Identification of Power Quality Disturbances in a Three- Phase Induction Motor using Fuzzy Logic

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ABSTRACT
This paper describes the application of fuzzy logic in diagnosing the power quality problems in a three-phase induction motor. A fuzzy logic fault detector (FLFD) was simulated to identify normal and abnormal operating conditions of the induction motor and to classify the operation based on current measurements at different time intervals. The FLFD is simulated using fuzzy logic toolbox in MATLAB. The performance of fuzzy logic fault detector has been analyzed through simulation studies with different inference techniques such as Mamdani type inference, Sugeno type inference and Adaptive Neuro –Fuzzy inference system. It was found that the Sugeno type of inference yielded results, which approximated the desired values. This analysis paves the way towards an ultimate objective of developing an intelligent power quality diagnosis tool capable of predicting the abnormal operation of any power system.

Keywords
Power Quality, Induction motor, Fuzzy logic and Inference techniques, ANFIS

1. INTRODUCTION
Power quality is a term used to describe the most important aspect of electric power supply. Power quality can be defined as any power problem manifested in voltage current or frequency that results in failure or missed operation of utility or the end user equipments [2]. Power quality refers to compatibility between the power source and the load, i.e., when a system operates as intended without disruption [1]. The study of power quality has helped in study of coordination between the power system behavior and equipment performance

The reasons for the increased emphasis on the overall power system efficiency is as follows:

The new generation load equipments like microprocessor based controls and power electronic devices are very sensitive to fluctuations in power.

Application of non-linear loads which results in the increase of harmonic levels in the power systems. This has given rise to concerns about the future impact on the system performance.
Increase in the customer awareness of PQ issues such as interruptions, sags, transients, harmonics, etc. Customers are also challenging the utilities to improve power quality.

1.1 Fuzzy Logic
In a broad sense fuzzy logic refers to a logical system that generalizes classical two- valued logic for reasoning under uncertainty. In particular ,it refers to all the theories and technologies that employ fuzzy sets, which are classes with un-sharp boundaries. Fuzzy logic is all about the relative importance of precision.

In fuzzy logic, the truth of any statement becomes a matter of degree. The tool that fuzzy reasoning gives is the ability to reply to a yes-no question with a not-quite- yes-or-no answer.

1.2 Induction Motor
Induction motor especially squirrel cage has a very important role in the industry. It is necessary to detect the faulty conditions, which might occur and take corrective action before they can result catastrophic failure. The manufacturers of motors are also keen to include diagnostic features in the form of software to decrease machine downtime and improve operational stability.

1.3 Diagnostic Techniques
Various diagnostic techniques are used to identify the starting problems that might occur in an induction motor. One such fault diagnostic technique discussed in this paper is application of intelligent system to power quality. This work uses Mamdani type inference system, Sugeno type inference systems and Adaptive Neuro –Fuzzy Inference system (ANFIS). Mamdani-type inference expects the output membership functions to be fuzzy sets. Sugeno-type systems can be used to model any inference system in which the output membership functions are

either linear or constant. Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or in combination with least squares method. This allows the fuzzy systems to learn from the data they are modeling [6, 7].

2. Problem Definition

The fault diagnosis system is designed to monitor the stator current of the induction motor at different time instances and to detect operational case. The fault signature is extracted on measuring the above parameters. The fuzzy model was simulated using commercially available software called MATLAB. The fault detection is carried out analyzing the fault signature through the fuzzy rules derived from expert's knowledge and experimental data.

This analysis is based on the following motor operational cases:

Full voltage on load starting (NORMAL)

The motor is started with full rated voltage applied to the motor terminals and with full load coupled with its shaft. With such a starting sequence, the current rises to between 6 and 8 p.u. and decays to 1 p.u. within 3 to 5sec.

Full load offload starting (NORMAL)

The motor is started under similar voltage conditions in case1, but the load is coupled to the shaft after the starting sequence. Under such conditions the motor current rises to between 4 and 8p.u. and then decays to 1p.u. (or less) within 3 sec.

Star/delta offload starting (NORMAL)

The motor is started using a star/delta switch that reduces the terminal voltage during starting by a factor of .57735. The motor load is coupled to the shaft after the starting is completed. The motor starting current is reduced by a factor of 1/3 from its value in case 2. The starting current is between 2 and 3.5p.u. and decays to 1 p.u within 3 to 5s.

Star/delta on load starting (NORMAL)

The motor is started using a star/delta switch with the load coupled to its shaft. The shaft current is between 2 and 3.5p.u. and decays to 1p.u between 10 to 15s.

Overload (NORMAL)

The motor is overloaded by up to 25% of its rated current. For most motors, the design will sustain this kind of overload for a certain period of time before tripping. The motor current will range between 1 and 1.25p.u.

Overload (ABNORMAL)

In this case, the motor is overloaded by between 25 and 100% of its rated current. The motor current will range between 1.25 and 2 p.u.

Single Phasing (ABNORMAL)

Supply outages are usually single –phase outages. When such a condition occurs, the voltage on one of the lines supplying the motor is lost. The 3 –phase motor now operates on a single –phase (2 lines) supply. This condition is reflected by an increase in current on the two healthy phases to be between 1.4 and 1.6p.u.

Short circuit up-stream (ABNORMAL)

If a short circuit occurs on the feeder supplying the motor at a point before the monitoring device, the motor turns into a generator and feeds its inertial current (full load current decaying towards zero). The current behavior picked up the monitor will be such that it goes from 1 to - 1p.u. and then drops to zero when the system protection trips the circuit breaker.

Short circuit Downstream (ABNORMAL)

If the short circuit occurs at the connection point between the feeder and the motor or on the motor windings, the monitored current will rise to between 10 and 15p.u. and then drop to zero upon the tripping of the circuit protection.

Locked rotor (ABNORMAL)

If for some mechanical reason, the motor, the motor rotor becomes obstructed and prevented from rotation, this is called locked –rotor condition. The motor current will rise from 1p.u. to between 6 to 8p.u until the motor overload protection system will trip the circuit breaker.

Unbalanced rotor (ABNORMAL)

The motor rotor becomes partially obstructed, or either the shaft or load becomes unsymmetrical around the shaft axis, the motor current displays intermittent excursion between .5 and 2 p.u.

Uncoupled motor load (ABNORMAL)

If the motor uncouples from the load, then the motor current will drop from its full –load value (about 1 p.u.) to a no load value between .1 and .3 p.u.

Under voltage (ABNORMAL)

If the supply voltage reduces below 95%, then the motor current will drastically increase to between 1.5 and 3p.u.

Under voltage (NORMAL)

If the supply voltage reduces to between 95% and 100%, a slight increase in the motor current will occur. The motor current increases to between 1 and 1.25p.u The experimental data for this paper was taken from [2]. Table 1 shows the experimental data in the form of current values in p.u. measured at time instances 1sec, 3sec, 5sec and 15sec. This table also shows the expected classification results.

3. SIMULATION

The fuzzy logic fault detector system was simulated using fuzzy logic toolbox in MATLAB. Seven different fuzzy model systems were simulated each differing in type of inference techniques used. This system is constructed with four inputs and one output. The values of current measured at time 1sec, 3sec, 5sec, and 15 sec are used as inputs and classification based on normal and abnormal operations is the output.System 1 is the first fuzzy system developed. This system classifies the motor operation as normal or abnormal depending on the current values at different instances of time. Three fuzzy models were simulated under system 1. System 1a is a Mamdani type of inference model with four inputs and one output as described above. The first three input variables are classified into six trapezoidal membership functions such as negative (NG), zero (Z), low (L), normal (N), high (H), and very high (VH) in its universe of discourse. The current range is taken as -.5 p.u to 8 p.u. The fourth input is classified into three membership functions such as very low, low and high and the range is taken from -1 to 11. The output variable is classified into two triangular membership functions, i.e., normal and abnormal on a range of 1 to 10. If the output is normal mode of operation then the result will be 1 and if the mode of operation is abnormal then the result will be 10. Sixteen fuzzy rules are obtained from experimental values and expert knowledge. The defuzzification was carried out using the centroid method.In system1b, Sugeno type of inference technique is used. The inputs and outputs was the same as that of system 1a. Gaussian membership functions are used for the inputs. The membership functions of the output are linear on a scale of 1 to 10. Nineteen rules are made based on expert knowledge.System 1c is computer generated Sugeno type fuzzy inference system- ANFIS. In order to validate the applicability of adaptive neuro –fuzzy techniques, adaptive neuro –fuzzy (ANF) procedures have been used to train system 1b using the given set of input/ output data pairs.

Table 1: Experimental data

S. No	Current at Time 1sec	Current at Time 3 sec	Current at Time 5sec	Current at Time 15 sec	rational case (refer above)	N=1 A=10
1	6.2	6.2	1	1	1	1
2	7	7	1	1	1	1
3	5	1	1	1	2	1
4	6.5	1	1	1	2	1
5	1.7	1.7	1	1	3	1
6	2.5	2.5	1	1	3	1
7	3.3	3.3	3.3	1	4	1
8	1	1.1	1.1	1.1	5	1
9	1	1.1	1.1	1.1	5	1
10	1	1.2	1.2	1.2	5	1
11	1	1.2	1.2	1.2	5	1
12	1	1.23	1.23	1.23	5	1
13	1	1.55	1.55	0	6	10
14	1	1.75	1.75	0	6	10
15	1	1.9	1.9	0	6	10
16	1	1.45	1.45	0	7	10
17	1	1.55	1.55	0	7	10
18	1	-1	0	0	8	10
19	1	15	0	0	9	10
20	1	7	7	0	10	10
21	1.6	1	1.6	1	11	10
22	2.9	1	2.9	1	11	10
23	1	0.125	0.125	0	12	10
24	1	1.55	1.55	0	13	10
25	1	2.5	2.5	0	13	10
26	1	1.15	1.15	1.55	14	1
27	1	1.22	1.22	1.22	14	1
28	1	1.4	1.4	0	7	10
29	1	1.5	1.5	0	7	10
30	1	1.5	1.5	0	13	10
31	1	1.5	1.5	0	13	10
32	1	2	2	0	6	10
33	1	2	2	0	13	10
34	1	1.18	1.18	1.18	5	1
35	1	1.2	1.2	1.2	13	1

Key : **N – Normal mode of operation A –Abnormal mode of operation**

The ANFIS training is performed with a new fresh set of input membership functions generated by the computer. The number of membership function for each input is similar to system 1b, but the membership functions are equally spaced, have equal widths, and identical edge slopes and overlap at cross over points

Another set of fuzzy system called System 2, which comprises of four fuzzy models are developed. All the fuzzy models in this system2 perform full motor operations diagnosis, which helps in classifying the faults into one of the fourteen faults, described in the previous section. Sugeno type of inference is used for diagnosis in this category. System 2 has four inputs as described in system 1.

System 2a has four inputs, which are exactly similar to those of system 1. It has 1 output and 16 rules. This output is comprised of 14 linear membership functions in its universe of discourse and represents one respective case of the motor conditions. System 2b is the computer trained (ANFIS) version of system 2a. The computer generated 648 rules. System 2c is similar to system 2a but the membership function of the output was chosen to be constant. System 2d included a fifth input voltage. This was done to differentiate between cases 6, 7 and 13.

4. RESULTS AND DISCUSSIONS

The simulations were successfully carried out using MATLAB fuzzy toolbox. Table 2 and 3 show the deviation of the simulated results from that of the desired results in the form of percentage errors.From the above simulation resulted the following conclusions can be derived:The Mamdani model produced very undesirable results. The error produced by this method was the maximum as compared with the other models. This is due to reason that the output variable in Mamdani inference technique is also fuzzified. Hence, accurate results cannot be obtained.The Sugeno model with linear membership variables gave approximately accurate result. But in some cases the error was large. This model was computationally less complex. Sugeno inference technique uses the fact that the output variable is either constant or linear. When the constant membership function was used for the output variable, the simulated results was found to be almost similar to the desired results.Through adaptive learning System1c gives a better result than system 1b. But this system is complex and takes a longer time to generate the results.System 2a was quite successful in diagnosing the motor operations except that it could not distinguish between case 6, 7 and 13 and between cases 5, 14 since each set lies in the same current range.System 2c trained the system 2a FIS according to the training data. This system performed better than system 2a, but could not differentiate between cases 6,7, and 13.System 2d was successful in distinguishing cases 6, 7 from case13 and cases 5, 14. But could not differentiate between cases 6 and 7.

Table 2: Simulation results for system1

S. No	N= 1 A= 10	System 1a		System 1b		System 1c	
		O	**E(%)**	**O**	**E(%)**	**O**	**E(%)**
1	1	3.97	74.81	1.03	2.91	1	0
2	1	3.97	74.81	1.03	2.91	1	0
3	1	3.97	74.81	1.02	1.96	1	0
4	1	3.97	74.81	1.03	2.91	1	0
5	1	4.93	79.72	1.01	0.99	1	0
6	1	4.93	79.72	1.01	0.99	1	0
7	1	4.03	75.19	1.02	1.96	1	0
8	1	4.1	75.61	1.01	0.99	1	0
9	1	4.1	75.61	1.01	0.99	1	0
10	1	5.05	80.20	1.01	0.99	1	0
11	1	5.05	80.20	1.01	0.99	1	0
12	1	5.42	81.55	1.01	0.99	1	0
13	10	5.5	81.82	9.98	0.20	10	0
14	10	5.9	69.49	9.99	0.10	10	0
15	10	6.9	44.93	9.99	0.10	10	0
16	10	5.5	81.82	9.98	0.20	10	0
17	10	5.5	81.82	9.98	0.20	10	0
18	10	5.5	81.82	10	0.00	10	0
19	10	5.5	81.82	9.98	0.20	10	0
20	10	7.73	29.37	9.97	0.30	10	0
21	10	4.53	120.75	1.1	809.09	10	0
22	10	7.03	42.25	9.98	0.20	10	0
23	10	6.85	45.99	10	0.00	10	0
24	10	5.5	81.82	9.99	0.10	10	0
25	10	7.03	42.25	9.99	0.10	10	0
26	1	4.51	77.83	1.01	0.99	1	0
27	1	5.3	81.13	1.01	0.99	1	0
28	10	5.5	81.82	9.99	0.10	10	0
29	10	5.5	81.82	9.99	0.10	10	0
30	10	5.5	81.82	9.99	0.10	10	0
31	10	5.5	81.82	9.99	0.10	10	0
32	10	4.64	115.52	9.99	0.10	10	0
33	10	4.64	115.52	9.99	0.10	10	0
34	1	4.82	79.25	1.01	0.99	1	0
35	1	5.05	80.20	1.01	0.99	1	0
	Avg error		76.99		23.20		0.00

Key: O – observed value during simulation E(%) – percentage Error

Table 3: Simulation results for system2

Desired Classification	SYSTEM 2C		SYSTEM 2A		SYSTEM 2B		SYSTEM 2D	
	O	E (%)	O	E (%)	O	E %)	O	E (%)
1	1	0.00	1.05	4.76	1	0.00	1.04	3.85
1	1	0.00	1.06	5.66	1	0.00	1.04	3.85
2	2	0.00	2.03	1.48	2	0.00	2.03	1.48
2	2	0.00	2.03	1.48	2	0.00	2.03	1.48
3	3	0.00	8.83	66.02	3	0.00	4.03	25.56
3	3	0.00	4.03	25.56	3	0.00	4.03	25.56
4	4	0.00	3.04	31.58	4	0.00	3.04	31.58
5	5	0.00	9.52	47.48	5.23	4.40	5.06	1.19
5	5	0.00	9.52	47.48	5.23	4.40	5.06	1.19
5	5	0.00	9.52	47.48	8.16	38.73	5.18	3.47
5	5	0.00	9.52	47.48	8.16	38.73	5.18	3.47
5	5	0.00	9.52	47.48	8.13	38.50	5.27	5.12
6	6.5	7.69	13	53.85	8.6	30.23	6.89	12.92
6	6.5	7.69	13	53.85	6.42	6.54	7.02	14.53
6	6.5	7.69	13	53.85	5.86	2.39	7.02	14.53
7	6.78	3.24	13	46.15	7.89	11.28	6.73	4.01
7	6.78	3.24	13	46.15	8.6	18.60	6.89	1.60
8	8	0.00	8	0.00	8	0.00	8.01	0.12
9	9	0.00	9.03	0.33	9	0.00	9.03	0.33
10	10	0.00	10.1	0.99	10	0.00	10.1	0.99
11	11	0.00	9.54	15.30	11	0.00	11	0.00
11	11	0.00	11	0.00	11	0.00	11	0.00
12	12	0.00	12	0.00	12	0.00	12	0.00
13	13	0.00	13	0.00	8.6	51.16	13	0.00
13	13	0.00	13	0.00	13	0.00	13	0.00
14	14	0.00	9.52	47.06	10.9	28.44	14	0.00
14	14	0.00	9.52	47.06	7.94	76.32	14	0.00
7	6.78	3.24	13	46.15	6.68	4.79	6.41	9.20
7	6.78	3.24	13	46.15	8.5	17.65	6.91	1.30
13	13	0.00	13	0.00	8.5	52.94	13	0.00
13	13	0.00	13	0.00	8.5	52.94	13	0.00
6	6.5	7.69	13	53.85	9.52	36.97	7.02	14.53
13	13	0.00	13	0.00	9.52	36.55	13	0.00
12	12	0.00	12	0.00	12	0.00	12	0.00
5	5	0.00	9.52	47.48	7.52	33.51	5.14	2.72
13	13	0.00	13	0.00	5.52	135.5	13	0.00
Avg error		1.22		25.89		20.02		5.13

5. CONCLUSION

The performance of fuzzy logic fault detector has been analyzed through simulation studies with different inference techniques such as Mamdani type inference, Sugeno type inference and adaptive neuro –fuzzy inference system. It was found that the Sugeno type of inference yielded results, which approximated the desired values. This analysis paves the way towards an ultimate objective of developing an intelligent power quality diagnosis tool capable of predicting the abnormal operation of any power system.

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