A Method for Impact Assessment of Faults on the Performance of Field-Oriented Control Drives: A First Step to Reliability Modeling

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Abstract—In this paper, the effects of certain component faults on the performance of three-phase inverter-fed induction motors are analyzed under indirect field-oriented control. Simulations of faults in the current sensors, speed encoder, three-phase inverter, and motor are presented. Sample hardware faults verifying the simulation results are also presented. Performance requirements are set based on typical performance measures of electric vehicles. These requirements are then used to determine whether or not the system survives a fault. A simple fault detection and isolation scheme using multiple speed encoders is also tested. The construction of a Markov reliability model of the overall system is a direct application of the results, and allows quantifying global reliability measures.

I. INTRODUCTION

Induction motors have been a main part of several traction systems and are currently being utilized in electric vehicles (EVs), e.g. Tesla Roadster™ [1]. They have been established as highly reliable for hybrid electric vehicles (HEVs) [2]. The main initiatives behind EVs and HEVs have been environmental friendliness and fuel savings. Safety and reliability also must be considered carefully by manufacturers. In this paper, the focus is on motor drive reliability in EVs and HEVs. This might be a limiting factor for the widespread acceptance of these vehicles, as both manufacturers and users demand reliability without compromise on performance.

Generally speaking, reliability of a motor drive can be explored via the emerging field of thermo-electrical analysis [3]. To achieve high reliability levels and fault-tolerant operation, which is important for safety considerations, two main elements should be engineered into the motor drive: i) component redundancy, and ii) fault detection and isolation (FDI) mechanisms. In this regard, a typical induction motor drive for a general application is shown in Fig. 1, with no redundancy or details about FDI. There are well-developed methods to evaluate the performance of such a drive under all operational conditions in the absence of faults, however, literature lacks systematic methods that quantify the system ability to tolerate faults and model its overall reliability. This poses a fundamental problem for designers.

In this paper, steps are taken to address this problem, i.e., a systematic method to analyze reliability and fault-tolerance in motor drives for EV and HEV applications. In particular, models are provided for faults that can occur in key components of an indirect field-oriented control (IFOC) induction motor drive, e.g., current sensors and speed encoders. A simulation-based framework to analyze the effect of these faults on system performance is developed. The results of this work can be directly applied to build a Markov reliability model of the drive, thus quantifying global reliability measures.

Literature shows significant work in all aspects of design for reliability and fault-tolerance in induction motor drives. Definition of fault models, which is key for fault-tolerant design, is extensively discussed, including inverter faults [4], control faults [5], supply faults [6, 7], and motor faults [8]. Aspects of fault detection and isolation have been extensively analyzed (see, e.g., [4, 9-16]). For example, pattern recognition is used in [13], while a short-time Fourier transform is used in [16] to identify faults. Redundancy has also been investigated with extensive work on multiphase motors [17] and split-wound motors [18]. At the control level, fault-tolerant control algorithms for permanent magnet synchronous machines (PMSMs) and induction machines were presented in [19-22]. Development of reliable communication and control hardware used in electric drives has also been investigated [23]. Other strategies for improving the reliability of a system include preventive maintenance [24, 25], component derating, and component count reduction.
Even though extensive work has been conducted on fault-tolerant drives and motor control design, literature on systematic methods for modeling and analysis of fault effects on system operation and reliability is limited. Such methods are key to assess whether or not a design meets reliability and fault tolerance requirements for all possible operational conditions, and to compare different design choices. Available work on reliability modeling usually targets the failure rate of the overall drive system. For example, the reliability of the motor and supply is presented in [26]. Component reliability analyses are presented in [27-29]. In [28], faults in control, power electronics, and the motor are addressed, while in [27] control faults are ignored and faults in the transformer and line filters are considered. The work presented in [29] also ignores control, but considers cooling faults. In terms of system reliability modeling, the application of Markov models, which are among the most powerful reliability modeling tools, to motor drives is rare. In [30], only power electronics failures are considered with open circuits, short circuits, and other component failure modes. The induction motor is considered as part of a larger power system for which a Markov model is developed in [31]. An excellent attempt to develop a Markov model of an induction motor drive is available in [32]. Even though sensors can suffer from significant faults, these faults and performance bounds are ignored in [32]. Multiple sensor faults in automotive applications and a multilayer control scheme that restructures faulted sensor signals are presented in [33].

In summary, a complete framework for fault modeling and reliability analysis of a motor drive, including the motor, control, sensors, and power electronics, is not available. This framework would have significant value in assisting designers of fault-tolerant motor drives. This paper sets the foundations for establishing such a framework, focusing on component fault modeling and the subsequent analysis of the impact of faults on overall drive performance. In this regard, there is significant work in the literature on modeling physical motor faults, e.g., broken rotor bars and stator winding short-circuits; however, fault modeling of non-physical effects in control and communication elements, e.g., sensors and controllers, and their impacts on system performance are usually not addressed.

Component fault models as well as system performance measures, the key elements of the proposed methodology, are discussed in Section II. Section III discusses the implementation of fault models and performance measures in a simulation environment. In Section IV, both simulation and experimental fault injection results are presented. Section V includes an overview of the expected Markov reliability model, and Section VI concludes with remarks and future work.

II. METHODOLOGY

The proposed methodology uses a model of motor-drive dynamics plus additional features to model component failures. These features include component failure modes (and associated failure rates) and how these failure modes affect the dynamic behavior of the component. Depending on the type of component fault, time of fault, and sequence in the event of multiple faults, the system will evolve from the nominal unfailed configuration to other configurations with different dynamics. Each possible system configuration will be analyzed to check whether its dynamic properties meet system performance requirements. Once all configurations have been evaluated, the performance metrics for each configuration and the probabilities of going from the nominal configuration to any other configuration are merged into a Markov model.

A. Fault Modeling

A system under no faults is considered to be in its nominal configuration. The transitions between configurations occur stochastically, triggered by random faults. Faults identified in literature include those within the motor, power electronics, control, and supply. Faults in sensors are also essential but have not been elaborated upon in FOC drives. While faults in other major components such as digital signal processors and interface electronics also have severe consequences, these are relatively unlikely except as consequences of other faults. Here, they are lumped into controller and sensor faults rather than treated separately.

The paper focuses on common faults that affect the performance of an IFOC drive from [34], and analyzes the status of the drive under such faults. Sensor faults include omission, incorrect gain, bias, constant value, and noise in current sensors and speed encoders. Inverter faults are also addressed and include short circuit (SC) to ground, SC to the dc voltage bus, and open circuit (OC) [4, 17, 30]. Motor faults studied here are phase-to-phase faults and broken rotor bars, which are the most common faults in induction machines. Motor OC and SC to ground faults can be modeled on the inverter side. Another squirrel-cage induction motor fault is a broken end ring in a motor, which follows a similar analysis as a broken bar [35]. The faults to be analyzed here are tabulated in Table I. The discussion addresses only single faults, although as the methodology develops, it will be important to evaluate the effects of multiple sequential faults to quantify system fault tolerance. The modeling process is simplified by symmetry. For example, a fault in inverter phase-leg a or its current sensor has the same impact as in phases b or c. This inherent symmetry could help with fault detection and isolation in motor drives by utilizing
multiphase motors, reconstructing faulted sensor signals from healthy signals, etc.

B. Performance Evaluation

Performance metrics are measurable properties of the system that quantify how well it performs its desired functions. Performance metrics can be related to system functionality, e.g., in a tracking-system, relevant performance metrics are the tracking error, the overshoot, or the settling time. However, non-functional metrics can be considered as well, e.g., in the tracking system, the power consumption may be important.

General performance metrics and associated requirements are presented for driving conveyors in [36]. Some of these can be extended to EVs. These requirements are typical for acceptable performance, including safety requirements, e.g., ability of the system to return to desired operation within 500 ms. A vehicle travelling at 65 mph (105 km/h) moves about 15 m during this interval, which is faster than a driver’s reaction time. Sample performance bounds are tabulated in Table II. These bounds are then scaled for a 1.5 hp induction machine used for experiments. The current bound is 10 A which is about twice the peak rated current. Note that the torque bounds are set and taken into consideration only in simulations, as they only provide results for open-loop torque control, while experiments, as explained later, provide results for closed-loop control.

For each system configuration arising from different faults, performance metrics are analyzed. Performance metrics are useful in determining whether each possible system configuration is declared as failed or non-failed, but it is necessary to define an aggregated measure of reliability, which can be later accomplished by constructing a Markov reliability model.

Table I

<table>
<thead>
<tr>
<th>Fault Types</th>
<th>Encoder</th>
<th>Speed</th>
<th>Phase Leg</th>
<th>Motor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault Types</td>
<td>• Omission</td>
<td>• Gain</td>
<td>• SC to bus</td>
<td>• Phase to phase fault</td>
</tr>
<tr>
<td>Omission</td>
<td>• Gain</td>
<td>• Bias</td>
<td>• OC</td>
<td>• Broken rotor bar</td>
</tr>
<tr>
<td>Gain</td>
<td>• Bias</td>
<td>• Constant</td>
<td>• SC to dc bus</td>
<td></td>
</tr>
<tr>
<td>Bias</td>
<td>• Constant</td>
<td>• Noise</td>
<td>•</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>• Noise</td>
<td>•</td>
<td>•</td>
<td></td>
</tr>
</tbody>
</table>

Table II

<table>
<thead>
<tr>
<th>Performance Metrics and Associated Requirements</th>
<th>Performance Requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed</td>
<td>Command speed ± 50 rpm</td>
</tr>
<tr>
<td>Current</td>
<td>Current peak not exceeding 12A</td>
</tr>
<tr>
<td>Settling time</td>
<td>Less than 500ms</td>
</tr>
<tr>
<td>Torque (Simulations)</td>
<td>Nominal load torque ±0.5 N·m</td>
</tr>
</tbody>
</table>

Table III

<table>
<thead>
<tr>
<th>Fault Type</th>
<th>Speed Encoder</th>
<th>Current Sensor</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gain</td>
<td>1.5</td>
<td>1.5</td>
<td></td>
</tr>
<tr>
<td>Bias</td>
<td>±10 rpm</td>
<td>±1 A</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>900 rpm</td>
<td>3 A</td>
<td></td>
</tr>
<tr>
<td>Noise</td>
<td>±10 rpm</td>
<td>±0.5 A</td>
<td></td>
</tr>
</tbody>
</table>

III. IMPLEMENTATION OF THE PROPOSED METHODOLOGY IN SIMULATION AND EXPERIMENT

Modeling faults in simulations is an essential step to emulate real-life operation of a faulted IFOC drive. It can be risky to inject certain faults in experiments.

A. Simulation Environment

Simulations provide a safe environment to evaluate even the most extreme faults, provided a simulation has been validated in hardware. Some commercial drives have fault detection and isolation, which would not be helpful if the target is to observe drive performance under faults, such as a phase-to-phase fault. In simulations, faults are mainly of two kinds: sensor faults where the sensor feedback signal can be faulted, and circuit faults, where the power electronics and motor electrical connections are modified in the faulted configurations.

Sensor faults can be modeled as shown in Fig. 2, which shows a simulation model for a sensor fault in MATLAB/Simulink. This modeling approach, proposed in [37], provides the flexibility of changing the gain, bias, constant, and noise values, in addition to the time of the fault injection. Values used for these faults are shown in Table III. The gain change fault results in a 50% increase in encoder and current sensor nominal gains. The bias faults imply the sensor output gives a biased value of the true quantity. Constant faults imply that sensor output gets stuck at a fixed value, while noise faults imply the sensor output is corrupted by additive Gaussian noise. These values could be swept over a wide range, but constants are used for this analysis based on logical expectations. Circuit faults can be modeled with switches that generate the faulted configurations. The controlled power electronics switches available in the SimPowerSystems toolbox provide a possible approach. A drawback of the SimPowerSystems toolbox is that any transition from a short circuit to an open circuit results in rapid changes in currents and voltages that could lead to numerical errors. This problem can be avoided with suitable parallel or series resistances, although in the real system, stray inductances and capacitances limit the rates of change during faults. Broken rotor bars require a different fault model in which rotor currents, resistances, and inductances are modified when the fault happens. A simple model used here ignores the change of rotor inductance and focuses on the change of rotor resistance [38]. Therefore, the induction motor in Fig. 3 employs around rotor model in which additional resistance is connected to represent a broken rotor bar fault.

Another approach to model circuit faults is the modification of the switching pattern. For example, an open circuit in the upper switch in an inverter phase-leg can be modeled simply by switch turn-off. These models give an appropriate idea of system behavior under faults and avoid severe failures in the experimental setup.
B. Experimental Environment

The experimental setup includes all control, power electronics, motor, load, and measurements. The control and some measurements are available on an eZdspF2812 platform [39] which is based on a Texas Instruments TMS320F2812 DSP. This control platform is integrated into the Grainger Center Modular Inverter [40] which also includes an inverter power stage rated at 400V and 100A. A dynamometer is used to set the load torque. Measurements include speed, torque, currents, voltages, and input and output power. All control and measurement devices, including the dynamometer, are controlled using MATLAB/Simulink through the Simulink Real-Time Workshop. Communication between the software and the DSP occurs through real-time data exchange (RTDX) via a parallel port. The experimental setup is shown in Fig. 4.

IV. SIMULATION AND EXPERIMENTAL RESULTS

An IFOC motor drive with a 1.5 hp motor was simulated in MATLAB/Simulink using the SimPowerSystems toolbox, as shown in Fig. 3. A load quadratic in speed emulates single quadrant operation of an EV. The speed command is 1000 rpm, which results in steady-state torque of about 2 N·m. The red blocks in Fig. 3 are the locations of the faults. All 15 faults shown in Table I were simulated, with emphasis on torque, speed, and current responses. The faults were injected at $t=2$ s.

Several simulation and experimental results are shown in Figures 5 through 10. The experimental setup is shown in Fig. 11. Waveforms in the experimental results are as follows: The top trace is the speed, scaled at 500 rpm/div, the center trace is the torque at 2 N·m/div, and the bottom trace is current at 10 A/div. Faults leading to failures with low risk of system damage, e.g. encoder omission, were experimentally validated. Table IV includes the system status after each fault. Current sensor faults and electrical faults were imposed on phase “a”. The broken rotor bar was modeled as a 0.1 Ω increase in rotor resistance. It is clear from Table IV that more than one third of the faults cause the system to fail in the sense of not meeting performance requirements. This is expected because IFOC, without any redundancy, uses four feedback signals: three for currents and one for speed; thus, with one of these four signals failing, the motor drive could fail. Figures 5 through 10 show that the simulation model accurately reflects the experimental setup, which simplifies the simulation of severe faults and failures. The general dynamic performance shown in simulations and the steady-state shapes and values of the speed and current waveforms match those in experiments.

Fig. 2. Sensor fault model.

Fig. 3. Simulink model of the IFOC motor drive.

Fig. 4. Experimental setup.

These results suggest that it should be possible to enhance a conventional IFOC algorithm with redundancy and fault detection to cover faults. For example, a 2-of-3 voting mechanism with three speed encoders will eliminate speed encoder problems, as shown in Fig. 11. Even though adding two more speed encoders might not be economically feasible, the functions could be provided by speed estimators. The reference speed could also be used as one of the three signals compared in a voting mechanism given an appropriate tolerance band among signals. Similar voting mechanisms can be implemented for current sensors. Alternatively, a faulty current can be reconstructed from healthy phase currents or from the dc link current and switching states [33].
Fig. 5. System failure after speed encoder omission (simulation results).

Fig. 6. System survival within performance bounds after current sensor constant (simulation results).

Fig. 7. System failure after an open circuit on phase “a” (simulation results).

Fig. 8. System failure after speed encoder omission (experimental results).

Fig. 9. System survival within performance bounds after current sensor constant (experimental results).

Fig. 10. System failure after open circuit on phase "a" (experimental results).
TABLE IV
SYSTEM RESPONSE TO FAULTS BASED BOUNDS IN TABLE III

<table>
<thead>
<tr>
<th>Fault</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed Encoder: Omission, Gain, Noise</td>
<td>Failed</td>
</tr>
<tr>
<td>Speed Encoder: Bias, Constant</td>
<td>OK</td>
</tr>
<tr>
<td>Current Sensor: Gain, Bias, Omission, Noise</td>
<td>OK</td>
</tr>
<tr>
<td>OC, SC phase-to-phase</td>
<td>Failed</td>
</tr>
<tr>
<td>SC to dc bus, SC to ground, Broken rotor</td>
<td>OK</td>
</tr>
</tbody>
</table>

![Figure 11](image1.png)

Fig. 11. System survival after speed encoder omission with a 2-of-3 voting system.

V. MARKOV RELIABILITY MODEL

The overall drive reliability can be obtained by formulating a Markov reliability model [41]. Unlike combinatorial reliability models such as fault trees or reliability block diagrams, state-dependent component failure rates can be naturally included in a Markov reliability model. Such a model can be represented graphically in terms of a state-transition diagram of the motor-drive system status (failed or operational) for each configuration reached after a unique sequence of component faults. The motor-drive system can evolve from the fault-free configuration to other configurations depending on the status of the components within the motor-drive system. The nodes of the state-transition diagram represent the status (failed or operational) of each system configuration, and the edges represent transitions between configurations triggered by component faults and described by the failure rate of the faulted component causing the transition. There are two types of nodes: absorbing nodes and non-absorbing nodes. The system will fulfill its function whenever it is in a non-absorbing node. System reliability is quantified as the probability the system is in any non-absorbing state, which can be obtained by solving the Chapman-Kolmogorov equations associated with the state-transition diagram [41].

The analysis conducted in Section IV focused on single fault occurrences. Table IV shows the system status after each fault considered. Figure 12 shows a portion of the Markov reliability model corresponding to the speed encoder faults in Table IV and the failure rates shown in Table V [42]. The green states represent post-fault operational states, whereas the red states correspond to failed system states. It is important to note that different faults yield very different results. Although not represented here, the sequences of faults involving more than one component can be incorporated in the Markov model.

Table V shows the failure rates for speed encoder faults. The failure rates are given in Table V for each fault type. The green states represent post-fault operational states, whereas the red states correspond to failed system states. It is important to note that different faults yield very different results. Although not represented here, the sequences of faults involving more than one component can be incorporated in the Markov model.

![Figure 12](image2.png)

Fig. 12. Snapshot of the motor-drive Markov reliability model.

VI. CONCLUDING REMARKS

Engineering methods for analysis of faults, failures, and general reliability of an IFOC induction motor drive can be used for system performance improvements. EVs and HEVs require special safety considerations, thus posing an essential challenge. All single faults and the resulting failures or survivals were analyzed based on preset performance bounds. Simulations of faults in the system were presented with experimental validation of several failures. Simple fault detection and isolation was presented based on a redundant speed sensor example.

ACKNOWLEDGMENT

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APPENDIX

<table>
<thead>
<tr>
<th>Motor Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated power</td>
<td>1.5 hp</td>
</tr>
<tr>
<td>Rated speed</td>
<td>1750 rpm</td>
</tr>
<tr>
<td>Number of poles ($p$)</td>
<td>4</td>
</tr>
<tr>
<td>Referred rotor resistance ($R_{\text{r}}'$)</td>
<td>0.7309 Ω</td>
</tr>
<tr>
<td>Stator resistance ($R_s$)</td>
<td>1.5293 Ω</td>
</tr>
<tr>
<td>Referred rotor leakage inductance ($L_{\text{r}}'$)</td>
<td>0.005343 H</td>
</tr>
<tr>
<td>Stator leakage inductance ($L_s$)</td>
<td>0.00536 H</td>
</tr>
<tr>
<td>Magnetizing inductance ($L_m$)</td>
<td>0.19778 H</td>
</tr>
<tr>
<td>Core Loss ($R_k$)</td>
<td>505 Ω</td>
</tr>
<tr>
<td>Inertia ($J$)</td>
<td>0.01 Kg.m²</td>
</tr>
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</table>

REFERENCES


