

Jover Rodríguez, P., Arkkio, A., 2008, Detection of Stator Winding Fault in Induction Motor Using Fuzzy Logic, Applied Soft Computing, Vol. 8, No. 2, pp. 1112-1120.

© 2008 by authors and © 2008 Elsevier Science

Preprinted with permission from Elsevier.

# **Detection of Stator Winding Fault In Induction Motor Using Fuzzy Logic**

Pedro Vicente Jover Rodríguez

Antero Arkkio

Laboratory of Electromechanics

Helsinki University of Technology

P.O. Box 3000, 02015 HUT, Finland

Phone: +358 9 4512391, Fax: +358 9 4512991

[Vicent@cc.hut.fi](mailto:Vicent@cc.hut.fi)

## **Abstract**

The online monitoring of induction motors is becoming increasingly important. The main difficulty in this task is the lack of an accurate analytical model to describe a faulty motor. A fuzzy logic approach may help to diagnose induction motor faults. This work presents a reliable method for the detection of stator winding faults (which make up 38% of induction motor failures) based on monitoring the line/terminal current amplitudes. In this method, fuzzy logic is used to make decisions about the stator motor condition. The fuzzy system is based on knowledge expressed in rules and membership functions, which describe the behaviour of the stator winding. The Finite Element Method (FEM) is utilised to generate virtual data that support the construction of the membership functions and give the possibility to online test the proposed system. The layout has been implemented in MATLAB/SIMULINK, with both data from a FEM motor simulation program and real measurements. The proposed method is simple and has the ability to work with variable speed drives. The fuzzy system is able to identify the motor stator condition with high accuracy. This work is an example of the fusion between soft and hard computing.

## **Key words**

Induction motor, fuzzy logic, winding fault, current, detection.

## 1. Introduction

Three-phase induction motors are the “workhorses” of industry and are the most widely used electrical machine. Because of its simple structure and high reliability, induction motor is used for many purposes such as: pumps, blowers, fans, compressors, transportation, etc. In an industrialised nation, they can consume between 40 to 50 % of total generated capacity of that country [3,15].

However, owing to the thermal, electrical and mechanical stresses, mechanical and electrical failures are unavoidable in induction motors. Early detection of abnormalities in the motor will help to avoid expensive failures. Operators of electric drive systems are under continual pressure to reduce maintenance costs and prevent unscheduled downtimes that result in lost production and loss of financial income.

The modern industry has widely used reliability-based and condition-based maintenance strategies to reduce unexpected failures and downtime. These techniques can increase the time between planned shutdowns for standard maintenance and reduce maintenance and operational costs. The operation of the machine in unsafe condition must also be avoided. Nevertheless, the failures are unavoidable, and failure statistics [15] has reported that the percentage of failures in induction motor components is as follows:

1. Bearing related faults: 40%
2. Stator winding related faults: 38%
3. Rotor related faults: 10%
4. Other faults: 12%

It is important to note that even if the stator fault account makes up 38 % of the all faults, it is very important to spot them in time because they can lead to the total destruction of the motor. A reliable system for the detection of such a fault should be able to detect the fault at an early stage, monitoring the motor condition online.

The fuzzy logic approach may help to diagnose induction motor faults. The concept of fuzzy logic was introduced by Professor Lofti A. Zadeh to present vagueness in linguistic terms and express human knowledge in a natural way [16]. It is well known that fuzzy logic can describe the characteristics of industrial process with linguistic terms [11]. The motor condition identification task requires the interpretation of data and makes decision from the data. Primarily, the motor condition constitutes a fuzzy set. In practice, the users are concerned about the condition of the motor in terms of a linguistic variable that can be expressed as “good”, “damaged” or “seriously damaged”. Further, a fuzzy system can store certain knowledge, which allows it to make decisions with a high percent of accuracy. This knowledge expressed in rules and membership functions is obtained from the analytical study of the motor, motor performance, simulated data and power engineer experience. From the point of view that sees induction motor condition as a fuzzy concept, there has been some fuzzy logic approaches for diagnosis. The lack of proper processing of fuzzy input data and the construction of the membership functions are presented as the major difficulties [4, 7, 11, 12]. This problem is tackled in this work by using FEM in order to generate reliable virtual data, which allows the construction of the membership functions in all faulty and load conditions.

The aim of FEM here is to foresee the changes of motor performance due to the changes in the internal parameters when the motor is working under faulty conditions. Numerical simulations generate useful data, which are used to test the diagnostic techniques. FEM permits the evaluation of the influence of different motor faults in an inexpensive and accurate manner [14].

Early work in the detection of induction motor faults using fuzzy logic is presented in [12]. This application corresponds to single phase induction motors. This paper suggests the application of the approach to other different machines by forming appropriate membership functions and rules knowing the machine behaviour. It is suggested that the rules should be known experimentally and with the help of an expert. This paper presents some guidelines for the derivation of rules.

Recently, some applications of fuzzy logic for the detection of faults in electrical machines and power electronic have emerged as a solution for online diagnosis. In reference [5] a neuro fuzzy system for the detection of faults in power transformer is presented. Reference [10] presents a system for detecting online fault in HVAC systems, where the fuzzy system is assisted by genetic algorithm to generate optimal rules. In both cases automated online diagnosis have been achieved. Reference [2] presents an adaptive neural fuzzy inference system (ANFIS) for the detection of winding and bearing faults in single-phase induction motors. In [2] experimental data is generated for five measurable different parameters, which constitute the inputs for the ANFIS detector. Such a synergy, between neural network, brings a better understanding of the heuristics and motor fault detection can be achieved. But still the main drawback the of all data-based identification methods remains: the performance of the classification can be only as good as the data it is based on. In fault classification this may be a problem, because often there are not much reliable data available from all the faulty operations. Further, another major difficulty in motor-fault detection and diagnosis is the lack of an accurate analytical model that describes a faulty motor.

In our research, fuzzy logic approach is used to make decisions about the motor condition. The task of the diagnostic system presented in this work is to detect an upcoming stator fault as early as possible, in order to save expensive manufacturing processes or to replace faulty parts. Since stator faults do not produce clear signatures in the current spectrum, it is necessary to use other means to identify stator faults instead of the traditional spectrum analysis technique. For that reason the fuzzy logic approach is applied to the motor current amplitudes in order to spot failures in the stator. The terminal current amplitudes contain potential fault information and constitute suitable measurements for diagnosing stator faults in term of easy accessibility, reliability and sensitivity [4].

## 2. Stator winding fault

In low voltage three-phase induction motors the stator-winding fault can be classified as follow:

- 1- Turn to turn shorts within a coil (inter-turn short circuit): motor will continue to operate, but for how long?
- 2- Shorts between coils of the same phase, motor can continue to operate but for how long?
- 3- Phase to phase short, motor fails and protection equipment disconnects the supply.
- 4-Phase to earth short: motor fails and protection equipment disconnects the supply.
- 5-Open circuit in one phase, motor may continue to operate, depending on the load conditions.

Pre-warning of motor failure, such as 3 and 4 can only be achieved if shorted turns within a coil (such as 1) can be initially diagnosed via online diagnostic technique. The general opinion of the users and manufactures is that there is a longer lead-time between the inception of shorted turns up to failure in low voltage motors. In modern production process, any lead-time can be extremely advantageous since unexpected failures of a drive can be very costly. If an inter-turn short (one or two shorted turns) can be diagnosed, a pre-planned shutdown can be arranged.

The common technique for online detection of motor faults is known as motor current signature analysis (MCSA) [15]. The objective of this technique is to detect certain components in the stator current spectrum that are only a function of a specific fault. However, it has been shown mathematically and experimentally by [9] that the spectral components due shorted turns are not a reliable indicator of stator winding fault.

In reference [9], the interaction between a faulted stator winding and healthy rotor cage is studied. The faulted, asymmetric stator winding may produce spatial harmonics of any wave number into the air-gap field. However, all these harmonics vary at a single frequency, i.e. the supply frequency of the sinusoidal voltage source. The stator harmonics induce currents in the rotor cage and reflect back from

the rotor as new air-gap field harmonics. Seen from the stator, the air-gap harmonics caused by the induced rotor currents vary at the frequencies

$$f_{rf} = f_1 \left[ 1 \pm \frac{\lambda n}{p} (1-s) \right] \quad (1)$$

$f_{rf}$  components reflected from the stator side, so-called rotor slot harmonics

$f_1$  supply frequency

$p$  number of pole-pairs

$s$  slip

$n$  number of rotor bars

$\lambda = 1, 2, 3, \dots$

The air-gap field harmonics induce electromotive forces in the stator winding and generate harmonic stator currents at these same frequencies. Unfortunately, these are the same frequencies at which a healthy machine produces harmonic stator currents.

According to this analysis, a stator fault may only generate harmonic stator currents, which vary at the fundamental and rotor-slot harmonic frequencies. A fault in a stator winding may change the amplitudes of the stator-current harmonics but it does not produce any new frequencies in the stator-current spectrum. This significant result implies that it may be difficult to detect a stator fault from a current spectrum using MCSA. Then, another technique is needed to spot this important fault.

A healthy three phases induction motor fed from a symmetric power supply has three balanced phase currents. Fig. 1 shows the phase currents of a healthy motor working at half load and fed from an inverter at 100 Hz. The induction motor is ideally a symmetry system. Any asymmetric in the stator winding produces unbalance in the motor currents. The most difficult case to identify might be when there is only inter-turn short circuit, as is shown in Fig. 2, where the lowest unbalanced is shown. Fig. 1 and Fig. 2 correspond to measured data. The main idea of the developed monitoring system is to

spot the unbalance in the input currents as fast as possible avoiding a major failure. The system should be able also to detect a short-circuited coil and open phase.

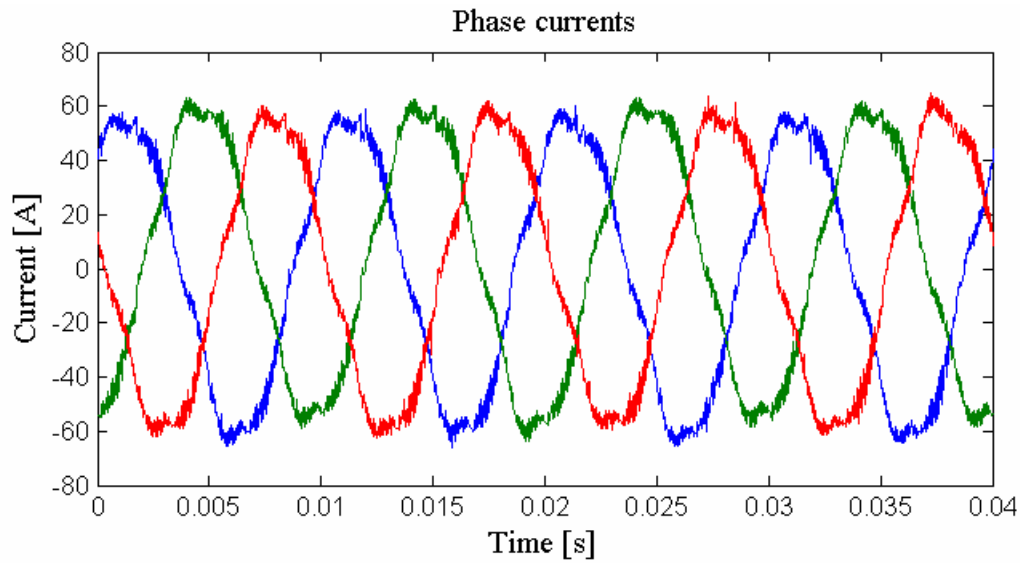


Fig. 1. Terminal phase currents in a healthy motor. Inverter supply at 100 Hz

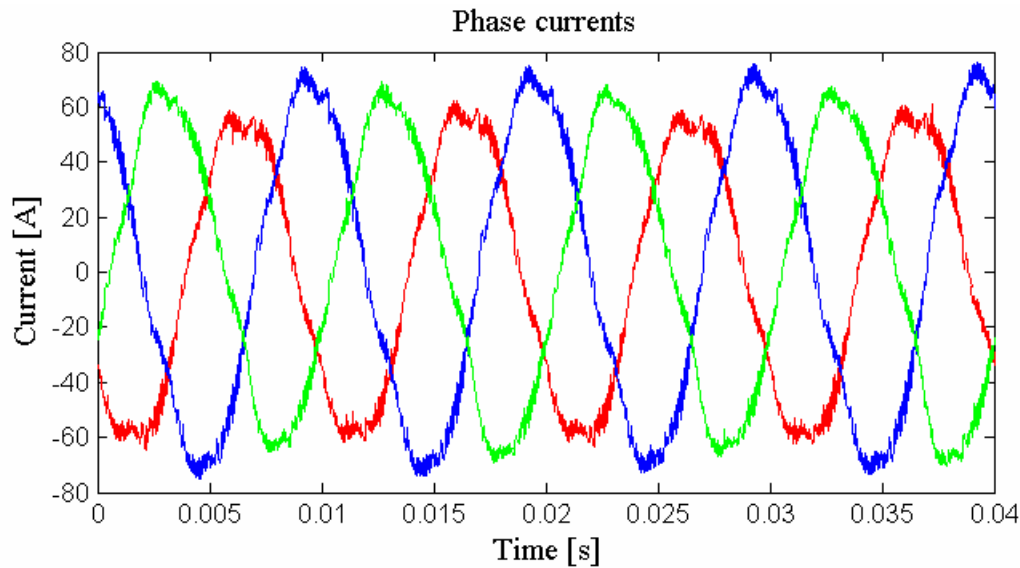


Fig. 2. Terminal phase currents in a faulty motor during an inter-turn short circuit. Inverter supply at 100 Hz.

### 3. Generating of data by FEM



In our software package, FEM is applied for solving electromagnetic problems, which are described by the Maxwell equations. This software is an in-house 2-D FEM program, in which the magnetic field in the cross-section area of the test machine is computed. This package was designed for the transient magnetic field analysis of electrical machines coupled with the circuit equations of the machine windings. This method allows the simulation of electrical machine fed from measured voltages of the power converter used in experiments. The software uses the time-stepping method, which takes into account the motion of the rotor and the induced voltage due to this motion. Some of the 3-D effects like flux fringing and end windings are also modelled with analytical and electric circuit approaches. A full description of the software and its accuracy is given in [1]. A detailed description about fault implementation in the program can be found in [14].

The FEM program permits the generation of data with the motor working in different condition of load as well as changing the severity of the fault. Data were generated for healthy motor, inter-turn short-circuits and inter-coil short-circuits. In every case three load conditions full, half and no load were considered. The membership functions are obtained from the calculated current, taking into account the healthy and faulty conditions.

#### 4. Detection system

A block diagram of the system can be seen in Fig. 3. The system monitors the amplitudes of the motor currents  $I_a, I_b$  and  $I_c$ . Firstly, the analogic measurements are converted in digital data through an A/D converter. Then, the root mean square (rms) of each phase current is calculated over a period of time using the standard formula,

$$rms = \sqrt{\frac{1}{T} \int_t^{t+T} I(t)^2 dt}$$

(2)

$I(t)$  Is the input current

$T$  Is the fundamental period

In this layout, the motor currents are considered as input variables of the fuzzy system and stator condition (SC) is chosen as the output variable. These variables are vague information. The digital output from the A/D converter is converted into suitable linguistic values.

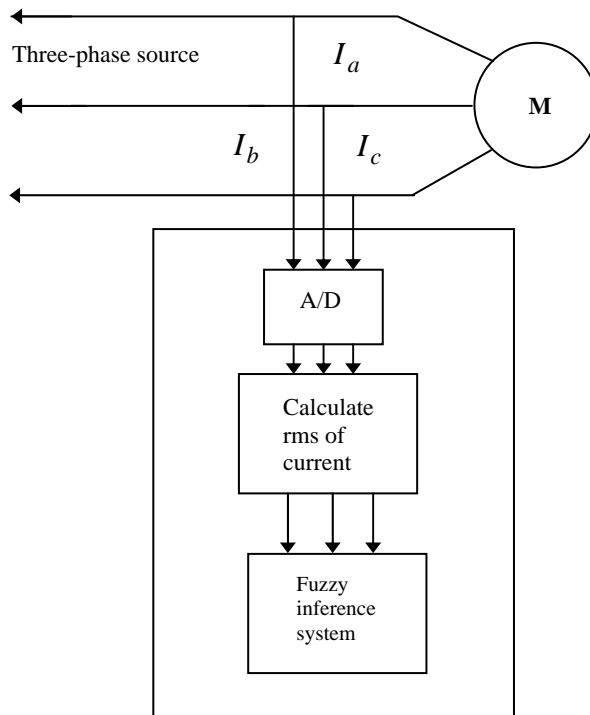


Fig. 3. Block diagram of the stator protection system.

#### 4.1 Membership functions

The stator condition can be known by observing the phase current amplitudes, being the relationship between the stator condition and the current amplitudes vague. Therefore, the numerical data are represented as linguistic information.

Thus, the amplitudes of the currents (inputs) are categorised using four linguistic variables. These categories are very small (VS), small (S), medium (M) and large (L). The linguistic variable “Stator

condition” (SC) (output), interpreting the stator condition could be “Good” (G), “Damaged”(D) or “Seriously damaged” (SD). “G” refers to a stator with no faults, “D” might be a stator with current unbalance (inter-turn short circuit), and “SD” a stator with an open phase or coil short-circuited. In other words and using fuzzy logic theory, the input and output of the system are defined as,

$$\text{Inputs: } I_a = \{ \mu_{I_a}(i_{aj}) / i_{aj} \in I_a \} \quad (3)$$

$$I_b = \{ \mu_{I_b}(i_{bj}) / i_{bj} \in I_b \} \quad (4)$$

$$I_c = \{ \mu_{I_c}(i_{cj}) / i_{cj} \in I_c \} \quad (5)$$

$$\text{Output: } SC = \{ \mu_{SC}(sc_j) / sc_j \in SC \} \quad (6)$$

$i_{aj}, i_{bj}, i_{cj}, sc_j$  are elements of the discrete universe of discourse

$I_a, I_b, I_c, SC$  are universe of discourse

$\mu_{I_a}, \mu_{I_b}, \mu_{I_c}, \mu_{SC}$  are corresponding membership functions

$T(SC)$  Term interpreting the stator condition: can be good, damaged or seriously damaged

The membership functions for the input and output variables are constructed by the analysis of data generated by FEM. Thus, the FEM program is run from no-load to full-load in the healthy situation and the rms values of the phase currents are calculated, obtaining values from 25 to 65 A (for the case of motor 1). These values are normalized between [0, 1], defining the membership function which corresponds with the linguistic term M, for a healthy motor. Similar process is repeated for the faulty conditions, defining the VS, S, and L. The VS condition is obtained when the motor has a fully open phase, L corresponds to a short-circuit in one phase and S corresponds with a no load motor. All these situations are simulated in FEM, allowing the definition of the trapezoidal membership functions.

The system was tested with triangular, trapezoidal and Gaussian membership functions. It was found that the combination of triangular and trapezoidal membership function is the most appropriated for fault diagnosis of induction motors. Reference [5] obtained similar results for the case of power transformers. Trapezoidal function has well defined corner as the motor has well defined rated parameters. Fig. 4 shows an example of input membership functions. Fig. 5 shows the output membership functions.

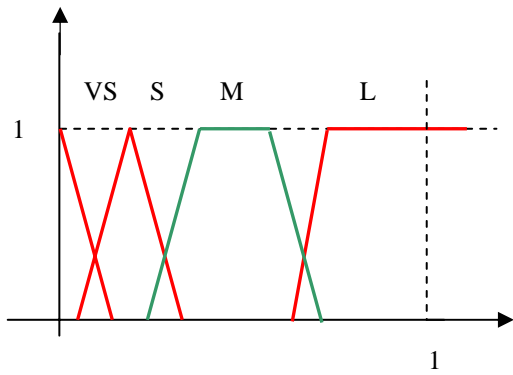


Fig. 4. Membership functions for the normalized currents  $I_a, I_b, I_c$ .

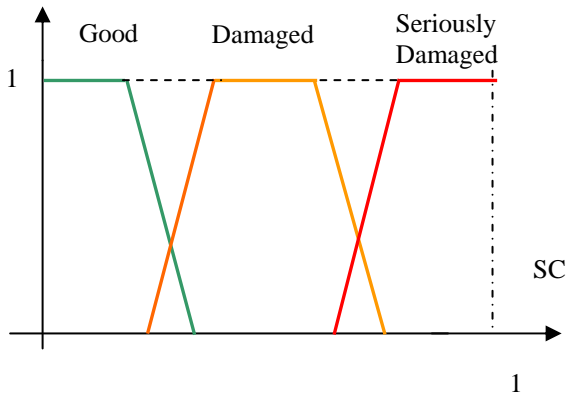


Fig. 5. Membership functions for the stator condition.

Another known power engineer fact is included that takes into account the amplitude variance, in order to improve the system sensitivity and reliability. The membership function for the amplitude “variance” of current is shown in Fig. 6. The variance is calculated as follow,

$$v = \frac{|I_a - \bar{I}|^2 + |I_b - \bar{I}|^2 + |I_c - \bar{I}|^2}{2} \quad (3)$$

where  $I_a, I_b, I_c$  are the rms values of the input currents

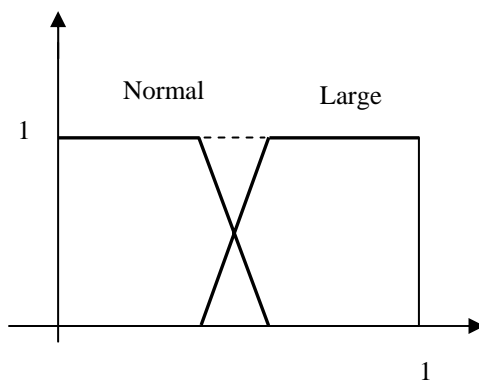


Fig. 6. Membership functions of the variable “variance”.

The membership function of the variance is also defined from the FEM calculation and normalized between [0, 1]. The amplitudes of the currents as well as the variance are transferred into the corresponding universe of discourse as inputs. The fuzzy inference engine evaluates the inputs based on power engineer experience.

## 4.2 Inference system

The design of rules in our case is based on the expert understanding. The process consists of two parts: knowledge acquisition and formation of rules and combination of rules. Our inference system will perform as a power engineer with an ammeter.

The knowledge acquisition starts, with the translation of the motor understanding to *if-then* rules. Firstly, it is important to remember that a three phase healthy induction motor is a symmetric system.

This is equivalent to say that the three currents have the same rms values (within a tolerance), this define the healthy situation, rules 9 and 10. On the other hand, it is enough that one of the phase currents is large (L) to imply the motor is seriously damage, rules 4, 5, 6. Moreover, it is also enough that one of the currents is very small (VS) to imply that the motor is seriously damage (SD). Totally, we have in the input of the system 64 possible combinations between the three currents and the four categories for every current. Many of the combinations are redundant. For example, if the three currents are large, the SC is seriously damage, but this condition is already included in one of the rules 4 or 5 or 6. Similarly happens when we have two large currents. This analysis is manually extended to cover all the combinations.

From the optimisation of all different possible combinations between the three currents and four linguistic variables the following set of rules is obtained. This set of rules contains the knowledge and description of the machine condition. They are universal for all three phases induction motors.

Rule 1: If  $I_a$  is VS then SC is SD

Rule 2: If  $I_b$  is VS then SC is SD

Rule 3: If  $I_c$  is VS then SC is SD

Rule 4: If  $I_a$  is L then SC is SD

Rule 5: If  $I_b$  is L then SC is SD

Rule 6: If  $I_c$  is L then SC is SD

Rule 7: If  $I_a$  is S and  $I_b$  is S and  $I_c$  is M then SC is D

Rule 8: If  $I_a$  is S and  $I_b$  is M and  $I_c$  is M then SC is D

Rule 9: If  $I_a$  is M and  $I_b$  is S and  $I_c$  is M then SC is D

Rule 10: If  $I_a$  is M and  $I_b$  is M and  $I_c$  is M then SC is G

Rule 11: If  $I_a$  is S and  $I_b$  is S and  $I_c$  is S then SC is G

Rule 12: If  $I_a$  is S and  $I_b$  is M and  $I_c$  is S then SC is D

Rule 13: If  $I_a$  is M and  $I_b$  is S and  $I_c$  is S then SC is D

Rule 14: If  $I_a$  is M and  $I_b$  is M and  $I_c$  is S then SC is D

Rule 15: If  $v$  is L then SC is D

In the final stage, the fuzzy actions are reconverted in crisp ones by using the center of area method. According to this method, each affected output membership is cut at the level indicated by the previous max-rule, then the gravity center of the possible distribution is computed and becomes the numerical output value [11].

#### 4. Simulation results

Two different motors, a 15 kW delta connected and 35 kW star connected machines were studied. The parameters are given in Appendix 1. The SIMULINK model of the fault detection system is shown in Appendix 2. The model is implemented online with the data.

The fault detection method was first tested online with data from FEM motor simulation program. As the FEM program takes into account the non-linearity and inhomogeneous characteristics of the materials, it is a good approximation to the actual motor. The sampling frequency in the FEM simulation program was 40 kHz and the number of samples simulated was 10 000. The simulation model was able to identify the fault with excellent accuracy as can be seen in Table 1.

During every data set, the fuzzy filter executes 25 validations of the stator condition. The duration time of every data set was 0.25 seconds. The test was carried out with the motor in three different load conditions, no-load, half-load and full-load. In order to prove the performance of the SIMULINK model under noise condition, a source of noise was added to each phase. Table 2 shows the results under noisy condition.

Table 1. Percentage of correct detection from simulated data

Motor condition	Data sets	15 kW	35 kW
Healthy motor	3	100%	100%
Open phase	9	100%	100%
Inter-turn short	3	100%	100%
Short circuited coil	3	100%	100%

Table 2. Percentage of correct detection under noise condition.

Motor condition	Data sets	Accuracy
Healthy motor	3	96%
Open phase	9	100%
Inter-turn short	3	92%
Coil short circuited	3	100%

## 6. Measurement results

A measuring setup was arranged to get data from a working motor. It is shown in Appendix 3. The data was recorded with a transient recorder. The sampling frequency used was 40 kHz. The motor was tested at four different frequencies. The tests were carried out with the motor in healthy condition and with a real inter-turn short circuit.

The real short circuit was done between two adjacent turns. The insulation of winding wires were scratched and two wires were soldered to them. These were long enough to be closed from outside the motor through a switch. The short circuit was made active during a short time, just enough to take the 0,75 seconds of data. The fuzzy filter makes a validation at a frequency equal to the main frequency of the line current, ensuring the fastest response time. For example: at 100 Hz supply frequency the refresh time is 0,01 seconds, which means 75 validations by data set. The results are shown in Table 3, the faulty condition refers to the real inter-turn short circuit. Measurements at full load were not carried out because of some concern whether or not the motor could withstand the short circuit



conditions. Fig. 7 shows a test result when the motor was working in healthy situation, half load at 100 Hz. Fig. 8 shows the test result for the faulty situation (inter-turn short circuit) for the same load and supply conditions. This corresponds with the worst case scenario to be detected.

The motor used in the measurements was the same as used with the FEM motor simulation program (35 kW). Thus, the SIMULINK model was able to work properly without any changes when run with the simulated and measured data.

Table 3. Percentage of correct detection. Measured data with Inverter supply for the 35 kW motor.

Frequency [Hz]	Load	Detection accuracy [%]	
		Healthy	Faulty
25	No-load	94,7	100
	Half load	97,2	94,4
	Full load	96,3	--
50	No-load	94,7	100
	Half load	96	100
	Full load	97,3	--
75	No-load	100	100
	Half load	100	100
	Full load	100	--
100	No-load	100	100
	Half load	100	100
	Full load	100	--

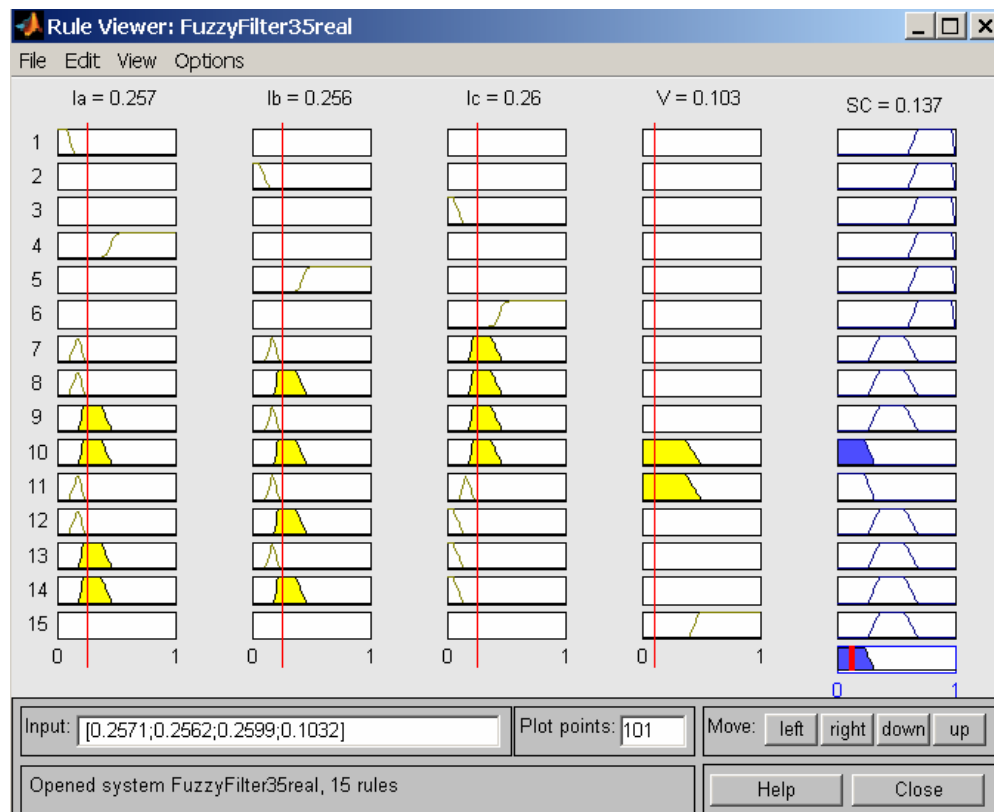


Fig. 7. Test result for the case of healthy motor, measured data, half load at 100 Hz.

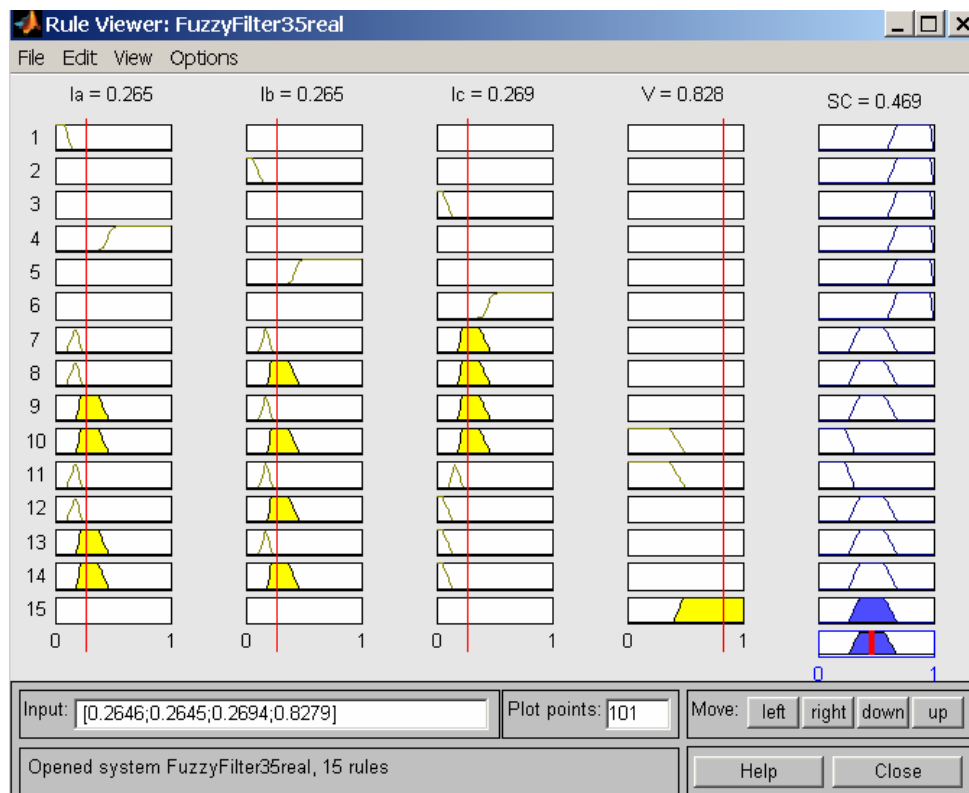


Fig. 8. Test result for the case of inter-turn short circuit, measured data, half load at 100 Hz.

## 7. Discussion

The main objective of this work was to establish an online system capable of detecting the stator condition of the cage induction motor by monitoring the motor currents. Throughout this work, fuzzy logic was used to analyse the data and make decisions. The method was able to detect the motor condition with high accuracy as can be seen in Table 3. Fuzzy logic is a good option because there is no general and accurate analytical model that describes successfully the induction motor under fault conditions.

The proposed motor protection system was implemented in the MATLAB environment. It was able to identify the stator condition with simulated and measured data. The model was able to identify the stator condition with good accuracy even under noisy condition. The performance of the model without noise was excellent. When noise was added to the simulation data, the performance in the accuracy detection rate decreased slightly.

Reference [4] considers the detection of an imitated inter-turn short circuit by adding resistance to one phase. This imitation is far from the real inter-turn short circuit, which is the worst case scenario to be detected. Our work has been tested with a real inter-turn short circuit and in variable speed drives online with the data. We obtained better accuracy than [4] e.g. for the case of an open phase (severe fault) we obtained 100% as can be seen in table 3 (even under noise condition), for the same fault reference [4] obtained 94% of accuracy. The better results are due to two facts. First, we improved the system sensitivity by adding a new rule. Second, our membership functions have better accuracy by the support given by FEM.

It is important to sign that in the case of stator faults in induction machines the most important fault to be detected is a primary inter-turn short circuit (the fault in an early stage, as it is detected in Fig. 8). Detecting at the early stage would avoid the total destruction of the stator winding.

We also tested the layout for both, the delta and star connections. For both cases, the detection accuracy were good. The model showed that comparing the rms values of the three terminal currents reveals changes in the internal electrical balance of the machine. It was sensitive enough to reveal only one shorted turn in the stator winding, where there were 11 turns per coil and 4 coils in series.

This inference system is universal for all kind of three phase induction motors. However, the membership functions must be defined from a FEM calculation. They depend of the motor size.

## **8. Conclusion**

This work shows the feasibility of spotting stator failures in an induction motor by monitoring the motor current amplitudes using fuzzy logic. Its forward application is in variable speed drives. This system could be implemented in the software of the inverter to monitor the stator condition online. It is able to work with motors connected in star and delta. In addition, it has two important abilities: to work in variable speed drives and a short delay time between fault and response. This work is also an example of fusion between soft computing (fuzzy logic) and hard computing techniques (FEM) in order to design a reliable system.

A possible drawback of the method is associated with the fact that a current unbalance originating from the supply source may be identified as a fault condition of the motor. But even this shortcoming can be overcome by monitoring the voltage and introducing new rules in the inference system.

## **9. Acknowledgements**

The authors thank TEKES (National Technology Agency of Finland) by the financial support to carry out this work.

## References

- [1] Arkkio A., “Analysis of induction motor based on numerical solution of the magnetic field and circuits equations”, Acta Polytechn. Scand. Electri. Eng. Series 1987, On. 59, pp. 97, available at <http://lib.hut.fi/Diss/list.html#1980>
- [2] Ballal M. S., Khan Z. J., Suryawanshi H. M., Sonolika R. L., “Adaptive Neural Fuzzy Inference System for the Detection of Inter-Turn Insulation and Bearing Wear Faults in Induction Motor”, IEEE Transaction on Industrial Electronics, Vol. 54, No. 1, February 2007.
- [3] Benbouzid M.E.H., “A Review of Induction Motors Signature Analysis as a Medium for Faults Detection, IEEE Transactions on Industrial Electronics”, Vol.47, No. 5, October 2000, 984-993.
- [4] Benbouzid M.E.H., “A Simple Fuzzy Logic Approach for induction Motor Stator Condition Monitoring”, Electric Machines and Drives Conference , *IEMDC 2001*, IEEE International 2001, 634 – 639.
- [5] Duraisamy V., Devarajan N., Somasundareswari D., Vasanth A. Antony Maria, Sivanadam S. N., “Neuro fuzzy scheme for fault detection in power transformer”, Applied Softcomputing, (7), 2007, 534-539.
- [6] Fillipetti F., Tassoni C. and Vas P., “Recent Developments Of Induction Motor Drives Fault Diagnosis Using AI Techniques”, IEEE Transactions on Industrial Electronics, Vol. 47, No. 5, October 2000, pp. 994-1000.
- [7] Gao X. Z., Ovaska S. J., “Soft computing methods in motor fault diagnosis”, Elsevier, Applied Soft Computing, Vol. 1, 2001, pp. 73-81.
- [8] Gao Xia-Zhi, “Soft Computing Methods for Control and Instrumentation”, *Thesis for the degree of Doctor of Science and Technology*, Helsinki University of Technology, Institute of Intelligent Power Electronics Publications, Espoo, May 1999.

- [9] Joksimovic G.M. and Penman J. , “The Detection of Inter-Turn Short Circuits in the Stator Winding of Operating Motors”, IEEE Transactions on Industry Applications, Vol.47, No. 5, October 2000, 1078-1084.
- [10] Lo C. H., Chan P. T., Wong Y. K., Rad A. B., Cheung K. L., “Fuzzy-genetic algorithm for automatic fault detection in HVAC systems”, Applied Softcomputing (7), 2007, 554-560.
- [11] Mendel J. M., “Fuzzy logic system for engineering: a tutorial” , Proceeding of the IEEE, Vol. 83, March 1995, 984-993.
- [12] Mishra M.K., Tarnekar S.G., Kothari D.P., Ghosh A., “Detection of Incipient Faults in Single Phase Induction Motors Using Fuzzy Logic”, *Power Quality*’98, 1998, pp. 117-121.
- [13] Pöyhönen S., Arkkio A, Jover P., Hyötyniemi H., “Coupling Pairwise Vector Machine for Fault Classification”, Elsevier, Control Engineering Practice, Vol. 13, Issue 6, June 2005, pp. 759-769.
- [14] Pöyhönen, S., Negrea, M., Jover, P., Arkkio, A., Hyötyniemi, H., “Numerical Magnetic Field Analysis and Signal Processing for Fault Diagnostics of Electrical Machines”, COMPEL, The Int. Journal for Computation and Mathematics in Electrical and Electronic Engineering, Vol. 22, 2004, No. 4, pp. 969-981, 2003.
- [15] Thonsom W.T. and Fenger M., “Current Signature Analysis to Detect Induction Motor Faults”, IEEE Transactions on Industry Applications, July/August 2001, 26-34.
- [16] Zadeh Lofti A., Fuzzy sets, Information and Control, Vol. 8, pp. 338-353, 1965, 853-872.

## Appendix 1. Motor parameters

### Motor 1

---

Star connection	
Power	35 kW
Rated current	64 A
Number of rotor bars	40
Number of poles pairs	2
Number of stator slots	48
Voltage	400 V
Rated frequency	100 Hz

---

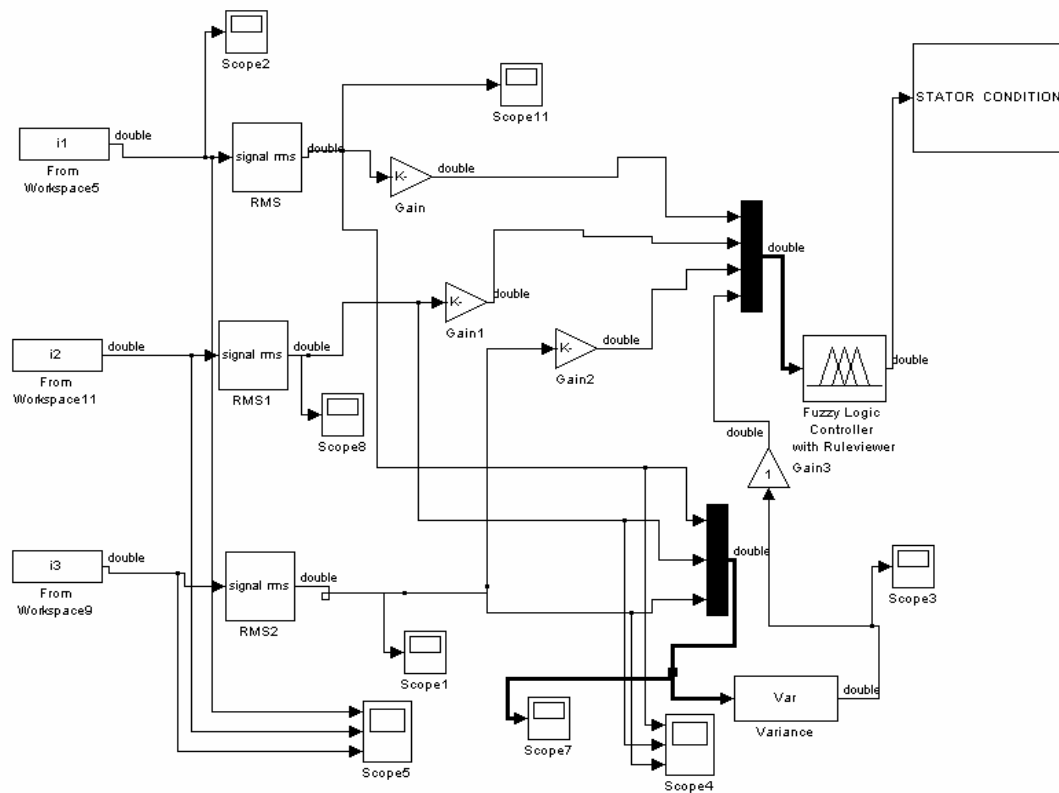
### Motor 2

---

Delta connection	
Power	15 kW
Rated Current	29 A
Number of rotor bars	34
Number of poles pairs	2
Number of stator slots	36
Rated frequency	50 Hz
Voltage	400V

---

## Appendix 2. Matlab/Simulink model.



## Appendix 3. Measurement setup

