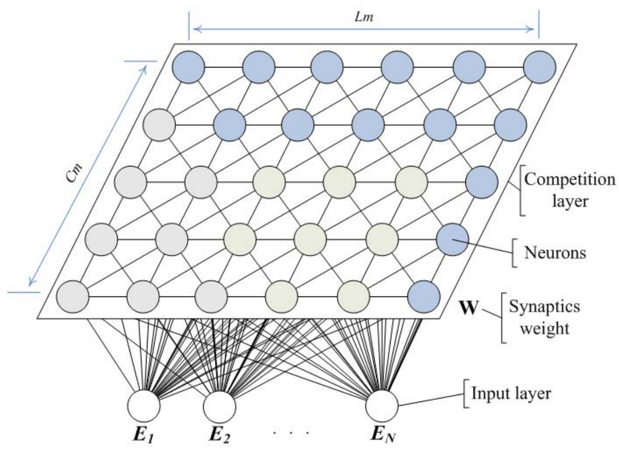

Figure 3. Basic SOM structure.

The Temporal Kohonen map is an unsupervised approach for time series prediction derived from the self-organizing map algorithm [15].

The temporal Kohonen map model uses leaky integrators to maintain the activation history of each neuron. These neurons gradually loose their activity and are added to the outputs of the other normal competitive units. These integrators, and consequently the decay of activation, are modeled through the difference equation:

$$A^k = \lambda A^{k-1} - \frac{1}{2}(D^{kj})^2 \qquad (13)$$

where:

$$D^{kj} = \left\| \mathbf{E}^k - \mathbf{W}^j \right\| = \sqrt{\sum_{i=1}^{N} (E_i^k - W_i^j)^2} \qquad (14)$$

where: $0 < \lambda < 1$ is a time constant, A^k is the temporal activation of the unit j at step k, D^{kj} is the Euclidean distance, $k = 1, 2, \ldots, K$; $j = 1, 2, \ldots, J$; K is the number of input vectors.

The neuron which presents the biggest value for A^k (maximum activity) is defined as the winner activation, A_{BMU}, analogously to the traditional self-organizing map.

Equation (13) preserves the trace of the past activations as a weighted sum. In fact it integrates a linear low pass filter to the outputs of the normal competitive units [11].

Except for the determination of the winner neurons, all other steps of the TKM are the same as in the SOM algorithm. On one hand, in the SOM algorithm, the winner neurons are determined by computing the Euclidean distance: the neuron with the shortest distance is the winner.

On the other hand, in the TKM, the winner neurons are obtained by computing the activation: the neuron with the highest activation is the winner. The activation values are computed through the recursive summing (also based on the Euclidean distance) of the current input vector and those previously stored in the map. The winner neurons will determine the trajectory in the TKM of the system behavior.

Three steps build the training phase: the competition, the cooperation and the adaptation. The competition step searches in the current map the neuron with the synaptic weights vector, **W**, that best matches the input vector, **E**, so minimizing the Euclidean distance. The cooperation step is in charge of identifying the direct neighbors of the winner neuron in the map. The adaptation step is in charge of updating the synaptic weights **W** of the direct neighbors as a function of the input vector **E**. Further details on these two steps can be found in [11, 15, 16].

For fault prediction, in recovery step, the map is colored such that the distance between neighboring neurons can be clearly visualized.

The distance is given by the difference between the synaptic weights of neighboring neurons. Closer neurons will appear clustered in the map and will be assigned the same color.

Different colors will denote neurons under different operation conditions: normal, degraded or faulty. Once the winner neuron is computed for a particular input vector **E**, the current system status can be identified in the colored map and, in deviated behavior; the degradation trajectory can be visualized in the map.

According to Fig. 1, one map is trained in our case study for fault prediction. For this purpose, the map is trained considering typical system situations of normal (fault-free valve operation), degraded and faulty situations, whose misbehaviors are simulated by injecting parameter deviations into the valve mathematical model.

For on-line testing, only the recovery step is performed considering the measured input vector **E**, the synaptic weights **W** of the neurons in the trained map and the activations A. Then, for fault prediction, the Euclidean distance, and the activation are computed and identified in the temporal Kohonen map.

III. EXPERIMENTAL RESULTS

To train the fault prediction map, a lot of simulations are performed to obtain typical values of torque and opening position under normal, degraded and faulty valve operations.

For the torque case, for example, the maximum fault-free value considered equals 250 Nm. However, to train the fault prediction map, in addition to fault-free, fault simulation is needed.

To exemplify, K_R, K_M, and C_a parameters, see (9), (10) and (11), are gradually incremented in the ranges shown in Table 1, such that degraded and faulty valve behaviors can be observed.

K_R deviations (9) simulate the degradation of the internal valve worm gear, till it breaks; K_M deviations (10) simulate the elasticity loss of the valve spring along time; and C_a deviations simulate an increase of friction between the valve stem and seal.

TABLE I. RANGE AND VARIATION RATE FOR K_R, K_M, AND C_a

Parameter	Range	Rate
K_R	11.00 – 12.00	0.01
K_M	4.215 – 5.215	0.01
C_a	16.00 – 21.00	0.05

As a consequence, for these faults for example the overtorque may reach 275 Nm and the valve may be prevented to open the gate beyond 80% of the full range (Fig. 4).

Training for the prediction of faults in K_R, K_M and C_a results in the map showed in Fig. 5. In the figure the neurons appear clustered around normal, degraded K_R, faulty K_R, degraded K_M, faulty K_M, degraded C_a and faulty C_a operation conditions. Each cluster, corresponding to different operation conditions, is assigned a different color.

As mentioned in Section 2.3, once the fault prediction map is trained, the D_{kj} and A_k are computed during the on-line testing phase.

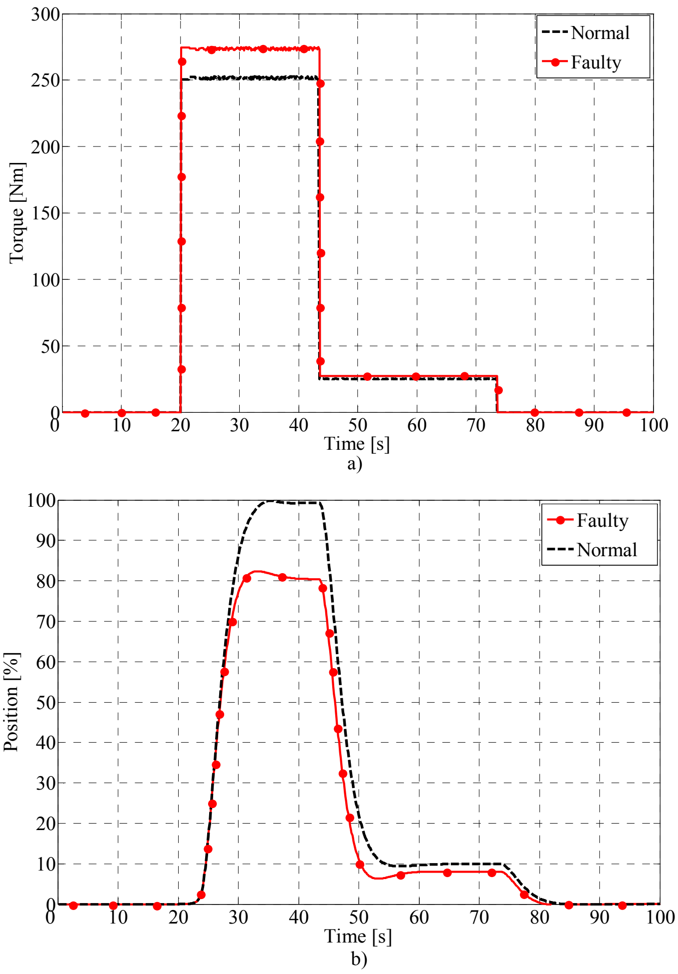

Figure 4. Fault simulation: a) torque and b) position.

During the on-line testing phase, a winner neuron computed for a measured input vector can be easily located in this map and, consequently, the current status of the system is straightforward determined. Still, using this map that was built during the training phase, the failure prediction is possible to be carried out.

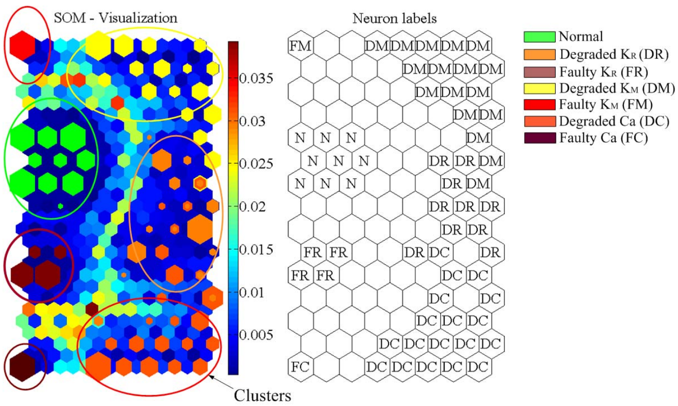

Figure 5. Fault classification map considering faults in K_R, K_M, and C_a.

In the temporal Kohonen map the system state can be visualized as a trajectory on the map and it is possible to follow the dynamics of the process.

This trajectory is described based on the winning neurons (A_{BMU}) for each temporal series. In a normal operation mode, the winners ought to follow a path inside the normal behavior region.

When a failure occurs, the winner will deviate from the normal region. The difference will depend of the type and severity of the fault.

The failure trajectory has important information about the failure mode. Thus, not only the start of degradation can be detected, but also a prediction of possible failure modes based on trajectory trend can be performed. It is noteworthy that in this work, the temporal Kohonen map is just used as a visualization tool.

Figures 6, 7 and 8 show the trajectory prediction of K_R, K_M and C_a considering normal, faulty and degraded behavior. It can be seen in these figures, three different paths. One for each simulated fault.

The trajectories started from neurons classified as normal, passed through neurons classified as degradation, and arrived to a neuron that represents the failure.

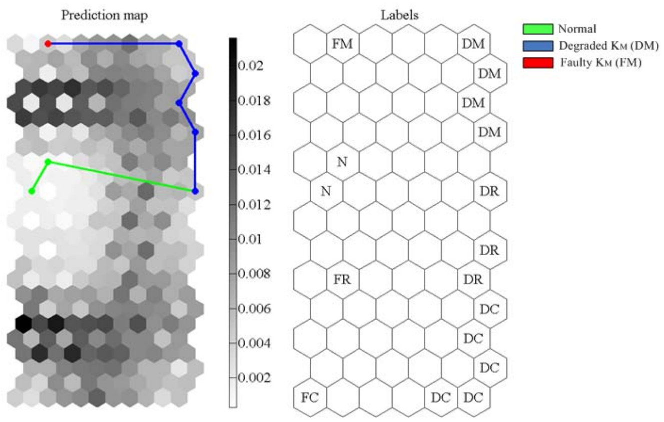

Figure 6. Fault prediction map considering faults in K_M.

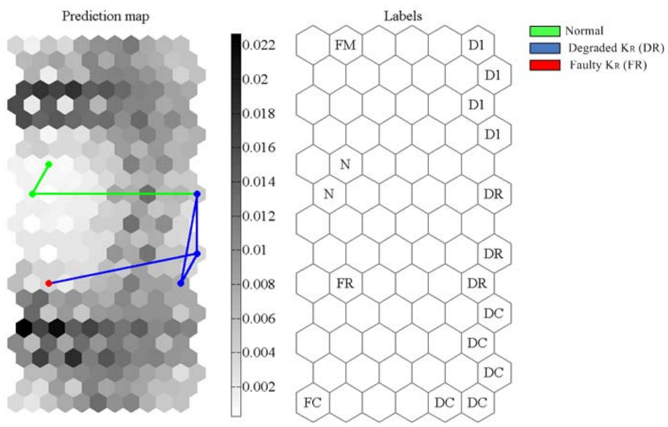

Figure 7. Fault prediction map considering faults in K_R.

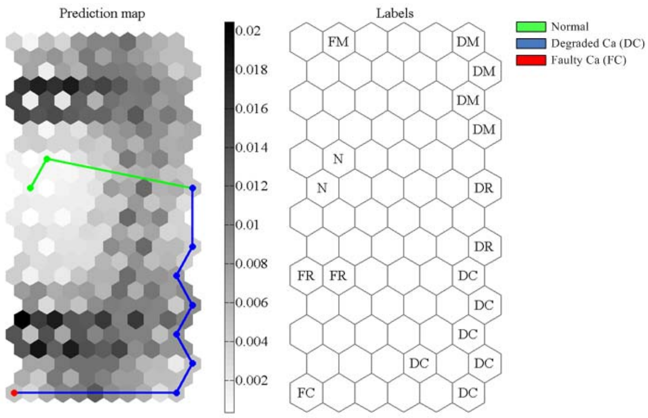

Figure 8. Fault prediction map considering faults in C_a.

IV. Conclusions

In this work, a proactive maintenance scheme is proposed for the prediction of faults in electrical valves. These valves are used for flow control in an oil distribution network.

To the best of our knowledge, this is the first attempt to apply a proactive maintenance methodology to this sort of actuators that have only known corrective and preventive practices so far.

Another novelty brought in by this work is that an implementation of TKM is proposed to solve the valve maintenance problem. An on-line monitoring system implements these maps for the prediction of faults that lead to deviations either on torque, or on the valve opening position.

For fault prediction, the TKM is trained using a mathematical model and a fault injection procedure is devised for the actuator, valve and pipe. During the on-line monitoring phase, the system computes the best matching between an acquired measure and the neurons of the trained map and respective temporal activations. This matching guides the fault prediction step that shows up very effective.

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