Stator Turn-to-Turn Fault Estimation of Induction Motor by Using Probabilistic Neural Network

Hamed Babanezhad[1], Hamid Yaghobi[2] and Mostafa Hamidi[3]

***Abstract*— Induction machines are extensively used in industry due to the wide demand and diverse applications. Managing dealing with various faults, accurately detecting the fault and its severity as one of the biggest challenges will have a significant impact on the induction machine health and the quality of system operation. Ignoring the faults will cause irreparable damage to the electrical machine and then to the industrial complex. Knowing about exact fault conditions is the most basic issue in dealing with fault management. In this paper, turn to turn fault as one of the major problems of induction machines is discussed. For this purpose first, the fault is evaluated by negative sequences current, and second, a mechanism is used to distinguish between the source imbalance fault and the turn-to-turn fault. With the help of the information obtained from the faulty machine and two layers of the probabilistic neural network, the number of the turn-to-turn fault will be estimated. The simulation was performed under normal conditions as well as under fault conditions for a specified number of turn-to-turn faults. This method is tested for non-training data with different common ranges and a number of turn-to-turn faults. Neural network output results are compared with the simulation in Matlab, which shows the correct training and high accuracy of the proposed method to detect the number of stator faults.**

***Index Terms*— Short circuit fault, negative sequence current, probabilistic neural network, turn to turn estimation, inter-turn fault.**

I. INTRODUCTION

MOTORS play a vital role in the industry as one of the most widely used electric machines due to their simplicity, high strength, low cost, low maintenance, and many other reasons. With the advancement in fault detection technologies, the focus of modern industry on fault detection methods has increased and many studies have been done in this section [1-3]. Induction motors are subjected to various stresses depending on their application in the industry, which causes numerous faults in the machine. The most common fault in this motor includes Inter Turn Short Circuit (ITSC), coil-to-coil, and phase-to-phase fault [4-7]. In these faults, several rounds of coils of one phase are shortened with each other or adjacent phase, and as a result, a high circulating current is created, then a lot of heat is generated. Studies show that 30-40% of three-phase induction motors failure is related to the stator winding [8, 9]. Therefore, fault detection is essential so as not to disrupt the normal operation process and the machine to be placed in the maintenances process faster. For this purpose, shorted circuit winding in stator phases is evaluated.

In [10-12] different Fault Detection (FD) methods as well as the causes of the fault, and review of them was discussed. Sequence impedance matrices and negative sequence components have been used to investigate and detect faults in the stator of inductor motor, which is a sensor-less method [13, 14]. However, various solutions have been proposed to obtain impedance or current sequences, including the use of multiple reference frame theory, concordia patterns and the behavior of the effective current values [15, 16]. In [17] generalized regression neural network has been used to FD and locate stator turn-to-turn fault in induction machine.

Online FD using sweep frequency response analysis is provided in [18], which is mentioned as a low-cost test, frequency of 2 KHz to 1MHz with a short sampling period to detect the fault in the stator winding. Also in [19] variations of phase with respect to time which is known instantaneous frequency(with the help of empirical mode decomposition)have been used for intern-turn fault detection. A new method for detecting ITSC in the line start permanent magnet synchronous motors with the help of frequency analysis of acoustic signals resulting from asymmetrical faults has been proposed [20]. In [21] coordinate transformation of the current vector method has been used to inter-turn fault detection in a three-phase induction motor. The high-frequency parameters of voltage source inverter induction motor have been evaluated in [22] to extract the response of a faulty motor driven by an inverter.

Another powerful tool for investigating FD in induction machines is neural networks. Due to the variety and flexibility in the structure of this network, most of the faults in the machine can be model and investigated with this method [23, 24]. Albrecht used a multilayer perceptron neural network to detect the ITSC fault of the induction machine [25]. This network has been trained by the post-propagation method. The information required for training has been obtained by considering the induction motor in different short circuit conditions. In [26], four different structures of the neural model are used to detect and classify the fault with 13 parameters of the stator current.

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In [27], in addition the evaluation of the number of broken bars, the neuro-fuzzy networks of the ANFIS-Type method is used to diagnose the location and number of ITSC in an induction motor. In [28] neural network based on growing curvilinear component analysis as the self-organized and non-stationary method has provided online FD which utilizes the stator current spectrum of induction motor. Due to the ability to learn different types of functions, low-cost, and non-invasive capability the feed-forward neural network has been used in [29, 30]. One of the important parameters of the induction machine is the rotor resistance, which Wong used the neural network to estimate ITSC. So that according to its value and the amount of flux error difference between the neural network model and the motor model in order to correctly detect the real resistance, and the fault can be realized [31].

The stator currents and voltages are used as fault indicators to detecting ITSC faults under different loading conditions. In [32] other non-invasive online methods based on a two-dimensional six-stage convolutional neural network with the help of steady-state current regardless of the load are used to detect stator intern-turn fault. Marbet used a multi-layer feed-forward perceptron neural network to detect and locate the internal short circuit fault of the induction machine [33]. This network has been trained by the post-propagation method and the information required for its training has been obtained by placing the induction motor in different short circuit conditions. Different neural model structures have been used to detect and classify faults with stator parameters [34]. The advantage of this method is that there is no need to use complex mathematical calculations to quickly access fault data. In [35] a comparison between perceptron neural networks and radial basis function networks has been performed to identify ITSC. The neural network has also been used to detect and monitor faults such as voltage imbalance, overload, and overvoltage. Usually, the input of such a network is the effective current, voltage and speed of the motor and the quality of the outputs depends on the number of faults that are checked [36].

In this paper, the short-circuit fault and its effects on the induction machine are investigated, and the number of turn-to-turn short-circuited in one of the stator windings is estimated using two layers probabilistic neural network (PNN). The proposed method is tested for non-training data with different common ranges. The information acquired from the neural network is compared with the output of the simulation, the number of ITSC for the induction machine is obtained with high accuracy and finally, the results will be used to manage the engine operation process. The contribution of the paper include:

- The negative sequence current analysis is performed as the main parameter of FD with the help of asymmetric components.
- Use a mechanism to differentiate fault current analysis due to short circuit and source imbalance considering PNN.
- Perform training with high accuracy and less time in the presence of two layers of hidden and external neurons considering non-training data with different common ranges.

II. INDUCTION MOTOR MODELLING

To investigate the behavior of the motor under normal conditions and in the event of a fault, we will need a model to consider the equations of the rotor and stator winding. Because the stator winding has a different turn but its distribution is uniform, Magnetic saturation has also been omitted (Eq. 1-3).

$$V^s_{abc} = r^s_{abc} i^s_{abc} + p\lambda^s_{abc} \tag{1}$$

$$r^r_{abc} i^r_{abc} + p\lambda^r_{abc} = 0 \tag{2}$$

$$p = \frac{d}{dt} \tag{3}$$

The equations will be transferred to the dqo static reference frame by applying a transfer matrix (Eq. 4-6).

$$V^s_{qdo} = r^s_{qdo} i^s_{qdo} + p\lambda^s_{qdo} \tag{4}$$

$$r^r_{qdo} i^r_{qdo} + p\lambda^r_{qdo} = 0 \tag{5}$$

$$r^r_{qdo} i^r_{qdo} - \omega_r \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \lambda^r_{qdo} + \rho\lambda^r_{qdo} = 0 \tag{6}$$

The coupling flux of the stator and rotor windings in the new coordinates in terms of current and inductance will be shown in Eq .7.

$$\begin{bmatrix} \lambda^s_{qdo} \\ \lambda^r_{qdo} \end{bmatrix} = \begin{bmatrix} \lambda^{ss}_{qdo} & \lambda^{sr}_{qdo} \\ \lambda^{rs}_{qdo} & \lambda^{rr}_{qdo} \end{bmatrix} \begin{bmatrix} i^s_{qdo} \\ i^r_{qdo} \end{bmatrix} \tag{7}$$

λ^s_d ,λ^r_d are Stator and rotor coupling flux on axis d.
λ^s_q,λ^r_q are stator and rotor coupling flux on axis q.
v^s_q,v^s_d are stator voltage along the q and d axes.

Considering equation (7) and inverting it, the stator and rotor currents can be obtained as Eq .8.

$$\begin{aligned} \lambda^s_q &= \int (v^s_q - r^s_{11} i^s_q - r^s_{12} i^s_d)dt \\ \lambda^s_d &= \int (v^s_d - r^s_{21} i^s_q - r^s_{22} i^s_d)dt \\ \lambda^r_q &= \int (\omega^s_r \lambda^r_d - r^r_r i^r_q)dt \\ \lambda^r_d &= -\int (\omega^s_r \lambda^r_q - r^r_r i^r_d)dt \end{aligned} \tag{8}$$

If T_{mech} as the external mechanical torque is applied in the direction of the rotor speed, T_{damp} as the adjusted torque is considered in the opposite direction to the rotor speed and “j” as the inertia of the motor, The electromagnetic torque on the machines’ shaft will be equal to Eq .9.

$$T_{em} = \frac{3}{2}\frac{P}{2}\int (\lambda^s_d i^s_q - \lambda^s_q i^s_d)dt \tag{9}$$

With the above torques, the machine speed $\omega_r$can also be achieved. (Eq .10)

$$\omega_r(t) = \frac{P}{2J}\int \left(T_{em} + T_{mech} - T_{damp}\right)dt \tag{10}$$

With the help of the above equations, a simulated model of a three-phase induction motor has been used. Simulation results have been performed for a 2 Hp induction motor. Figs.1 and 2

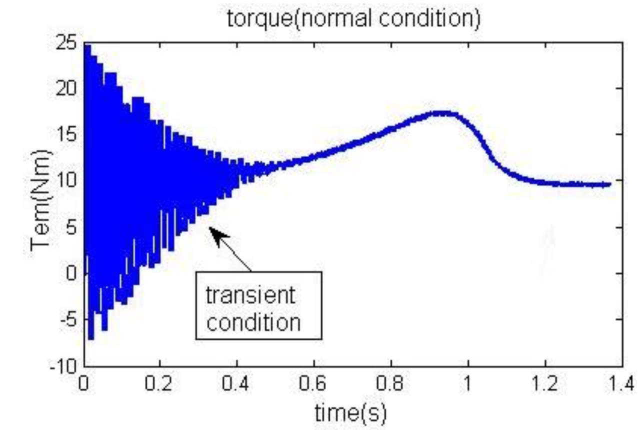


Fig. 1. Torque curve under normal conditions

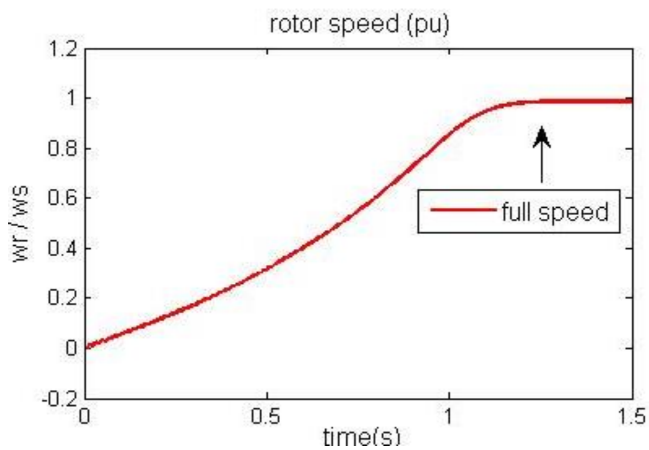


Fig. 2. Speed curve under normal conditions

show the torque and speed changes of the motor in the event of a fault from no load to full load respectively. Initially, the motor currents are asymmetric due to the transient state caused by the start-up, this negative sequence current remains until the motor is stable.

Figs.3 and 4 show the same process by applying 4 short-circuit turns to one of the coils. As can be seen in the torque curve due to the presence of a turn-to-turn fault, more distortion in the transient state has been shown. This indicates the asymmetry of the current in the phases. Significant changes are also seen in these conditions for the speed curve according to Fig 4.

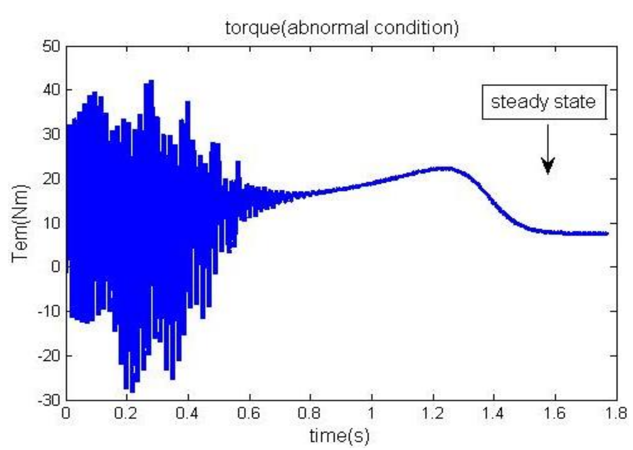


Fig. 3. Torque curve under 4 shorted circuit turn

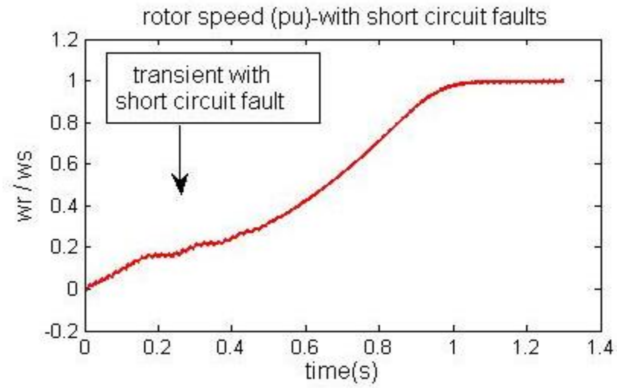


Fig. 4. Speed curve under 4 shorted circuit turn

III. NEGATIVE SEQUENCE CURRENT ANALYSIS

With the occurrence of a fault, the balance of currents is lost. By evaluating the three-phase currents resulting from the simulation, it is not possible to show the real situation in the motor well, but using sequence components will be a better way to express the conditions. Therefore, by using the matrix of symmetric components as Eq.11, the negative sequence current will be obtained, which can be used to determine changes in the number of turn-to-turn faults in the motor to train the neural network. Negative sequence currents for fault with 1, 5, and 10 short-circuits turn in stator phase "A" are shown in Fig .5 At the start of the fault, a large negative sequence current is generated, and after a fraction of a second, this current will reach its steady state. It is observed that with increasing the number of shorted connection turn, this current will increase.

$$\begin{bmatrix} I_0 \\ I_p \\ I_n \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix}\begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \tag{11}$$

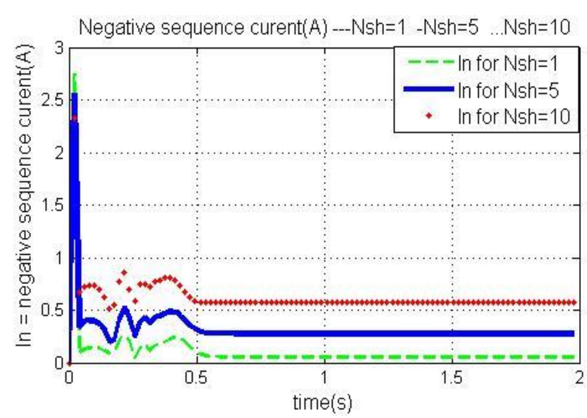
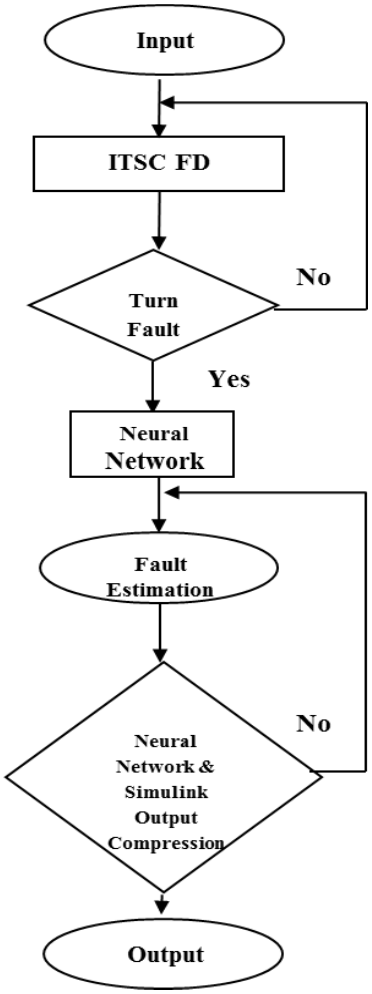


Fig. 5. Negative sequence current changes

IV. FAULT DETECTION METHOD

As mentioned in section III, negative sequence current is a proper parameter to investigate ITSC. According to Fig. 6a the process of the proposed method is done by estimating the error and the presence of ITSC with the help of a PNN to estimate the number of shorted circuit turns in one of the stator windings. Then the data obtained from the neural network is compared with the output of the simulation, and finally, the number of



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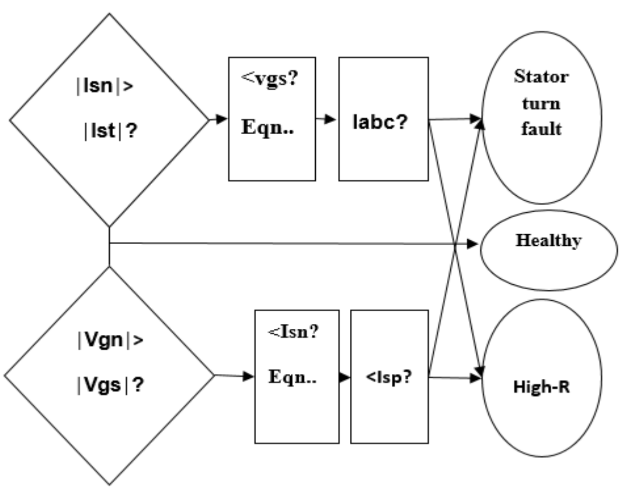

b

Fig. 6. Flowchart for propose method (a) FD process (b) turn estimation Error block diagram

turn-to-turn faults for the induction machine is obtained with high accuracy.

Any change in the negative sequence current does not indicate a short circuit fault, but the change may be due to an imbalance in the input sources because an imbalance between the input sources will increase the negative sequence current too. Therefore, Fig. 6(b) is used to show how a distinction is made between short circuit fault and input source imbalance fault. In this figure Ist, vgs and Isn,Vgn are the value for imbalance and ITSC condition respectively. By performing the above step, if the fault in the machine is due to ITSC, we use the values obtained from the negative sequence current as of the PNN input. The probabilistic neural network is one of the radial basic networks, which has more neural cells, but its advantage is less design time and increase accuracy in case of increasing the number of training data. These networks consist of two layers, the hidden layer has 2 neurons and the outer layer has 1 neurons. A comparison will be made between the output of the neural network and the simulation information so that the received information is more accurate. Finally, the number of short circuit turn is provided to the user to decide whether to continue operating the machine or not.

V. RESULT

The probabilistic neural network is implemented for an induction machine 2hp-4p, 3ph [37]. In the case of an ITSC fault in one of the stator winding phases, the number of short-circuit turns in the same phase is estimated. Figs.7 and 8 show the output of the neural network as well as the results obtained from the simulation, which shows a very close estimate and proper operation of the implemented neural network base on less and more training data respectively. At less number of short circuit turn, the sequence current is very small, but its increase will indicate the formation of more short-circuit turns, so that the negative sequence current of 0.5 amps indicates 10 short-circuit turns in the winding.

Table I shows the results obtained from the simulation for currents of 0.03 to 500(ma) and the number of short-circuit turn (0 to 10). In this table, Nsh is the number of turns short-circuited in phase A, Ip (A) and In (A) are positive and negative sequence currents, respectively, and these values are taken from their steady-state condition. As can be seen from data, an increase in the number of short-circuited turns in phase A will increase the current in that phase, and the other phases have very small current changes.

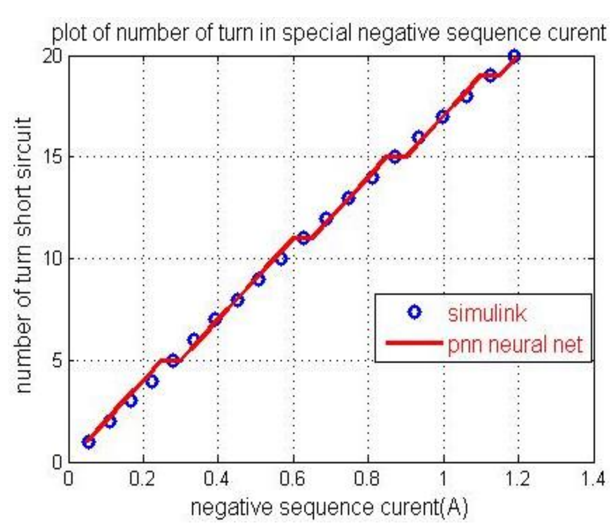

Fig.7. Estimate the number of turn-to-turn fault with less non-training data

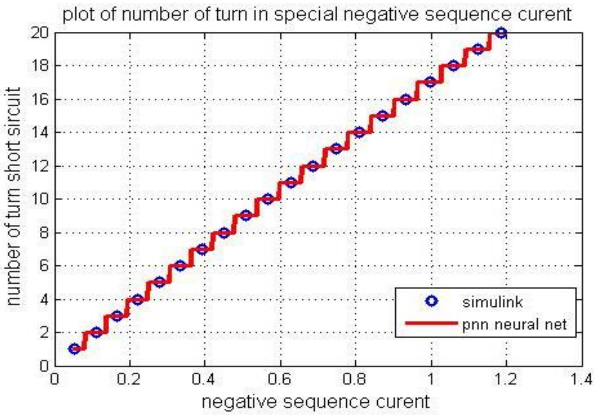

Fig.8. Estimate the number of turn-to-turn fault with more non-training data

The data obtained from the neural network are also shown in Table II, with the difference that for the sequence current between 0.05 to 1.2 the estimated number of short-circuited turns is between 1-20. The results show that the training and management of the neural network have been done in such a way that it has a proper response to non-training data and the created network has a high generality. This is shown in Fig. 8 while more non-training data is provided to the neural network. So that for data with a less common range with very high accuracy of 90% and for data with a more common range the estimated accuracy will reach 88%.

TABLE I
Simulation Results In Different Number Of Shorted Circuit Turn

Nsh	In(A)	Ip(A)	IA(A)	IB(A)	IC(A)
0	3e-4	2.725	2.725	2.725	2.72
2	0.11	2.722	2.83	2.69	2.64
4	0.23	2.719	2.92	2.667	2.58
5	0.28	2.717	3.01	2.64	2.54
6	0.32	2.711	3.05	2.625	2.51
8	0.45	2.720	3.166	2.61	2.55
10	0.56	2.727	3.29	2.58	2.41

TABLE II
PNN Results In Different Number Of Shorted Circuit Turn

In(A)	Nsh	In(A)	Nsh	In(A)	Nsh
0.05	1	0.45	8	0.85	15
0.1	2	0.5	9	0.9	15
0.15	3	0.55	10	0.95	16
0.2	4	0.6	11	1	17
0.25	5	0.65	11	1.05	18
0.3	5	0.7	12	1.1	19
0.35	6	0.75	13	1.15	19
0.4	7	0.8	14	1.2	20

VI. Conclusion

In the proposed method, two layers probabilistic neural network and negative sequence current has been used to estimate the number of turn-to-turn fault in a stator phase. A mechanism has been presented to differentiate fault current analysis due to short circuit and source imbalance considering PNN. Results were tested for non-training data with different common ranges. This method shows high accuracy (above 90%) of the neural network output in estimating the ITSC, which confirms the accuracy of this method. The information obtained from this method can be classified for management levels so that the correct decision is made regarding the continuation of the machine.

References

[1] L. Hou and N. W. Bergmann, "Novel Industrial Wireless Sensor Networks for Machine Condition Monitoring and Fault Diagnosis," *IEEE Transactions on Instrumentation and Measurement*, vol. 61, no. 10, pp. 2787-2798, 2012.

[2] M. Seera, C. P. Lim, D. Ishak, and H. Singh, "Fault Detection and Diagnosis of Induction Motors Using Motor Current Signature Analysis and a Hybrid FMM–CART Model," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 23, no. 1, pp. 97-108, 2012.

[3] G. H. Bazan, P. R. Scalassara, W. Endo, A. Goedtel, R. H. C. Palácios, and W. F. Godoy, "Stator Short-Circuit Diagnosis in Induction Motors Using Mutual Information and Intelligent Systems," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 4, pp. 3237-3246, 2019.

[4] "Report of Large Motor Reliability Survey of Industrial and Commercial Installations, Part I," *IEEE Transactions on Industry Applications*, vol. IA-21, no. 4, pp. 853-864, 1985.

[5] P. F. Albrecht, J. C. Appiarius, R. M. McCoy, E. L. Owen, and D. K. Sharma, "Assessment of the Reliability of Motors in Utility Applications - Updated," *IEEE Transactions on Energy Conversion*, vol. EC-1, no. 1, pp. 39-46, 1986.

[6] A. H. Bonnett and G. C. Soukup, "Analysis of rotor failures in squirrel-cage induction motors," *IEEE Transactions on Industry Applications*, vol. 24, no. 6, pp. 1124-1130, 1988.

[7] O. V. Thorsen and M. Dalva, "Failure identification and analysis for high voltage induction motors in petrochemical industry," *in Conference Record of 1998 IEEE Industry Applications Conference. Thirty-Third IAS Annual Meeting (Cat. No.98CH36242)*, vol. 1, pp. 291-298 , 1998.

[8] M. A. Awadallah and M. M. Morcos, "Application of AI tools in fault diagnosis of electrical machines and drives-an overview," *IEEE Transactions on Energy Conversion*, vol. 18, no. 2, pp. 245-251, 2003.

[9] M. Negrea, P. Jover, and A. Arkkio, "Electromagnetic flux-based condition monitoring for electrical machines," *in 2005 5th IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives*, pp. 1-6,2005.

[10] R. M. Tallam et al., "A Survey of Methods for Detection of Stator-Related Faults in Induction Machines," *IEEE Transactions on Industry Applications*, vol. 43, no. 4, pp. 920-933, 2007.

[11] H. Yaghobi, K.Ansari and H.Rajabi mashhadi, "Analysis of Magnetic Flux Linkage Distribution in Salient-Pole Synchronous Generator with Different Kinds of Inter-Turn Winding Faults," *Iranian Journal of Electrical & Electronic Engineering*, Vol., No. 4, pp.260-272, Dec. 2011.

[12] H. Yaghobi, H.R.Mashhadi and K.Ansari,"Artificial neural network approach for locating internal faults in salient-pole synchronous generato "*ELSEVIER, Expert Systems with Applications*, Vol. 38, pp.13328–13341, 2011.

[13] Y. ChiaChou, R. J. Povinelli, B. Mirafzal, and N. A. O. Demerdash, "Diagnosis of stator winding inter-turn shorts in induction motors fed by PWM-inverter drive systems using a time-series data mining technique," *in 2004 International Conference on Power System Technology, PowerCon*, Vol 1, pp. 891-896,2004.

[14] W. Long, L. Bin, H. Xianghui, T. G. Habetler, and R. G. Harley, "Improved online condition monitoring using static eccentricity-induced negative sequence current information in induction machines," *in 31st Annual Conference of IEEE Industrial Electronics Society*, vol IECON, p. 6 pp,2005.

[15] L. Tong and C. Huahua, “Detection of stator turn fault in induction motors using the extension of multiple reference frames theory,” *in 31st Annual Conference of IEEE Industrial Electronics Society*,vol IECON , p. 4 pp,2005.

[16] I.F. El-Arabawy, M.I. Masoud, A.E.Mokhtari, “Stator Inter-turn Faults Detection and Localization using stator currents and concordia pattern,”*Neural Network Applications," 5th International Conference-Workshop Compatibility in Power Electronics, CPE* 2007.

[17] H.Yaghobi,”Stator Turn-to-Turn Fault Detection of Induction Motor by Non-Invasive Method Using Generalized Regression Neural Network,” *Iranian Journal of Electrical & Electronic Engineering*, Vol. 13, No. 1, March 2017.

[18] G. Bucci, F. Ciancetta, and E. Fiorucci, “Apparatus for Online Continuous Diagnosis of Induction Motors Based on the SFRA Technique,” *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 7, pp. 4134-4144, 2020.

[19] R. Sadeghi, H. Samet, and T. Ghanbari, “Detection of Stator Short-Circuit Faults in Induction Motors Using the Concept of Instantaneous Frequency,” *IEEE Transactions on Industrial Informatics*, vol. 15, no. 8, pp. 4506-4515, 2019.

[20] L. S. Maraaba, S. Twaha, A. Memon, and Z. Al-Hamouz, “Recognition of Stator Winding Inter-Turn Fault in Interior-Mount LSPMSM Using Acoustic Signals,” *Symmetry*, vol. 12, no. 8, 2020.

[21] E. Solodkiy, D. Dadenkov, and S. Salnikov, “Detection Of Stator Inter-turn Short Circuit In Three-Phase Induction Motor Using Current Coordinate Transformation,” *in 2019 26th International Workshop on Electric Drives: Improvement in Efficiency of Electric Drives (IWED)*, , pp. 1-4,2019.

[22] A. V. B, M. F. Alam, G. Jagadanand, and A. A. K, “Stator Inter Turn fault diagnosis by High-Frequency Modeling of Inverter Fed Induction Motor,”*in 2020 IEEE International Conference on Power Electronics, Smart Grid and Renewable Energy* (PESGRE2020), pp. 1-5,2020.

[23] H. Chen, G. Han, W. Yan, S. Lu, and Z. Chen, “Modeling of a Switched Reluctance Motor Under Stator Winding Fault Condition,” *IEEE Transactions on Applied Superconductivity*, vol. 26, no. 4, pp. 1-6, 2016.

[24] N. R. Devi, D. V. S. S. S. Sarma, and P. V. R. Rao, “Diagnosis and classification of stator winding insulation faults on a three-phase induction motor using wavelet and MNN,” *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 23, no. 5, pp. 2543-2555, 2016.

[25] P. F. Albrecht, J. C. Appiarius, R. M. McCoy, E. L. Owen, and D. K. Sharma, “Assessment of the reliability of motors in utility applications - updated,” *IEEE Power Engineering Review*, vol. PER-6, no. 3, pp. 31-32, 1986.

[26] V. N. G. a. S. V, “Fault Diagnosis of Three Phase Induction Motor Using Neural Network Techniques,” *IEEE, Second International Conference on Emerging Trends in Engineering & Technology*, pp. 922-928 ,2009.

[27] L. Souad, B. Azzedine, C. B. D. Eddine, B. Boualem, M. Samir, and M. Youcef, “Induction machine rotor and stator faults detection by applying the DTW and N-F network,” *in 2018 IEEE International Conference on Industrial Technology (ICIT)*, pp. 431-436,2018

[28] R. R. Kumar et al, “Induction Machine Stator Fault Tracking Using the Growing Curvilinear Component Analysis,” *IEEE Access*, vol. 9, pp. 2201-2212, 2021.

[29] L. S. Maraaba, Z. M. Al-Hamouz, and M. A. Abido, “An Accurate Tool for Detecting Stator Inter-Turn Fault in LSPMSM,” *IEEE Access*, vol. 7, pp. 88622-88634, 2019.

[30] M. B. K. Bouzid and G. Champenois, “Neural network based method for the automatic detection of the stator faults of the induction motor,” *in 2013 International Conference on Electrical Engineering and Software Applications*, pp. 1-7,2013.

[31] G. Sheng-wei, W. You-Hua, C. Yan, and Z. Chuang, “Design and Simulation of Artificial-Neural-Network-Based Rotor Resistance Observer of Induction Motors,” *in Second International Conference on Intelligent Networks and Intelligent Systems*, pp. 593-596,2009.

[32] L. S. Maraaba, A. S. Milhem, I. A. Nemer, H. Al-Duwaish, and M. A. Abido, “Convolutional Neural Network-Based Inter-Turn Fault Diagnosis in LSPMSMs,” *IEEE Access*, vol. 8, pp. 81960-81970, 2020.

[33] M. B. K. Bouzid, G. Champenois, N. M. Bellaaj, L. Signac, and K. Jelassi, “An Effective Neural Approach for the Automatic Location of Stator Interturn Faults in Induction Motor,” *IEEE Transactions on Industrial Electronics*, vol. 55, no. 12, pp. 4277-4289, 2008.

[34] V. N. Ghate and S. V. Dudul, “Fault Diagnosis of Three Phase Induction Motor Using Neural Network Techniques,” *in Second International Conference on Emerging Trends in Engineering & Technology*, pp. 922-928,2009.

[35] R. N. Dash, B. Subudhi, and S. Das, “A comparison between MLP NN and RBF NN techniques for the detection of stator inter-turn fault of an induction motor,”in International Conference on Industrial Electronics, Control and Robotics, pp. 251-256,2010.

[36] E. M. T. Eldin, H. R. Emara, E. M. Aboul-Zahab, and S. S. Refaat, “Monitoring and Diagnosis of External Faults in Three Phase Induction Motors Using Artificial Neural Network,” in IEEE Power Engineering Society General Meeting, pp. 1-7,2007.

[37] M. Arkan, D. Kostic-Perovic, and P. J. Unsworth, “Modelling and simulation of induction motors with inter-turn faults for diagnostics,” *Electric Power Systems Research*, vol. 75, no. 1, pp. 57-66, 2005/07/01/ 2005.