# *Self Organizing Maps for Monitoring Parameter Deterioration of DC and AC Motors*

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***Abstract*—A novel method for the detection of faults in DC and AC motors using Kohonen Networks (Self Organized Maps) is presented in this paper. The advantage of this technique is that it only requires input samples to perform the training of the network, a difference from other Neural Network architectures that need both inputs and outputs to perform the training. This technique generates fault maps based only on the inputs that are received from the motor under test. The maps can be used to clearly identify different types of faults in DC and AC motors since similar faults generate the same type of map. The main advantages of this technique are that it can be used to test motors in real time and on-site, without having to disconnect the motor for testing. The technique can be applied for testing motors used in production lines without having to stop operation for testing.**

***Keywords — Faults, Motors, Classification, Neural Networks, Unsupervised, SOM***

## I. Introduction

In industry motors are some of the most common devices used to execute or actuate different production processes. These motors usually run non-stop, and sometimes they fail because of their continuous operation in extreme temperatures, dirt and other bad environmental situations. In a factory setting a faulty motor can be disastrous because the process or task that the motor executes will have to be stopped until the motor is repaired or changed. To avoid this kind of unforeseen and costly setback, a fault detection method that could be easily applied when the motor is operating under its normal environmental conditions, without having to do production line shutdowns or motor disconnections, would be very valuable. Also an intelligent method that could be used to identify and classify the different types of faults of a typical DC or AC motor would be very desirable to have. Many recent fault detection techniques have been presented in the literature [1-7], but all of these methods are designed to identify a specific type of fault [8], and other methods need the motor to be disconnected and be tested in a laboratory or special testing location. In this work we present a method based in Kohonen networks or Self Organizing Maps that can be trained to detect faults in motors in real time and identify the type of fault within the motor before the motor can no longer be used.

Artificial neural networks have traditionally been used to predict motor faults, such as the Backpropagation network, the Hopefield network, and many others. The main reason why the SOM architecture was chosen was due to simplicity to implement and to the fact that no matter how many variables are added, the network retains its simplicity and accuracy. Also with the Kohonen Network the output does not need to be known in order to train and test the network. Other types of networks need to know what the output should be when predicting faults in motors; therefore the user has to already know what is wrong with the motor in order to train the classifier. Using other networks means there is no prediction, just testing for a fault that has already occured.

## II. Kohonen Networks

A Kohonen Neural Network is similar to a topological map. In any topological map units that are located next to each other will react to a set of input vectors that are also next to each other. When using input vectors that have dimensions larger than two the vectors can be projected onto a two dimensional plane. This reduction of dimensionality makes it easier to see the effect that higher dimensional input vectors have. This kind of map is a topological preserving map called a self-organizing map. The Kohonen Neural Network is a competitive learning network. The inputs are usually ordered as a two dimensional vector, or array, a graphical representation of the map is shown in Fig. 1.

Kohonen Neural Networks are best to use when the outcome cannot be foreseen. The Kohonen Network will be able to cluster the input data together in a uniform manner so patterns in the input data can be seen. In other words the Kohonen Network can classify data. There are different methods for clustering data together; one method is to cluster the data sequentially [9-11]. This method is very easy to implement, but any relationship between different data is lost. Another way to organize data is through a statistical method by using matrices and comparing eigenvalues and eigenvectors to each

other to see a relationship in the data [12]. However, this method is more difficult to implement because it usually requires the solution to a very large matrix. Kohonen networks or SOMS provide an easy way to cluster data topologically using competitive learning. This method is simpler than other methods, and the data is grouped in a way that patterns and relationships between data can be seen.

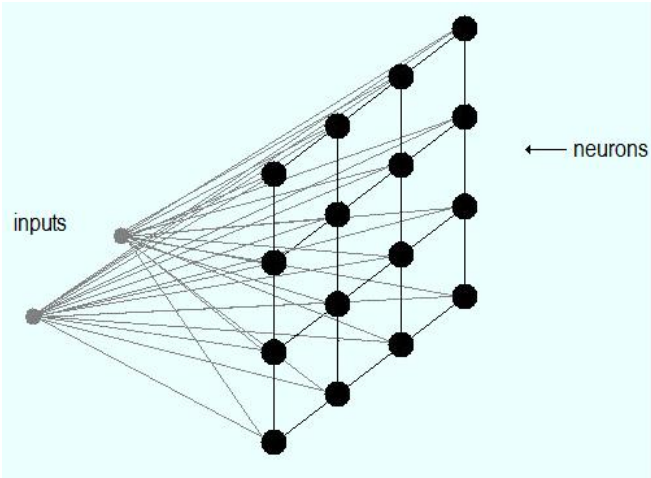


Figure 1. SOM Topology

In the Kohonen Network the topological relationship of the organized information is maintained. Initially a large area is treated as one "learning area". As the learning progresses the "learning area" shrinks until the desired outcome occurs. The Kohonen Neural Network uses the winner take all method, meaning one neuron wins and the output from the one neuron is used. The Kohonen Neural Network has a very simple construction in that it usually only has an input layer and an output layer.

The method in which the Kohonen Network works is very simple compared to other neural networks. Inputs to the network must be normalized. This normalization insures all of the input data is on the same scale. The Kohonen Network has one layer of neurons that are organized into one, two or higher dimensional arrays. Each neuron has as many input connections as there are number of attributes that will be used for classification. So if someone wanted to classify cups by size and color, then each neuron would have two input connections. During the training of the network the winning neuron is determined by how close the weight of the neuron was to the input data. Then weights of all the neurons in the vicinity, or neighborhood of the winning neuron are adjusted by the inverse of their distance to the winning neuron. The radius of the neighborhood decreases with each iteration. The training process is over if the network is within an acceptable error range or a specified number of iterations is reached. The way the network determines similarity between vectors and neurons is by obtaining the scalar product of the inputs after they are weighted by the neuron.

## III. System Implementation

To implement the intelligent classification system, a Digital Acquisition (DAQ) board from National Instruments and MATLAB where used. MATLAB's Neural Network Toolbox has different types of networks available to train. The toolbox has the most common types of neural networks such as the back-propagation network, the Hopfield network, and the Self-Organizing Map, or Kohonen Network. The Neural Network Toolbox lets the user decide how many epochs to train the network, how many data points will be used as inputs, and how many outputs there are. The Toolbox also displays the outputs using different types of graphs. To gather data from the motors the DAQ board was used to gather signals from the motors.

## IV. Designed Network

To create a neural network first the training vector must be loaded into the workspace in Matlab. The training vector is simply the one row, or one column matrix that contains the necessary data, or it can be a matrix. To start creating the network the number of weights need to be chosen. The default is a ten by ten network. Different sized networks were created and tested. The different network sizes were a three by three network, a five by five network and a ten by ten network. Next the training data can be entered as a row or as a column. Whether the data is a row or column makes a difference because one way will give one output and the other way will give the maximum outputs. The choice between row or column depends on the structure of the network and the data being entered. Next the network is trained; the default number of iterations is 200. When the training is complete there are different plot options available. A plot of the weights can be viewed as densities or as points in a Cartesian plane. The hits can also be viewed. The hits represent how the network mapped the data. The user does not know what the actual position of the hit means, or how it was mapped there, but when similar data is put into the network another map will be produced and corresponding hits mean similarities between the data sets. The meaning of the positions of the hits can be determined by examining all of the weight vectors. Once the network has been trained it can be turned into a .m file, or code and can be modified from there. When using the toolbox different results from the neural network can be plotted. The following results are from a set of sample data already loaded into Matlab. This particular data is a 2 by 1000 matrix which means that there are two individual sets of data each representing a different component that will be clustered together. The size of the network will depend on the data being entered.

## V. Faults Tested At Georgia Southern

Initially, small motors were used, in the lab at GSU, to test the SOM fault detection and classification technique. First, simple types of failures were tested in DC motors. The tests included: Vibrations, Temperature spikes and Harmonics.

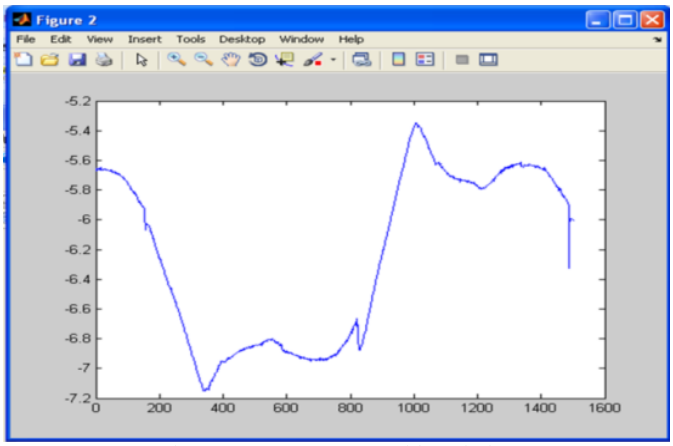


Figure 2. Motor Response with no faults.

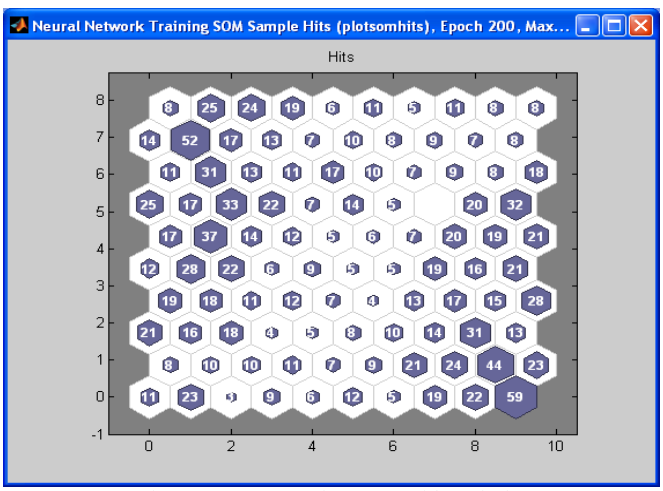


Figure 3. SOM Map for Motor with no faults

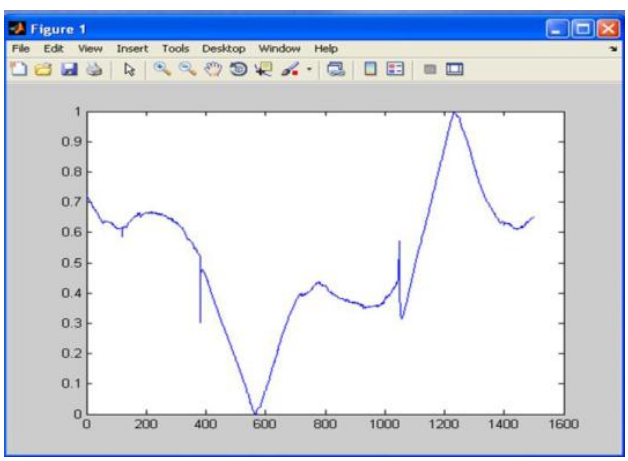


Figure 4. Motor Response with Vibration Fault

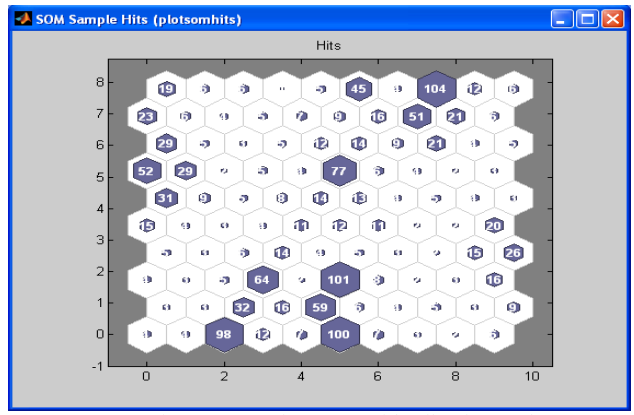


Figure 5. Map for Motor with Vibration Fault

These tests were selected because main failures in electric motors are generated by extra vibrations, overheating or harmonics that result from a broken or cracked rotor bars, rotor laminations, shorted end rings, and defective or loose rotor bar joints in the motors. Also, extra vibrations can be caused by mechanical wear or an uneven load on the motor. To test for vibrations in the motor an accelerometer was used, for the temperature testing a temperature to voltage sensor was used. In particular an ACH 01 [13] accelerometer was used to test a 0.125 horsepower DC motor. Figures 2 & 3 show the typical signal response and map for a motor with no faults. When vibrations were introduced to the same motor, new data was collected again, and Figures 4-5 show the corresponding signal response and map of the motor with vibrations

## VI. Faults Tested at Georgia Pacific

After the successful testing of small motors in the lab at GSU, the next step was to try the method in an actual industrial environment. Georgia Pacific has motor testing on site for maintenance. For most of the motor testing that is done at Georgia Pacific a DAQ unit is used to collect the data from the motors. There are two basic categories of tests that were performed in this location. The first is called MCE (Motor Circuit Evaluation) which refer to de-energized motor testing and EMAX (Energized Motor Analysis eXtra testing) refers to predictive maintenance without requiring a shutdown of the motors for access and can be used for process analysis with motor current signature analysis and also provides voltage, power, and efficiency data. The equipment that was used for the MCE and EMAX data collection is a MCEmax from PDMA Corporation, due to its capability to test a de-energized and an energized motor with the same equipment. These types of tests are critical to a company's up-time. Electrical faults are responsible for approximately 50% of all of the motor failures.

The MCE tests allow for the testing of de-energized electric motors. It is able to test both large and small AC and DC motors, and determine the condition of the motor and the power circuit of that motor all in a very short period of time.

The data that is taken in by the tester from the motor is then stored where it is available for trending and comparison to previous readings. This allows the user to perform condition based maintenance by comparing the data that is collected to previous data that has been collected by the motor and determine if the motor is showing signs of failure. For the purpose of this project the data was collected and inserted into the neural network and then the results from the ANN were compared to the results that had been given by the DAQ board.

Three different types of motor faults were tested using the SOM classification system: an index polarization test, a gap eccentricity test, and a frequency spectrum test. The polarization index (PI) test was performed on AC and DC motors. This test calculates a PI ration and a profile of the Resistance to Ground (RTG) vs. Time are plotted. For the purpose of this research, these results were compared to the results that are given by the ANN classification system, in order to verify that both systems obtain consistent results when analyzing the motor.

The Polarization Index (PI) is used to determine the fitness of a motor or generator for use. The index is derived from calculating measurement of winding (electrical) insulation resistance. The polarization index gives an indication of the buildup of dirt or moisture, the deterioration of insulation and the suitability for operation of the motor or generator. If the PI test indicates that there is not an excessive amount of leakage, then a step voltage test is performed. In this test the voltage will exceed the rated level in order to safely stress the dielectric material [14]. Figures 6 & 7 show the corresponding signal response and map of a motor with no faulty Polarization Index, while Figures 8 & 9 show the corresponding signal response and map of a motor with faulty Polarization Index.

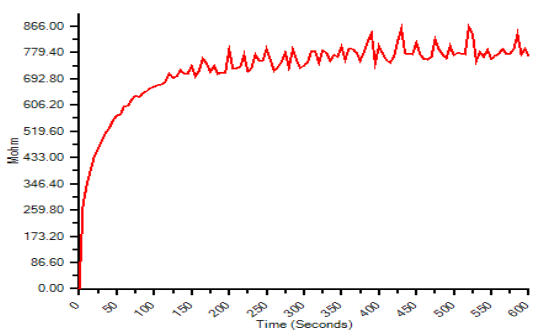


Figure 6. A PI test from MCE MAX, with no faults

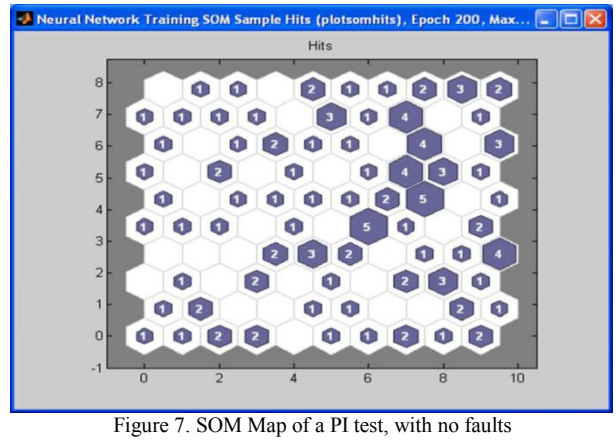


Figure 7. SOM Map of a PI test, with no faults

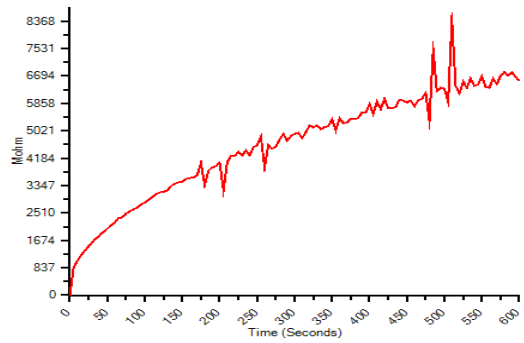


Figure 8. MCE MAX PI test, faulty motor

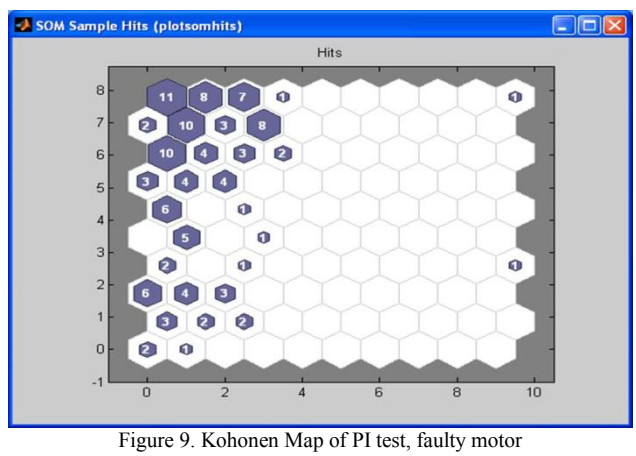


Figure 9. Kohonen Map of PI test, faulty motor

During operation, several stresses are brought to bear upon key components of a motor. An air gap eccentricity results in increasing these stresses during operation. A motor operated with an eccentric air gap results in increased mechanical vibration, accelerated insulation degradation due to increased coil movement, and possible rotor/stator rubbing due to unbalanced magnetic pull.

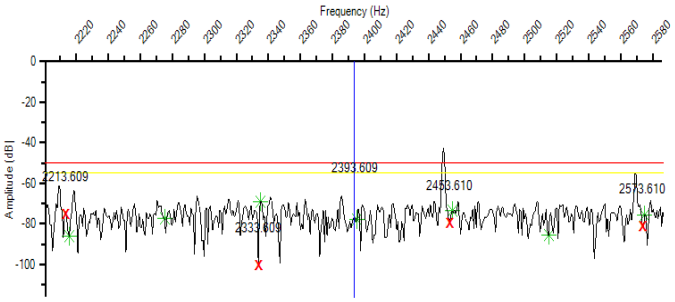


Figure 10. MCE MAX good eccentricity

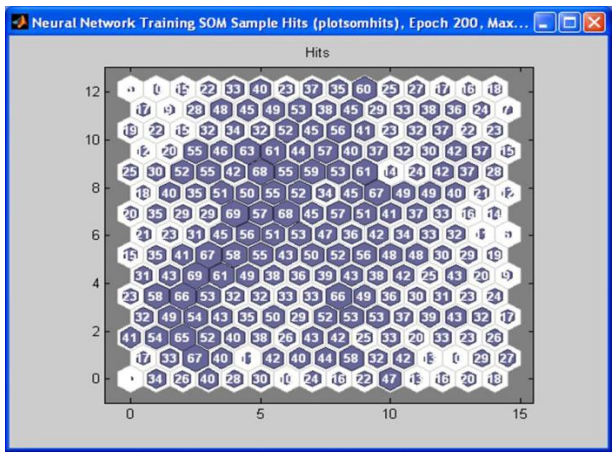


Figure 11. Good eccentricity Kohonen Map

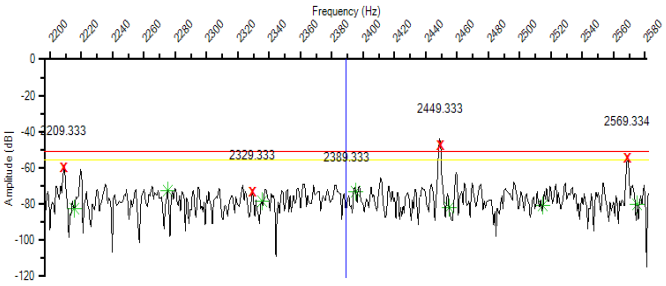


Figure 12. Bad eccentricity MCE MAX

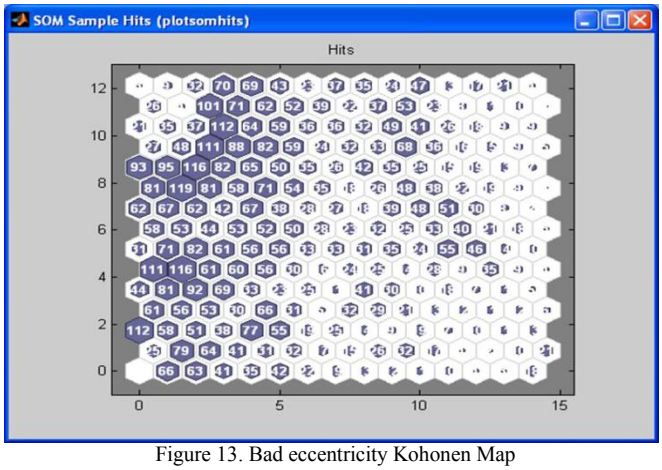


Figure 13. Bad eccentricity Kohonen Map

Eccentricity is the measure of the center of the conductor's location with respect to the cross sectional area surrounded by the insulation, or eccentricity is the non-uniformity of the air gap between the rotor and stator. The eccentricity test can be performed on an energized AC motor. There are two types of non-uniformity that can occur, static and dynamic. Static eccentricity means that at one point the rotor is misaligned with the stator. Dynamic eccentricity occurs when there is a precession of the misalignment. Dynamic eccentricity can occur is the rotor is bowed. Eccentricity in a motor can cause the rotor to rub against the stator reducing the life of the motor. Figures 10 & 11 show the corresponding signal response and map of a motor with no faulty eccentricity gap, while Figures 12 & 13 show the corresponding signal response and map of a motor with faulty eccentricity gap.

The spectrum of a motor is also referred to as the harmonics of the motor. The larger motors that were tested had natural harmonics at 60 hertz. If there are harmonic distortions in the motor then it will increase electrical loss and decrease efficiency. The harmonic distortion can be tested in the applied voltage to the motor. Harmonic distortion is commonly referred to as total harmonic distortion [15]. Figures 14 & 15 show the corresponding signal response and map of a motor with no faulty spectrum, while Figures 16 & 17 show the corresponding signal response and map of a motor with faulty spectrum.

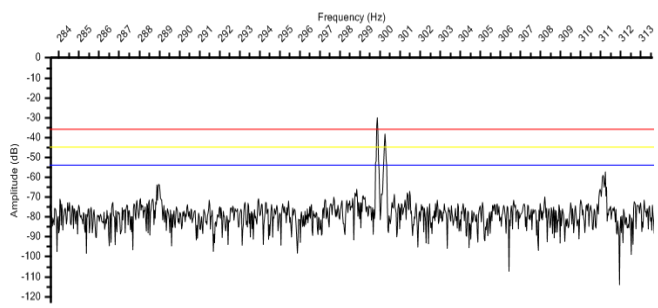


Figure 14. Good spectrum MCE MAX

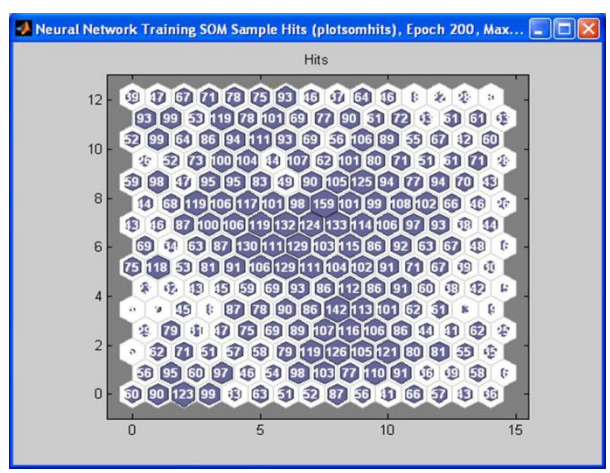


Figure 15. Good spectrum Kohonen Map

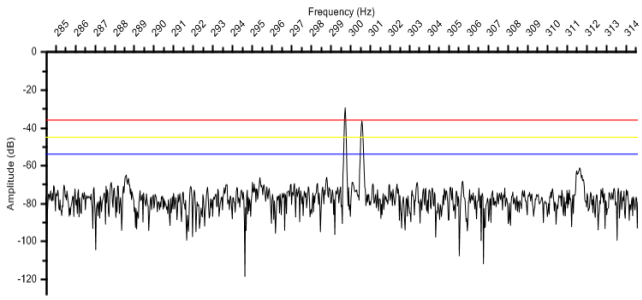


Figure 16. Bad spectrum MCE MAX

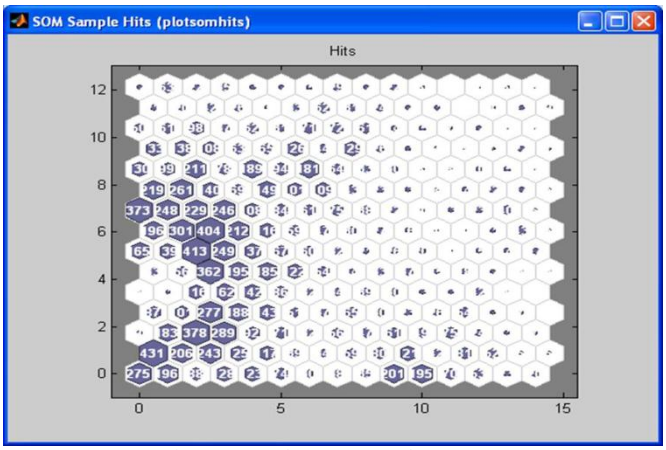


Figure 17. Bad Spectrum Kohonen Map

## VII. Conclusions

Through testing the Kohonen Neural Network produced consistent results. For some of the tests more neurons had to be used because of the amount of input data. Generally, if there was more input data, then there needed to be more neurons to see a pattern. The maps always matched the results of the MCE MAX which is already known to be a highly regarded test. Observing the maps that the Kohonen Networks produced, when there is a fault in the motor the network clusters to a certain side. This may indicate an underlying pattern with motor faults of all types. The Kohonen Network was more practical to train than other networks because the output did not need to be known before the testing was conducted.

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