Data-Driven Modeling of Inverter-Fed Induction Motor Drives using DMDc for Faulty Conditions

Muhammed Ali Gultekin
University of Connecticut
Storrs,CT
muhammed_ali.gultekin@uconn.edu

Zhe Zhang
University of Connecticut
Storrs,CT

Ali Bazzi, *Senior Member, IEEE*
University of Connecticut
Storrs,CT

***Abstract*—Modeling faulty behavior of systems has benefits in diagnosis and control. In this paper a data-driven method, dynamic mode decomposition with control (DMDc), is employed for modeling an inverter-fed induction machine. Results are shown and compared for two scenarios: A step input change and an inverter fault. For both cases, the algorithm can correctly predict behavior of the system. The advantage of this model is its independence from the system parameters. The results show promise for data-drivenfault diagnostics and system modeling.**

***Index Terms*—Data-driven modeling, induction machine modeling, dynamic mode decomposition**

I. Introduction

Modeling faulty behavior of any system helps in establishing strategies to mitigate faults. This can be achieved through control actions by predicting the next states. If the next states are known, more precise and effective control signals can be generated. For electric drives, there are different types of faults such as those in the inverter, machine or sensors. In [1], faults and some of their mathematical modeling guidelines are summarized. The generated fault model can then be used for diagnosis and control when that specific fault occurs [2], [3]. Major drawback of mathematical modeling is that there is no guarantee that a modeled fault will occur, even if it is a common fault, and that modeling is susceptible to model parameter variations and uncertainty. Data-driven modeling techniques are advantageous in fault modeling since a mathematical model can be easily generated with no reliance on system parameters. Dynamic mode decomposition (DMD) is such a technique that does not require any system information to model a system. DMD uses state measurement snapshots to model system dynamics [4]. If input information is available, more precise models can be generated through DMD with control (DMDc) [5]. DMD and DMDc methods are mostly used in fluid dynamics research, and their application to power electronics is limited. One attempt is in [6], where the authors used models obtained by DMD to solve Riccati equation for permanent magnet synchronous motor drives.

In this study, faulty state trajectories of an inverter-fed induction machine are explored. Because control signals are present, DMDc method is preferred. Since the system itself is already a low-order system, order reduction is not necessary. To make continuous guesses, DMDc is calculated through a moving window in each time step, with a predefined window size. Simulations show that faulty states can be modeled using DMDc with low error margin.

This work is supported by the National Science Foundation under Award 1752297.

The paper organized as follows: In Section II, the DMDc algorithm and mathematical background are shown. In Section III, predictive modeling is shown. In Section IV, simulation results verify that DMDc can accurately model system behavior under healthy and faulty conditions. In Section V, experimental results are presented where DMDc can follow system behaviour, also some design considerations are discussed. Section VI concludes the paper.

II. DMDc Algorithm and Background

Assume that there is a discrete-time system where *A* is the system matrix, *B* is the input matrix and *C* is the output matrix. x[n] denotes the present state matrix, it is a vector for one dimensional measurements.

$$x[n+1] = Ax[n] + Bu[n] \tag{1}$$

$$y[n] = Cx[n] \tag{2}$$

If $u[n] = 0$, i.e. no inputs are present, matrix *A* can be solved as:

$$x[n+1] = A\,x[n] \tag{3}$$

$$A = x[n+1]\,(x[n]){-}1 \tag{4}$$

Equation (4) can be rewritten as,

$$A = x[n]\,(x[n-1])^{-1} \tag{5}$$

An interpretation of this equation is that if we have the state measurements $x[n]$ and a shifted version of the state measurements $x[n-1]$, we can find matrix *A*. To improve this method, control signals can be added. To solve the system given in (1) with the same methodology, new matrices will be defined. Let,

$$G = \begin{bmatrix} A & B \end{bmatrix},\ \Upsilon[n] = \begin{bmatrix} x[n] \\ u[n] \end{bmatrix} \tag{6}$$

Then, A and B matrices can be found as:

$$x[n+1] = G\,\Upsilon[n] \tag{7}$$
$$G = x[n+1]\Upsilon^{-1}[n] \tag{8}$$
$$G = x[n]\Upsilon^{-1}[n-1] \tag{9}$$
$$\tag{10}$$

Normally, the DMDc algorithm uses single value decomposition and order reduction. However, since the induction machine model is already a low-order system, no order-reduction steps of the algorithm are necessary [5]. To apply DMDc, the following matrices are needed: State snapshots X, input snapshots U, and augmented control matrix Υ. By using these three matrices, the matrix G containing A and B will be found. X_1 is defined to be the sub-matrix of X with first component excluded. Similarly, X_2 and U_2 are sub-matrices of X and U where the last components are excluded. To form Υ, U_2 will be used. Fig. 1 illustrates such formations.

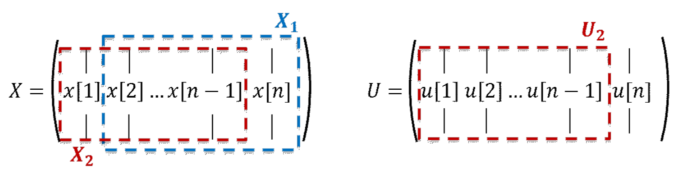

Figure 1: Formation of matrices

Matrix G can be found as,

$$\Upsilon = \begin{bmatrix} X_2 \\ U_2 \end{bmatrix},\; G = X_1\,\Upsilon^{-1} \tag{11}$$

Matrix Υ will likely not be square matrix, and therefore its inverse is not defined. In this case it is better to use the pseudo inverse, denoted by superscript (†). Matrix G can then be found as,

$$\Upsilon = \begin{bmatrix} X_2 \\ U_2 \end{bmatrix},\; G = X_1\,\Upsilon^{\dagger} \tag{12}$$

III. PREDICTIVE FAULT MODELING

Predicting future states is not a new topic in control, and there are established methods to do these. Any observer-based system can be considered as a predictor, as well as Kalman filters. While these are viable alternatives they require system information in terms of system matrices, as well as information regarding environment (noise, disturbance etc.). The power of DMD-based methods is that it can model a system based on state measurements or simulation results, without requiring any data of the system. For induction machines, it does not require stator or rotor inductances and winding resistances. This makes a DMD-generated model robust against parameter variations. DMD is also flexible for combination with other methods, e.g. with a Kalman filter as shown in [7].

In this paper, DMDc is used for future state prediction by considering an N-sized window. Using the last N state and input data, the system is modeled and system matrices A and B are generated. Using generated system matrices, the next state is synthesized. The algorithm describing this process is given in Fig. 2.

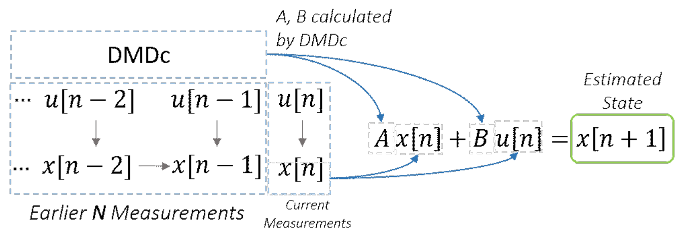

Figure 2: Predictive modeling process

IV. SIMULATION RESULTS

For this paper, an inverter-fed induction machine with indirect field-oriented control (IFOC) system is simulated. The induction machine and IFOC are modeled using equations provided by [8]. A hysteresis current control technique is employed. The Simulink diagram of the system is given in Fig. 3. Two test scenarios are applied; in the first scenario a step change is applied on the torque signal from 5 N•m to 10 N•m at t=1s and the output is observed. In the second scenario, a fault is injected to one of the inverter phases, specifically bottom switching device is shorted to ground. For both cases sampling time is set to $50\mu s$.

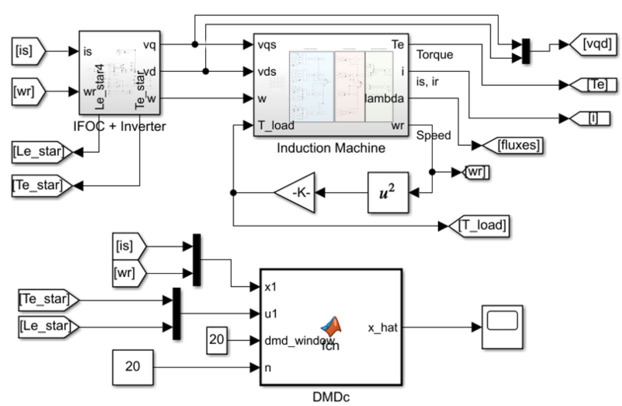

Figure 3: Simulink diagram

To form matrices G and Υ, dq-stator currents and rotor speed are used as state variables since currents are almost always available rather than fluxes. Torque command and the d-component of the rotor flux are used as control commands to form the U matrix. Even though the torque and rotor flux are not available as measurements, their commands are available through the control unit. The DMDc algorithm is implemented into a MATLAB function block in Simulink which runs alongside with the simulation setup given in Fig. 3. for given scenarios. Results of the estimation algorithm are presented in Figures 4 and 5. The first scenario has a stepped torque command, whereas the second scenario has an inverter fault. Note that no system information is provided to the DMDc algorithm, only current and speed measurements, and input reference information. As can be seen from Figures 4 and 5 , there is a small amount of error between estimated states and simulated states. Maximum percentage error for i_q and i_d are 8% while maximum percentage error for rotor speed is less than 1%.

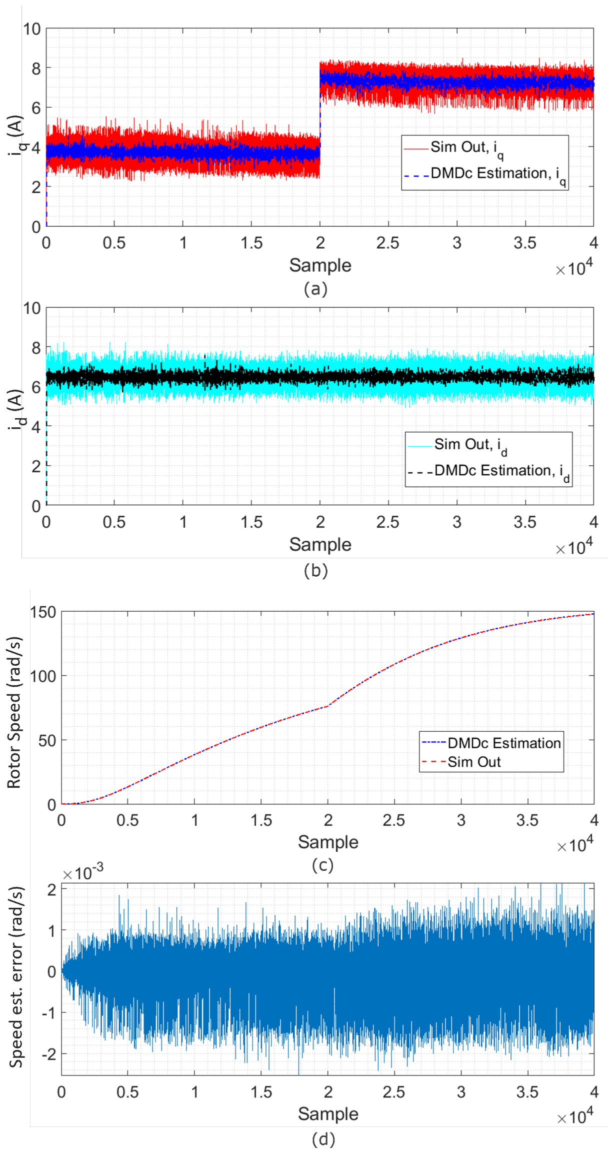

Figure 4: Simulation results for the first scenario, sampling time is . (a) and (b) i_q and i_d simulation results and estimation results, respectively; (c) w_r simulation and estimation results, (d) the difference between estimated and simulated results.

V. EXPERIMENTAL RESULTS

A. Setup Details

To carry this study further, the experimental setup is prepared in a previous study [9]. The picture of the experimental setup is provided in Fig. 6, which includes an inverter-fed

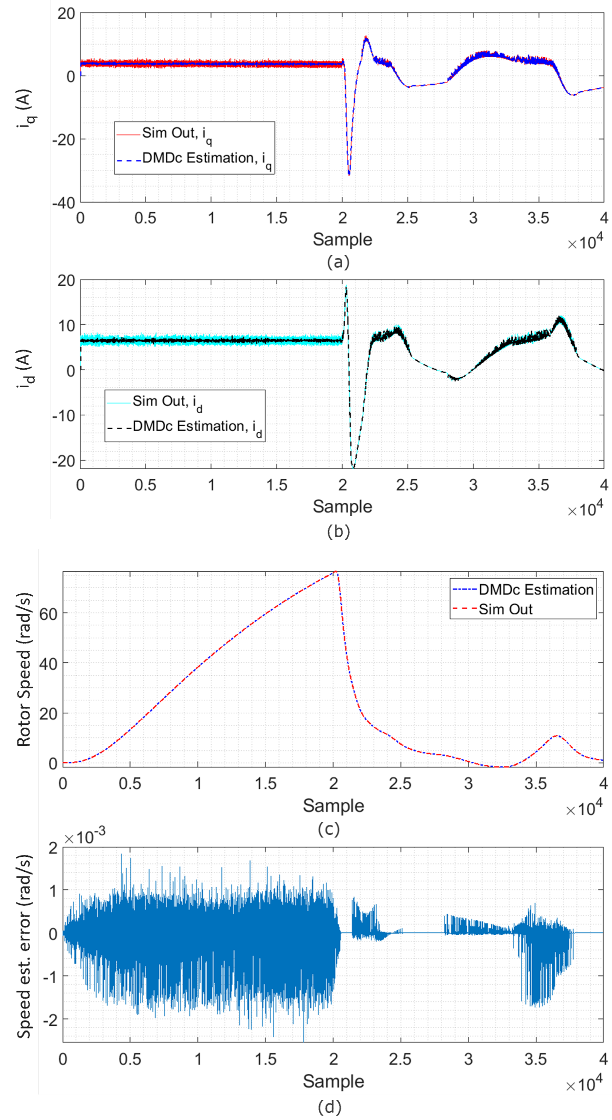

Figure 5: Simulation results for the second scenario. a) and (b) i_q and i_d simulation results and estimation results, respectively; (c) w_r simulation and estimation results, (d) the difference between estimated and simulated results.

1.5-hp induction motor and dSPACE DS1104 digital control platform. For experimental studies, constant V/f control method is implemented instead of IFOC. DMDc algorithm is embedded to dSPACE and runs with the system. To test the estimation performance, a step-type command is applied to the speed input; the output current sensor readings, speed sensor readings as well as DMDc estimations are logged. The results are presented in Fig. 7. Estimation performance is proven to be close to the simulation results with some implementation considerations.

B. Implementation Considerations

There are two parameters that affect the estimation performance, one is the DMDc window size *'N'*, the other one is the

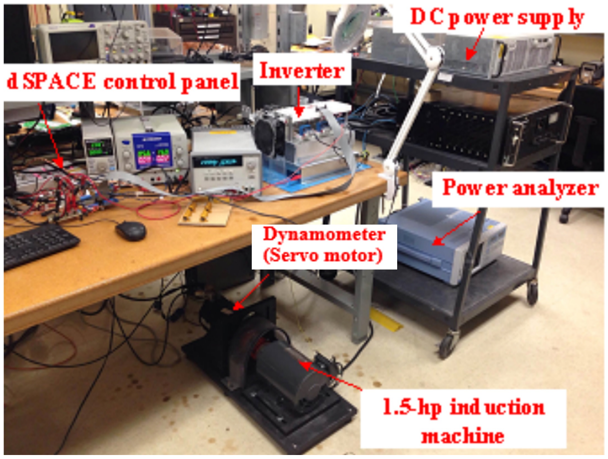

Figure 6: Experiment setup

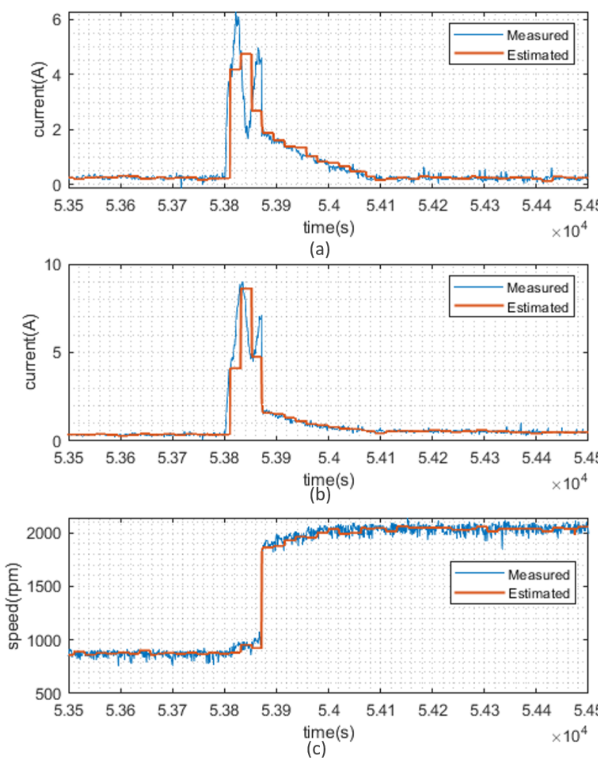

Figure 7: Experimental results for V/f controlled system for a step reference change, *N/n*=20/20 (a) measured and estimated i_q, (b) measured and estimated i_d, (c) measured and estimated speed

shifting index *'n'*. DMDc uses *N*-sized input vector to calculate the next state and it updates or shifts the measurements every *n* samples. Tests showed that a smaller N/n ratio results in a better estimation performance, but it creates a peaky response if a sudden change occurs. Also, a smaller N/n ratio will create a noisy estimation whereas a larger N/n ratio also acts a moving average filter in the steady state. Selection of window size N is important and can be restrictive in terms of calculation cost, larger N requires more computational power. Moreover if the measurement contains low frequency characteristics, they might be missed if a smaller window size is used. Experiment results with different (N, n) pairs are presented in Fig 8. Since the main point of this study is to model faulty cases, larger N/n ratios are preferable as power stage faults tends to create sudden changes.

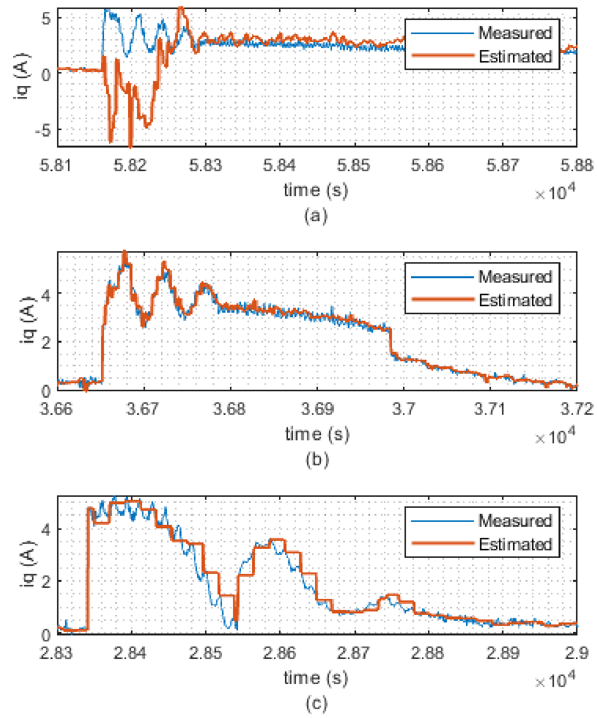

Figure 8: Experimental results for different window sizes and shifting indices, (a) N=100, n=2. (b) N=20, n=2. (c)N=20, n=20

VI. CONCLUSION

A predictive fault model using DMDc method is presented for inverter-fed induction machines. Simulation and experimental results are shown to verify that DMDc can accurately predict the machine states without requiring any system parameters. DMDc is a promising method with a lot of application potential in power electronics and drives.

REFERENCES

[1] D. Campos-Delgado, D. Espinoza-Trejo, and E. Palacios, "Fault-tolerant control in variable speed drives: a survey," *IET Electric Power Applications*, vol. 2, no. 2, pp. 121–134, 2008.
[2] C. Sui, Y. He, Z. Li, and M. Chen, "The post-fault current model of voltage source converter and its application in fault diagnosis," *IEEE Transactions on Power Electronics*, vol. 36, no. 2, pp. 1209–1214, 2020.

[3] H. Lu, J. Li, R. Qu, D. Ye, Y. Lu, and R. Zhang, "Post-fault model predictive control of asymmetrical six-phase permanent magnet machine with improved mathematical model," in *2017 IEEE International Electric Machines and Drives Conference (IEMDC)*. IEEE, 2017, pp. 1–7.

[4] P. J. Schmid, "Dynamic mode decomposition of numerical and experimental data," *Journal of fluid mechanics*, vol. 656, pp. 5–28, 2010.

[5] J. L. Proctor, S. L. Brunton, and J. N. Kutz, "Dynamic mode decomposition with control," *SIAM Journal on Applied Dynamical Systems*, vol. 15, no. 1, pp. 142–161, 2016.

[6] A. Stevens, S. Agoro, and I. Husain, "Data-driven current control of the pmsm with dynamic mode decomposition and the linear quadratic integrator," in *2020 IEEE Applied Power Electronics Conference and Exposition (APEC)*. IEEE, 2020, pp. 271–278.

[7] T. Nonomura, H. Shibata, and R. Takaki, "Extended-kalman-filter-based dynamic mode decomposition for simultaneous system identification and denoising," *PloS one*, vol. 14, no. 2, p. e0209836, 2019.

[8] P. C. Krause, O. Wasynczuk, S. D. Sudhoff, and S. Pekarek, *Analysis of electric machinery and drive systems*. Wiley Online Library, 2002, vol. 2.

[9] Z. Zhang, Y. Liu, and A. M. Bazzi, "An improved high-performance open-loop v/f control method for induction machines," in *2017 IEEE Applied Power Electronics Conference and Exposition (APEC)*. IEEE, 2017, pp. 615–619.