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Review of Electrical Machine Diagnostic Methods Applicability in the Perspective of Industry 4.0

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***Abstract* – Digitalization of the industrial sector and Industry 4.0 have opened new horizons in many technical fields, including electrical machine diagnostics and operation, as well as machine condition monitoring. This paper addresses a selection of electrical machine diagnostics methods that are applicable for the use in the perspective of Industry 4.0, to be used in hand with cloud environments and the possibilities granted by the Internet of Things. The need for further research and development in the field is pointed out. Some potentially applicable future approaches are presented.**

***Keywords* – Fault diagnosis; Induction motors; Inverse problems.**

I. Introduction

It is claimed that with preventive maintenance programs total motor rewinds reduced from 85 % to 20 % of the total motor repairs [1]. Moreover, the proper, reliable, accurate and efficient fault diagnostic techniques are becoming more and more essential as the world is moving towards Industry 4.0 standard. Industry 4.0 is the next industrial revolution, which is taking place. This industrial revolution has been preceded by three other industrial revolutions in the history of mankind [2].

The first revolution was the era of mechanical engineering, it started in the middle of the 18th century and intensified throughout the 19th century. During the second revolution, electrification and scientific management, known as Taylorism, evolved. The invention and implementation of advanced electronics and information technology initiated the third revolution at around the 1970s, which is now called the Digital Revolution. The term "Industry 4.0" was proposed by the German government in 2011 at the Hannover Fair. The architecture first recommended by the Industry 4.0 Working Group is based on three components: The internet of things (IoT), cyber physical systems (CPS) and smart factories [2]. The detailed description of different industrial revolutions is presented in Fig. 1.

Industry 4.0 standards are promising due to their advantages, which include the increase in industrial efficiency because of the decrease in labor and increase in automation of the processes. It will accelerate industrial processes; deeper understanding of both product and process design will bring more innovation in the industry, and the costumers will get better services due to availability of deep information. After the initial investment, Industry 4.0 will lead to lowering the costs because of fewer human related manufacturing problems and lower operating costs. All these advantages will lead the manufacturer towards increasing revenues.

It goes without saying that with such massive change of the paradigm in the industrial sector, different technical fields also have to change and adapt in order to be applicable within the new concept of industry. The diagnostics and condition monitoring of electrical machines is one of these fields.

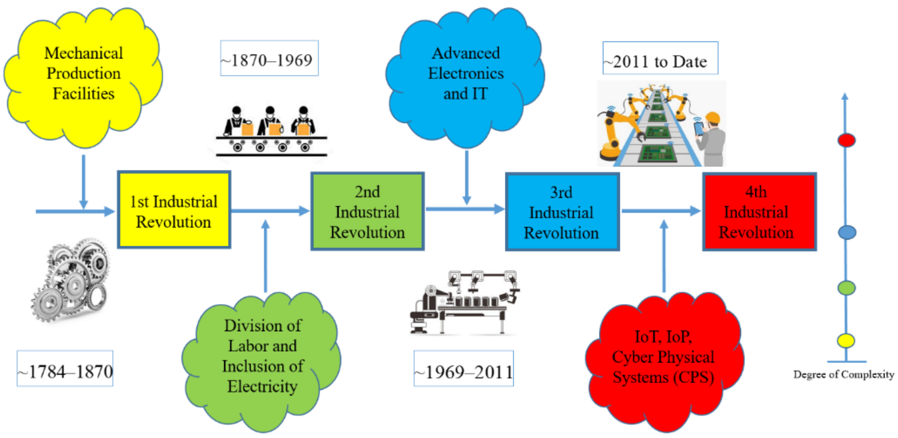

Fig. 1. Trends of industrial revolutions.

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II. Conventional Techniques

The key role played by the induction motors in the industry has made its condition monitoring very important. A variety of fault diagnostic techniques can be found in the relevant literature, such as the intelligent techniques, chemical analysis, acoustic measurements, infrared recognition, radio frequency emission, motor current signature analysis (MCSA), mechanical vibration signal analysis, etc. [3] Out of all main diagnostic areas, the MCSA is gaining more and more popularity, because most of its variants require only a clamp meter to detect the stator's current. In addition, almost all MCSA based diagnostic techniques are non-invasive in nature, making them suitable for online fault diagnostics without any disturbance in the process, also requiring less computational cost [4]. However, with the development of Industry 4.0 standards and cloud computing, the benefits of inverse problem theory, parameter estimation and artificial intelligent techniques can be exploited. In the following sections, an overview of some well-known conventional and advanced techniques is presented in the perspective of their pros and cons for fault diagnostics of induction motors.

A. Notch Filter

The notch filter is a band stop filter and can be used to attenuate fundamental component having high energy spectrum as compared to sideband harmonics due to the broken rotor bar. A general second order band pass filter (BPS) can be represented by the following transfer function [5],

$$BPF(s) = \frac{k\omega_0 s}{s^2 + k\omega_0 s + \omega_0^2} \tag{1}$$

and

$$NF(s) = 1 - BPF(s). \tag{2}$$

The authors of [5] proposed a modified adaptive notch filter, named the second order generalized integrator adoptive notch filter (SOGI-ANF), which is capable of rejecting DC offset from the quadrature signal. This DC offset can result in the errors in drives and phase lock loop used for synchronization purposes, etc. The proposed filter can be represented by the following equations:

$$\dot{x}_0 = k_0 \omega e, \tag{3}$$

$$\dot{x}_1 = -\omega x_2 + k\omega e, \tag{4}$$

$$\dot{x}_2 = \omega x_1, \tag{5}$$

$$\dot{\omega} = -\gamma e x_2, \tag{6}$$

where e is the error between actual and estimated signal, x_0 is the DC offset signal, k and γ are the positive valued constants controlling different performance parameters, such as accuracy and convergence speed. A complete analysis of the improved second order generalized integrator-based quadrature signal generator (SOGI-QSG) can be found in [6].

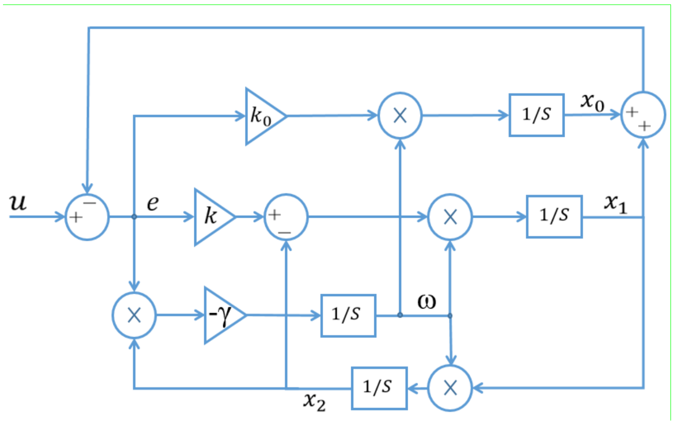

Fig. 2. Schematic diagram of the notch filter.

The authors of [7] used the second order generalized integrator-adaptive notch filter (SOGI-ANF) for envelope detection of stator currents both in the steady state and transient intervals. The author claimed the SOGI-ANF to be more accurate than Hilbert transform because of its adaptive nature. In [8] it is proposed that the sampling rate can be reduced by using digital notch filter with discrete time Fourier transform (DTFT) along with auto regressive spectrum analysis method.

B. ESPIRIT and MUSIC

Estimation of signal parameters via rotational invariant technique (ESPRIT) was first proposed by R. Roy *et al.* [9]–[12]. It is a technique to estimate the parameters of cisoids (complex sinusoids) observed in noise. As opposed to Pisarenko's algorithm, which was designed to deal with uniformly sampled data [13], ESPRIT is equally applicable to non-uniformly sampled data. Later on, the multiple signal classification (MUSIC) [14] algorithm generalized Pisarenko's method by relaxing the uniform sampling restriction.

The authors of [15] used ESPIRIT for the analysis of the modulus of the analytical signal (envelope signal). The authors claimed that the frequency domain and frequency-time domain analysis techniques, such as FFT, subdivision FFT, zoom FFT and discrete wavelet approach (DWT), are inefficient for fault diagnosis because of limitations like spectral leakage of fundamental component. Moreover, to get high resolution, measurement time needs to be increased, which means that the steady state condition required for FFT analysis will not exist in reality. This spectral leakage problem can be removed by using Hilbert transform as in [16], but the conflict between measurement time and resolution becomes a problem. For high resolution, a long measurement time (100 s in [16]) is required, which may lead to speed and slip variations. To eliminate the above-mentioned problems, [15] used Hilbert transform in conjunction with estimation of signal parameters via rotational invariance technique (ESPRIT) rather than FFT.

The main objective of many signal processing techniques is to find out the set of parameters upon which the signal depends, such as the maximum likelihood (ML) [17] proposed by Capon, and maximum entropy [18] proposed by Burg. Pisarenko extended these techniques to get further benefits by removing some limitations, such as sensitivity. Later, Schmidt developed a complete model to obtain a reasonable solution in the presence of noise. The resulting algorithm is known as MUSIC and is used in literature extensively for signal processing. More precisely, MUSIC is an extension of Pisarenko's algorithm and it can estimate frequency contents of a signal using the eigenspace method.

The authors in [19] used the MUSIC algorithm along with the discrete resampling method to compute the time frequency response of motor's stator current having one broken rotor bar (BRB) at different load conditions. They claimed that this approach can give a better resolution and is feasible to detect BRB at a very low slip, under transient conditions and in inverter fed machines.

The authors of [20] used high resolution spectral analysis techniques, also known as subspace techniques, i.e. MUSIC and ESPRIT, for detection of bearing and BRB related faults of the induction motor. The proposed method was accomplished in four steps: model order selection, frequency estimation, amplitude estimation and fault severity criterion. In [1], the authors proposed Spectral-MUSIC or Root-Music for frequency estimation of a faulty machine. In [21] spectral MUSIC and finite impulse response filter bank were used to separate the original current and vibration signals into different fault related bandwidths. This technique can be used for BRB and bearing fault detection of the induction motor. The author of [22] used the short time MUSIC algorithm to get high resolution time-frequency pseudo representation for BRB detection. A modified version of MUSIC algorithm, based on fault characteristic frequencies, has been proposed in [23], as well as amplitude estimator and fault indicator has been derived for fault severity measurement.

C. Speed Sensorless Methods (Magnetic Field Space Vector Orientation)

In the majority of MCSA based fault diagnosis schemes of induction motors, speed or slip estimation is a fundamental element of diagnostics, because the fault harmonic frequencies are directly related to the slip. The accurate measurement of slip or speed may produce errors whether it is sensors-based measurement or mathematical equations-based estimation.

The authors of [8] proposed a method to diagnose rotor broken bars based on rotor magnetic field space vector orientation. The authors used the stator current and voltage to compute and observe the rotor magnetic field orientation and showed that with BRB, the rotor's magnetic field orientation shifts at some angle from its actual position at any particular time. The magnitude of this angle depends on the number of broken rotor bars. Moreover, they proved that as time t progresses, the rotor's MMF will be continuously changing and its magnetic field orientation vector will start swinging around the actual magnetic axis of the healthy machine. The authors claimed that it is a good method to detect BRB faults even at very low slip conditions.

In [24], the authors have investigated the effect of load changes on pendulous oscillations of the rotor magnetic field orientation. In [25] slip independent BRB fault diagnostic technique using discrete wavelet approach was proposed and the authors claimed that the squared stator current magnitude and the squared stator current space vector magnitude are good indicators of fault in low frequency bandwidth. The authors of [26] proposed a novel differential magnetic field measurement (DMFM) method by placing two measurement coils in the stator of a motor and calculating the potential difference between both. In a healthy machine, the potential difference was found to be zero, because the same voltage is generated in both coils, but under faulty conditions, the induced voltages are different, which gives a value of some potential difference. Stator transient current was used in [27] and the authors studied its homogeneity as the classification index. The author used the field programmable gate array (FPGA) for online homogeneity estimation, because of its suitability for rapid prototyping, high performance and low cost as claimed.

D. Wavelet Approach

Fourier transform converts a signal form time domain to the frequency domain, or, in other words, it decomposes the signal into sine and cosine functions having different frequencies and extending till infinity. This leads to a problem of resolution just like Heisenberg's uncertainty principle, that is, when one tries to be sure about time, s/he will increase uncertainty in the frequency and vice versa. Unlike the Fourier transform, wavelet transform decomposes a signal into wavelets of the same shape but different in scale being added together and gives the time frequency analysis of the signal. The wavelets are short waves, which quickly die after appearance unlike sine and cosines of the Fourier transform. There are many types of wavelets used for the signal decomposition but most common are Haar, Shannon, Gaussian, Biothogonal and Mexican Hat, etc. Due to the problems of poor resolution and spectral leakage in the Fourier transform, wavelet approach is used extensively in literature for fault diagnostics of the induction motors. A continuous wavelet transform can be represented by the following formula;

$$x_{\mathrm{w}}(\alpha, \beta) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \varphi\left(\frac{t-b}{a}\right) \mathrm{d}t, \tag{7}$$

where b is the shift of the mother wavelet in time, a is the scaling factor, $\frac{1}{\sqrt{a}}$ ensures energy normalization and $\varphi(t)$ is called the mother wavelet, its purpose is to generate daughter wavelets, which are simply translated and shifted versions of the mother wavelet.

Discrete wavelet transform can be represented as,

$$i[n] = A_k[n] + \sum_{j=1}^{k} D_j[n] = \sum_{i=1}^{N/2k} a_i^k\, \varphi_i^k[n] + \sum_{j=1}^{k} \sum_{i=1}^{N/2j} d_i^j\, \psi_i^j[n], \tag{8}$$

where φ^k and ψ^k are the scaling factor and the mother wavelet at level k and j, respectively.

Paper [28] proposed a method to detect BRB by doing transient analysis of the motor startup currents using the wavelet approach. In [29], BRB diagnostics using wavelet under varying load conditions is proposed in a specific frequency band. The authors of [30] applied the discrete wavelet transform on instantaneous reactive power of BRB fault baring induction motor, operating under the time varying load conditions. In [31], stationary wavelet transform (SWT) was used and the authors claimed that the drawback of the invariant translation as mentioned in [32] can be avoided using SWT, rather than the discrete wavelet transform (DWT). The authors further used three modular neural networks (MNN) for fault classifications. The first MNN is used to detect the supply unbalances, sudden load changes, under voltage and stator phase faults, etc. The second one is used to identify the stator winding phase faults and the third one is used to classify stator inter-turn faults.

In [33], a 2-D wavelet transformation based on Shannon mother wavelet is used and it is claimed that this approach is more efficient for analysis of non-stationary and non-deterministic vibration signals. The created 2-D gray level images are used to generate global neighborhood structure maps to extract global image features. The authors compared the proposed approach with five conventional algorithms, proposed by [34]–[38], and proved that the proposed technique is better in terms of accuracy. The authors claimed that the proposed technique is equally accurate in noiseless and noisy environment.

The authors in [39] proposed a model based fault diagnostic system, in which the measured stator current is compared with the estimated current using actual speed and voltage. The model uses recurrent dynamic neural networks for transient response prediction. The estimated and actual current signals are then analyzed using the wavelet transform to segregate different harmonic frequencies. The accuracy of the model is very much dependent on the accuracy of the healthy machine model.

In [28], DWT was used for transient analysis of motor startup current to get the characteristic component. This continuous valued signal is then converted into discrete signal and an intelligent icon-like approach is applied to condense the relative information into a representation that can be easily manipulated by the nearest neighbor classifier. The tests are carried out for perfectly broken bar case only where there is no contribution of other faults or some external factors. [40] proposed a technique called the discrete harmonic wavelet transform (DHWT) to perform analysis of stator current in the transient regime with the cost of a single FFT. The author claimed that this technique is capable to eliminate the inherent drawbacks of DWT, such as dependency of sampling rate and frequency bands, spectral leakage due to non-ideal nature of filters, and computation cost.

III. Advanced Techniques

As the computational power of computers is increasing day by day, the researchers are focusing on the implementation of advanced fault diagnostic techniques. These techniques may contain some artificial intelligence-based algorithms, such as neural networks [41], [42] and Fuzzy Logic [43], etc., or some analytical algorithms, such as the finite element analysis [44]–[47] and the inverse problem theory [48]. Unlike conventional forward model-based fault diagnostic techniques, these advances algorithms can lead to more precise and accurate results, but at the same time they require more sophisticated hardware for implementation.

The authors of [46] used the time-stepping coupled finite element state space (TSCFF-SS) model for predictive non-invasive BRB fault diagnosis of the induction motor. The authors used the model to predict characteristic frequency component, which can be used to diagnose rotor bar and connector breakages. [44] used TSCFE-SS model and time series data mining technique for detection and categorization of dynamic/static eccentricities and bar/end-ring connector breakages in squirrel-cage induction motors. In [49], the author used a commercial finite element package to simulate the BRB faults. The simulation results were then compared with the experimental results to validate the model. In [50], the author used time-stepping coupled finite-element approach for BRB fault diagnostics. [51] presented a study on the feature signatures for the induction motor internal faults by utilizing coupled circuit-FEM and DWT. The motor behavior was investigated under both sinusoidal and non-sinusoidal voltage supplies.

Artificial neural networks (ANN) are computing systems mimicking the brain to analyze and learn a specific task without *a priori* knowledge and task specific programming. In the field of machine fault diagnostics, the researchers are trying to implement ANN as artificial intelligent technique to get better and more precise results. In [52] the authors use ANN to prove the possibility of fault detection through smartphone recorded sound files. [41] proposed ANN along with wavelet packet decomposition (WPD) for detection of BRB and claimed that this method is better in accuracy, exact measurement of slip is not required, and diagnostics can be performed with reduced load conditions.

In [42] the authors claimed that multiple discriminant analysis (MDA) and artificial neural networks (ANNs) provide appropriate environments to develop BRB fault-detection schemes because of their multi-input processing capabilities. The authors have proposed that multiple signature processing is more efficient than single signature processing. In [53], the authors proposed a novel approach to detect and classify the comprehensive fault conditions of induction motors using a hybrid fuzzy min–max (FMM) neural network and classification and regression tree (CART) and claimed that the hybrid model, known as FMM–CART, exploits the advantages of both FMM and CART for data classification and rule extraction problems. Successful implementation of these advanced schemes can offer a promising solution for fault diagnostics but at the cost of the required high computational power and storage memory.

IV. Inverse Problem Theory

In almost all fault diagnostics techniques mentioned above, the forward problem is used. In the forward problem theory, one usually moves from the input towards the output as shown in Fig. 3. In conventional techniques of fault diagnostics, the current signature of machine is compared with the current signature of the healthy machine using some signal processing techniques or algorithms, as discussed earlier. Since there are many types of faults and every fault can change the pattern of the current signature, the conventional techniques are not good enough to get to the root cause of the fault.

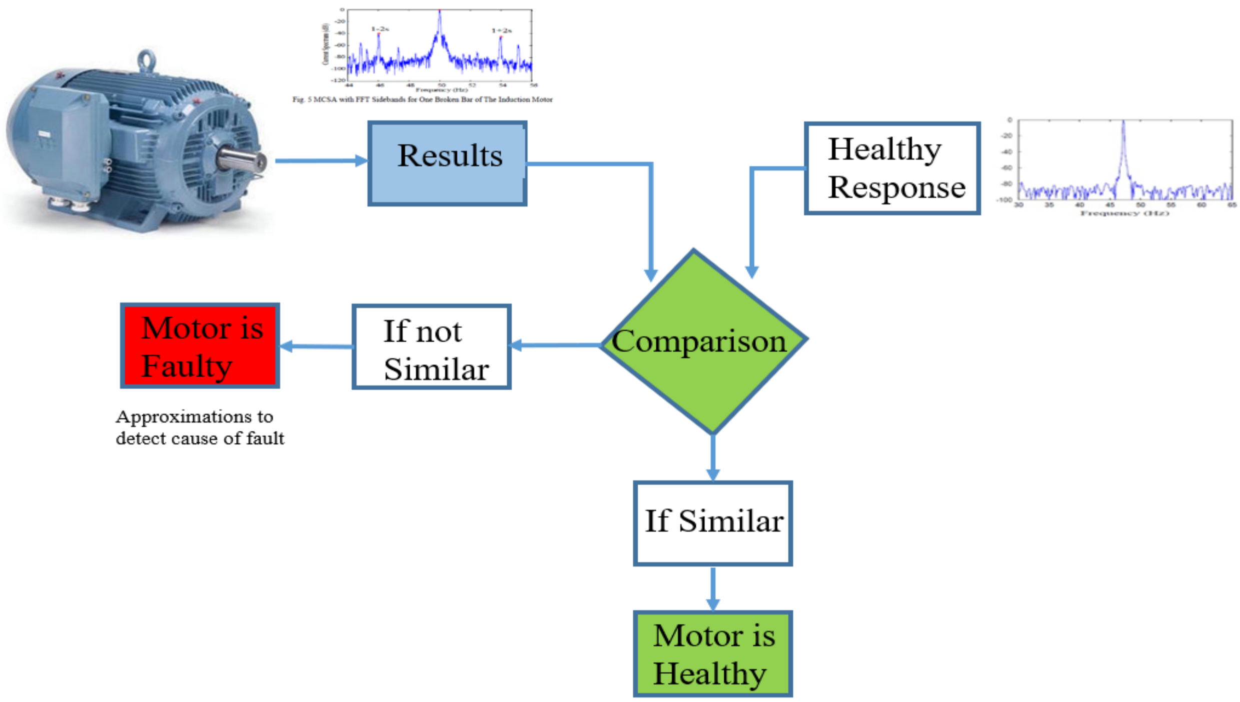

Fig. 3. Schematic diagram of the conventional forward model for fault diagnostics.

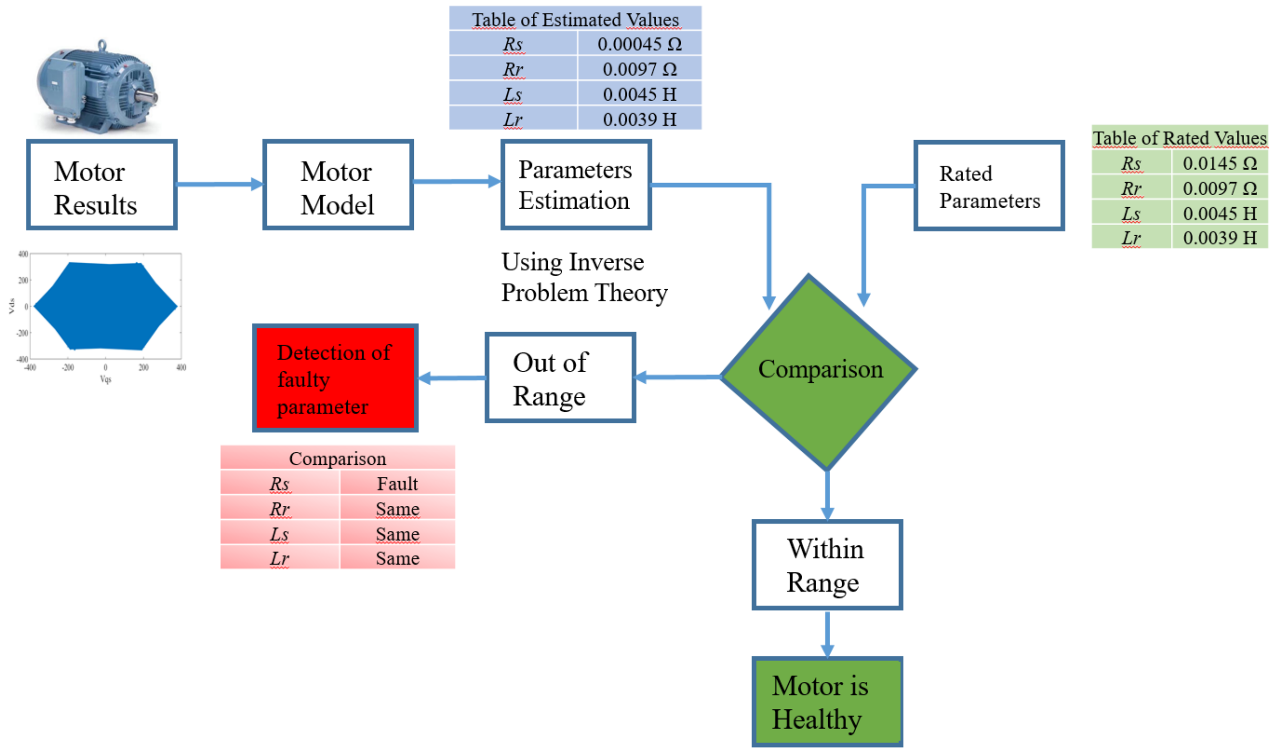

Fig. 4. Schematic diagram of the proposed inverse model for fault diagnostics.

The process of parameter estimation using the system model and data from a set of observations (output in case of forward model) is called the inverse problem theory [48]. Successful implementation of this approach can lead us to the approximation of the faulty parameter of motor, as shown in Fig. 4.

Inverse problem theory has been implemented in various fields like medical sciences [54], geosciences [55], disaster preparedness of infrastructure, signal processing [56] and electrical machine design. [57]–[62] used the inverse problem theory to determine the magnetic induction in the air gap of a machine by measuring the external magnetic field. In [63], inverse problem theory is used to determine the magnetic material characteristics of a wound field synchronous machine. It was shown that the magnetization characteristic can be constructed using core loss and no-load curve measurements.

The author claimed that this method is applicable even without any prior knowledge of magnetization curves, if parameter ranges can be defined by some other means. In [64] the inverse problem theory is used in conjunction with neural networks for optimal design of the switched reluctance motor. The authors of [65] used the inverse problem approach to evaluate the homogenized electromagnetic and thermal characteristics of stator winding of asynchronous motor.

In Table I, a comparison of some advanced fault diagnostic techniques is presented and the main attributes are highlighted.

V. Conclusions

Below, the authors of the given paper propose some solutions for electrical machine diagnostics in the context of Industry 4.0. In the light of above-presented discussion, the following key points can be highlighted.

- The main objective of almost all fault diagnostic techniques available in literature is the reduction of computational cost in terms of hardware.
- This leads to a trade-off between simplicity of the algorithm and the accuracy of results.
- The conventional, so-called harmonic analysis techniques fail to give a complete picture of the faults in the presence of some other harmonics due to some secondary internal or external factors.
- The picture becomes even more blurred when there are more than one kind of faults or there are some external noise factors, i.e. the segregation of faults is almost impossible.
- Most of techniques are always vulnerable to wrong fault alarms.
- The coming trends of cloud computing and IoT in Industry 4.0 have considerably contributed to solving the problems related to hardware.
- The algorithms are no longer needed to be implemented in DSP kits or just in drives besides the motor.
- The diagnostic algorithms can be placed and solved in some powerful hardware anywhere in the world using cloud computing.
- Unlike forward diagnostic techniques, inverse problem theory can give a very good picture of faults in terms of parametric values rather than harmonics, etc.
- Almost every kind of complicated diagnostic algorithms can be implemented without any need for simplification.

TABLE I

Some Advanced Fault Diagnostic Techniques

Technique	**Group and Assisting Techniques**		**Speed Estimation**	**Mathematical Calculations**	**Memory Required**	**References**	**Attributes**
Sliding mode observer	MCSA + analytical	FFT	No	High	High	[66]–[68]	Noninvasive. Can be used for faults segregation. Difficult to implement under varying load conditions
Datamining	MCSA	Wavelet	No	High	High	[69], [70]	Noninvasive. Can be used for faults segregation
Fuzzy Logic, Neuro-Fuzzy	MCSA	FFT + ANFIS	Yes	High	High	[71], [72]	Noninvasive. Can be used for faults segregation. Sophisticated hardware required
Neural Network	MCSA	WPD	Yes	High	High	[41], [42]	Noninvasive. No need for exact measurement of slip, high accuracy, can be problematic under increasing fault situations and segregation of various faults.
Kalman Filter	MCSA + analytical	State estimation	Yes	High	High	[68]	Noninvasive, dependent on accuracy of the system model, the complexity of states estimation increases with the increase in different types of faults.

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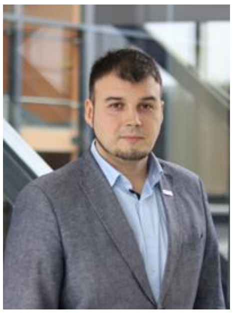

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