International Journal of Power Electronics and Drive System (IJPEDS)
Vol. 9, No. 1, March 2018, pp. 433~442
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v9.i1.pp433-442

Real Time Validation of EKF Estimator for Low Speed Estimation in DTC IMD

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Article Info

Article history:

Received Jul 28, 2017
Revised Jan 9, 2018
Accepted Jan 21, 2018

Keyword:

DTC
EKF
IMD
PIL
Real time testing
Sensorless

ABSTRACT

Low speed estimation in DTC IMD is not accurate due to the presence of transient offset, drift and domination of ohmic voltage drop in the measured stator voltages and currents used for estimating the stator flux required for accurate estimation of speed. EKF is a nonlinear, recursive adaptive algorithm capable of estimating speed ranging from very low speed to rated speed using equation of motion from noisy measured currents and voltages based on state space technique. In the previous work a new state space model of IM was developed for estimation in EKF by feeding load torque profile as an input variable instead of estimating it by considering load torque as constant, validated using MATLAB-Simulink software. In this paper real time validation of the EKF controller with load profile fed as input for speed estimation in DTC IMD is carried out using OPAL-RT simulator and real time results validates the simulation results and proves the effectives of the new EKF for low speed estimation in DTC IMD.

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1. INTRODUCTION

The advancement in power electronics, vector control and direct torque control resulted in unprecedented growth in induction motor (IM) variable speed drives. The control of IM is more complex due to rotating stator magnetic field and inaccessibility of rotor current for measurement. [1,2] Takahashi and Noguchi [3] introduced DTC for low and medium voltage induction motor drives in 1985 and DTC developed by M. Depenbrock [4] for high voltage induction motor drives became very popular in industry. DTC offers excellent independent control of electromagnetic torque and stator flux linkage by the optimum selection of voltage space vector to obtain excellent dynamic torque response and greater efficiency. Conventional DTC has variable switching frequency and posses torque ripples due to the hysteresis band controllers and the voltage space vector selection was based on a switching table with limited optimum voltage switching states. [5,7]. Space vector modulation (SVM) technique used for optimum voltage space vector selection offers reduction of ripples in torque, flux and speed and gives constant switching frequency. [6,8,9].

Sensorless control is the norm of industry due to reduction in complexity and cost, ruggedness, reliability, noise immunity and operation in a hostile environment. Sensorless control needs different types of speed estimation techniques to estimate the rotor speed from measured stator voltages and currents. Open loop estimators and closed loop observers are used for speed estimation. Open loop estimators are used where no closed loop speed control is required and it lacks the speed estimation correction term which most of the closed loop observers are having. [10] Open loop estimator performance degrades during low speed operation due to parameter variation, pure integrators used, drift and dc offset in measurements, noise in the system etc. Hence low speed estimation of DTC IMD is a research challenge.

Closed loop observers like MRAS, EKF, Luenberger, Sliding mode control were investigated by pervious researchers [11-13]. Among that Extended Kalman filter(EKF) is a is a promising solution for low speed estimation because it is a recursive, stochastic algorithm suitable for nonlinear systems. EKF is suitable for joint parameter and state estimation and hence EKF is investigated as the most suitable observer for low speed estimation in DTC IMD. In sensorless DTC IMD, EKF estimates the rotor flux linkages, stator currents and rotor speed. [14-18]. Previous researches shows that rotor speed is estimated in EKF considering it as a constant [1]. From literature survey it is observed that speed information can be extracted from the equation of motion, relating load torque and electromagnetic torque. Electromagnetic torque can be obtained using the rotor flux linkages and stator currents obtained from the EKF state variable estimate.

The load torque required for the speed estimation is taken as an additional state variable in EKF and considered it as a constant [19]. But this method offers sluggish performance during low speed operation. A new method was proposed by the authors [20] which also uses the equation of motion for rotor speed estimation by EKF but the load torque required for speed estimation is fed as an input to the EKF for estimating the speed. This method offers fast convergence and reduced estimation even at very low speed including zero speed. The software validation of new approach of estimating speed using EKF observer is carried out using MATLAB-Simulink software and observed the effectiveness of the technique for low speed estimation in sensorless DTC IMD. In this paper real time validation of the new EKF approach using the load profile input to EKF estimator for rotor speed estimation is carried out using Processor- In-The -Loop (PIL) real time validation technique using OPAL-RT real time simulator OP4500. The results and analysis are presented.

2. SENSORLESS SVM DTC INDUCTION MOTOR DRIVE

DTC is a powerful control technique which can directly and independently control the electromagnetic torque and stator flux linkages of an induction motor. Space vector modulation(SVM) is used for the optimal selection of inverter voltage switching space vector. In conventional DTC optimal switching-voltage vectors are to be selected from the optimum switching-voltage vector look-up table. But in conventional DTC hysteresis band controllers the optimum selection of voltage space vector from the look up table and cause torque ripples and gives variable switching frequency. In SVM PI controllers replace the hysteresis band controllers and offers constant switching frequency and reduction in torque ripple.

Sensorless drives reduce the complexity and cost of system but sensorless drive performance greatly depends on the speed estimator. Basic open loop estimators have low speed estimation issues due to stator resistance parameter variation during low speed operation of the drive. Along with that system and measurement noise, drift, dc offset etc present in the system will affect the low speed estimation. EKF is a closed loop observer which can be used for any nonlinear adaptive system to estimate the parameter from any noisy environment using state space technique and recursive algorithm and hence EKF estimator is an ideal choice for mitigating low speed estimation issues in sensorless DTC IMD.

3. INDUCTION MOTOR MODEL DESCRIPTION

Speed estimation using EKF needs state space model of induction motor for the prediction of states at any instant from previously estimated values. The two axis state space model of induction motor in stationary reference frame can be used where the stator current and rotor flux linkages are the state variables and rotor speed is augmented as the fifth state variable and is estimated using equation of motion. The model developed in this paper is feeding the load torque profile as an input to EKF estimator instead of considering load torque as constant as given by previous researchers. The mathematical model of the induction motor with five state variable.

$$\frac{d}{dt}\begin{bmatrix} i_{ds} \\ i_{qs} \\ \psi_{dr} \\ \psi_{qr} \\ \omega_r \end{bmatrix} = \begin{bmatrix} -(\frac{R_s}{L'_s} + \frac{R'_r L_m{}^2}{L'_s (L'_r)^2}) & 0 & \frac{L_m}{L'_s L'_r T_r} & \frac{\omega_r L_m}{L'_s L'_r} & 0 \\ 0 & -(\frac{R_s}{L'_s} + \frac{R'_r L_m{}^2}{L'_s (L'_r)^2}) & -\frac{\omega_r L_m}{L'_s L'_r} & \frac{L_m}{L'_s L'_r T_r} & 0 \\ \frac{L_m}{T_r} & 0 & -\frac{1}{T_r} & -\omega_r & 0 \\ 0 & \frac{L_m}{T_r} & \omega_r & -\frac{1}{T_r} & 0 \\ -\frac{P}{2J} * \frac{3}{2} * \frac{P}{2} * \psi_{qr} & \frac{P}{2J} * \frac{3}{2} * \frac{P}{2} * \psi_{dr} & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ \psi_{dr} \\ \psi_{qr} \\ \omega_r \end{bmatrix} + \begin{bmatrix} \frac{1}{L_{s'}} & 0 & 0 \\ 0 & \frac{1}{L_{s'}} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -\frac{P}{2J} \end{bmatrix} \begin{bmatrix} V_{ds} \\ V_{qs} \\ T_l \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ \psi_{dr} \\ \psi_{qr} \\ \omega_r \end{bmatrix} \quad (2)$$

The electromagnetic torque required for estimating the rotor speed is derived from stator currents and rotor flux linkages in Equation (3).

$$Te = \frac{3}{2}\frac{p}{2}\frac{L_m}{L'_r}\,(\psi dr i_{qs} - \psi qr\, i_{ds}) \quad (3)$$

The load torque required to be fed to EKF estimator for rotor speed estimation is incorporated in the mathematical model of machine by feeding the load profile as the third element to the input matrix along with the stator voltages.

4. EXTENDED KALMAN FILTER ALGORITHM

Extended kalman filter algorithm (EKF) is a stochastic and recursive adaptive observer which can be used for joint state and parameter estimation of a nonlinear dynamic system. EKF will take care of the noise in the system during estimation by using covariance matrices of the state variable (P), system noise (Q) and voltage measurement noise (R_u) and the current measurement noise (R_e). These noise sources take care of measurement and modeling inaccuracies. EKF algorithm consists of two stages of calculation, first stage is prediction of states using mathematical model which contains previous estimates and in second stage the predicted states are continuously corrected by a feedback correction scheme. The prediction stage needs the discretized model of the IM. The weighted difference of the measured and estimated output is added to the predicted values.[20].'

$$\begin{bmatrix} i_{ds}(k+1) \\ i_{qs}(k+1) \\ \psi_{dr}(k+1) \\ \psi_{qr}(k+1) \\ \omega_r(k+1) \end{bmatrix} = \begin{bmatrix} 1-(\frac{R_s}{L'_s} + \frac{R'_r L_m{}^2}{L'_s (L'_r)^2})T & 0 & \frac{L_m T}{L'_s L'_r T_r} & \frac{\omega_r L_m T}{L'_s L'_r} & 0 \\ 0 & 1-(\frac{R_s}{L'_s} + \frac{R'_r L_m{}^2}{L'_s (L'_r)^2})T & -\frac{\omega_r L_m T}{L'_s L'_r} & \frac{L_m T}{L'_s L'_r T_r} & 0 \\ \frac{L_m T}{T_r} & 0 & -\frac{T}{T_r} & -T\omega_r & 0 \\ 0 & \frac{L_m T}{T_r} & T\omega_r & -\frac{T}{T_r} & 0 \\ -\frac{P}{2J} * \frac{3}{2} * \frac{P}{2} * \psi_{qr} * T & \frac{P}{2J} * \frac{3}{2} * \frac{P}{2} * \psi_{dr} * T & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds}(k) \\ i_{qs}(k) \\ \psi_{dr}(k) \\ \psi_{qr}(k) \\ \omega_r(k) \end{bmatrix} + \begin{bmatrix} \frac{T}{L_{s'}} & 0 & 0 \\ 0 & \frac{T}{L_{s'}} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -\frac{P}{2J}T \end{bmatrix} \begin{bmatrix} V_{ds}(k) \\ V_{qs}(k) \\ T_l(k) \end{bmatrix} \quad (4)$$

$$\begin{bmatrix} i_{ds}(k) \\ i_{qs}(k \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{ds}(k) \\ i_{qs}(k) \\ \psi_{dr}(k) \\ \psi_{qr}(k) \\ \omega_r(k) \end{bmatrix} \quad (5)$$

The EKF algorithm was developed to estimate the states and the estimated states of previous instant and the stator voltages are used for predicting the values of the state variables at the present instant. The deviation of predicted values from actual values are obtained by comparing the predicted stator currents and the measured stator currents. This difference in value is the error which is tuned using a correction factor to get an accurate estimate of the states. The corrected error is then summed up with the predicted values for estimating the values of the state variables. EKF is used to estimate the rotor speed of the sensorless DTC IMD.

A 20hp DTC IMD using EKF estimator is developed in MATLAB-Simulink software and validated the performance of the drive for speed estimation from rated speed to very low speed including zero speed. Simulation results proves the effectiveness of this new load profile input feed EKF estimator for low speed estimation in DTC IMD and presented the results in [20]. The motor parameters are given in Table 1. In this work a real time validation of the controller using Processor- In-The -Loop (PIL) real time validation technique is carried out and real time performance of the controller is validated and compared with simulation results.

Table 1. Motor Parameters

Power(kw)	15	R_s (ohm)	0.2147
Frequency(Hz)	50	R_r'(ohm)	0.2205
J(kg/m^2)	0.102	L_{ls}(H)	0.000991
B(Nm/rad/s)	.009541	L'_{lr}(H)	0.000991
No of poles P	2	L_m(H)	0.06419
Voltage(V)	400	N_m(rpm)	1460
Current(A)	36	T_l(Nm)	98

5. REAL TIME SIMULATION

Model driven development approach has gained tremendous demand in testing and validating the controller in real time simulator environment. This helps to reduce the time taken for development of embedded system and to produce rapid and reliable product in a short interval of time. RT-PIL is a verification and validation technique used towards the development of a hardware prototype. The performance analysis obtained from this real time PIL will provide the details required for hardware and computational resources for the implementation of future prototype. The advantages of this approach are the simulation time scale is the same to clock time scale, the real time controller code generation from the simulated algorithm can be done automatically, the time taken for developing, cost to design and prototype the controller and testing of algorithm at extreme conditions with high accuracy can be achieved. In PIL the specific driver functions installed in a simulation integrated environment of the host PC will communicate with the non real time environment target processor.

5.1. Structure of Opal-RT real time simulation system

Opal-RT's real time simulator enables to link software simulations made in MATLAB/Simulink SimPowerSystems models on a dedicated real-time computing platform. Real time simulation helps to link the controller board to the simulation model. The structure of RT lab real time simulator is shown in the block diagram Figure 1.

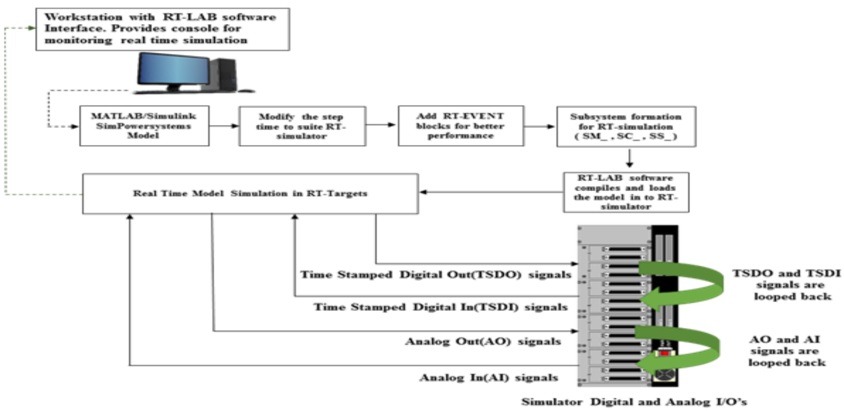


Figure 1. Processor in the loop block diagram

Target machine is equipped with programmable DSP/FPGA and I/O channels to communicate with the simulation host computer and the real controller. The pulse resolution of RT-LAB simulation platform is 10ns, hence many events can be generated in one simulation step and offer high precision timing to the IGBT switches in the inverter. The minimum simulation time step in RT Lab simulator is 20µs. For real time simulation we need to convert the simulation model made in MATLAB-Simulink to be transformed to real time model with a time step of 20µs, then segmentation, editing, compilation and finally code will be generated from the mathematical model, then the model will be loaded to operate in real time simulation platform [23-24].

5.2. Modification required for the existing model

The existing model was running with a fixed step size of 2 µs and to work the model in real time simulator the model step size needs to be increased to 20µs. But when we increase the step size, reconstruction of output signal is not correct due to reduced number of samples and error in the pulse width of PWM signal due to increase in time step. RT EVENTS module tool equipped with timestamp offered by RT LAB give solutions for this issue. The MATLAB simulation modules affected by events can be replaced by RTEVENTS equipped with timestamp to reduce the impact on simulation output due to increase in time step. The PWM pulse generated by RTEVENTS with timestamp, control the pulse changing accurately between two simulation steps.

5.3. Procedure to convert MATLAB model to RT LAB real time model

MATLAB-Simulink model needs to be grouped to three subsystems to use in RT-LAB and the naming of top level subsystem should use SM, SC and SS to ensure functions of different parts by RT LAB. SM (master subsystem) will take care of all real time calculations, SS(slave subsystem) is required only if computational elements are distributed across multiple nodes if complexity of the SM subsystem is too large to handle and it will take care of real time calculations and SC (console subsystem) consists of real time monitoring and data communication of key parameters, scopes, displays etc and it is the only subsystem available to us while simulation is running [21-22] Next step is to add OpComm blocks to enable and save communication setup details between console and computation nodes. All signals must go through the Opcomm module before going to subsystem on the top model. Figure 2 shows the RT lab compatible model of the DTC SVM IMD with Load profile input feed EKF estimator.

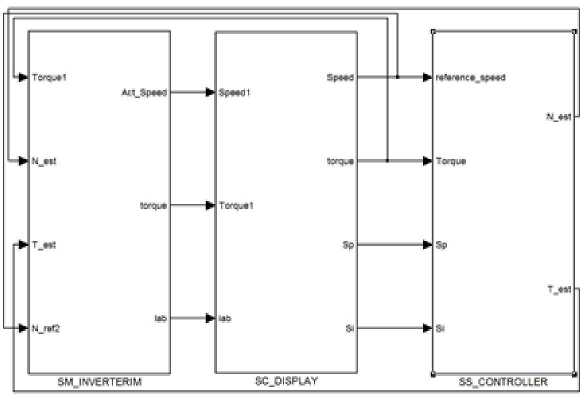


Figure 2. RT lab compatible model of the overall system

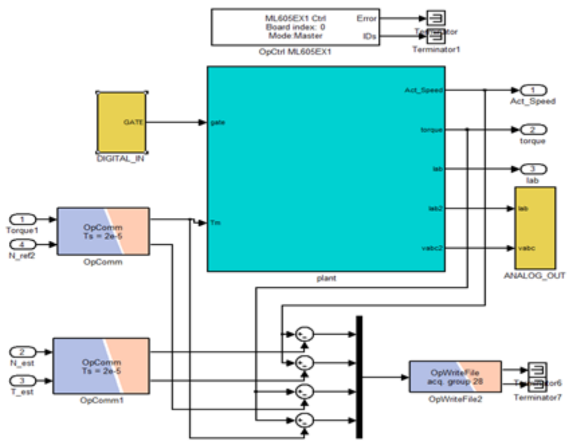


Figure 3. RT Lab real time simulation diagram of SM (master) subsystem

The RT Lab compatible model of the overall system consists of three subsystems namely the SM_ Master subsystem, SS_ Slave subsystem and SC_Console subsystem. The real time simulation models of each subsystem is shown in Figure 3,4 and 5 respectively.

The Master subsystem consists of dc input source, inverter, 20hp induction motor. Here the universal inverter bridge used in the MATLAB Simulink model is replaced by 2 level times tamped bridge. From this subsystem 3 stator voltages and two stator currents are taken out through analog output block provided by RT Lab I/O. The actual values of voltages and currents in from the model has to be scaled down in between ±16V, which is the maximum allowable limit of analog out card of the simulator. The 2 level TSB will receive gating pulses from Time Stamped Digital in (TSDI) port through event detector block. An

Opctrl block needs to be added in this subsystem which provides an interface to the Opal-RT evaluation board to control all the I/O lines.

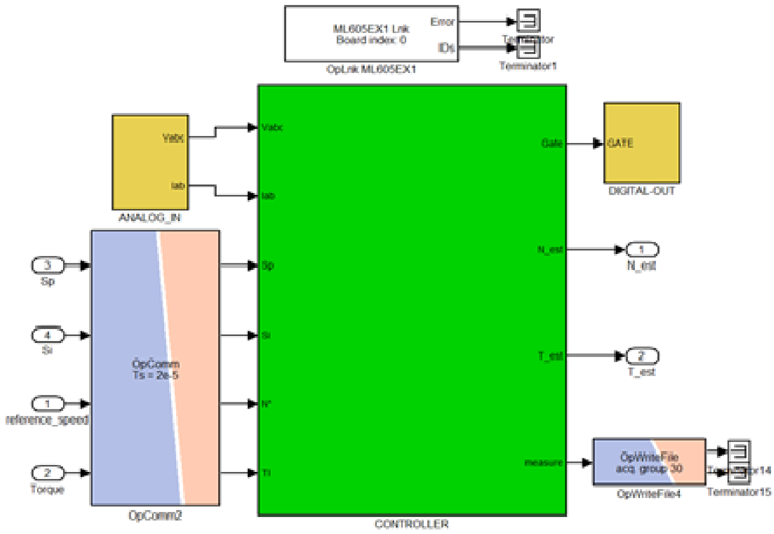


Figure 4. RT lab real time simulation diagram of SS(slave) subsystem

The SS (Slave) subsystem consists of the main controller of sensorless DTC SVM IMD with Load profile input feed EKF as the estimator. The controller will receive three stator voltages and two stator currents required for the estimation through the analog in block. The signals received from analog in block has to be rescaled before giving to the controller. The blocks used to generate PWM signals needs to be replaced by RTEVENT - blocks as shown in Figure 5 The PWM pulses generated by the controller taken out via Time Stamped Digital Out(TSDO) through Event generator block.

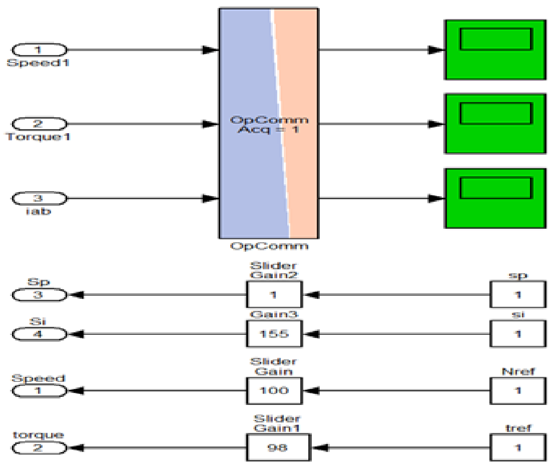


Figure 5. RT lab real time simulation diagram of SC (console)subsystem

The SC subsystem consists of all the user interface blocks like scope, slider gain etc. Using slider gain we can control the system even under running condition.

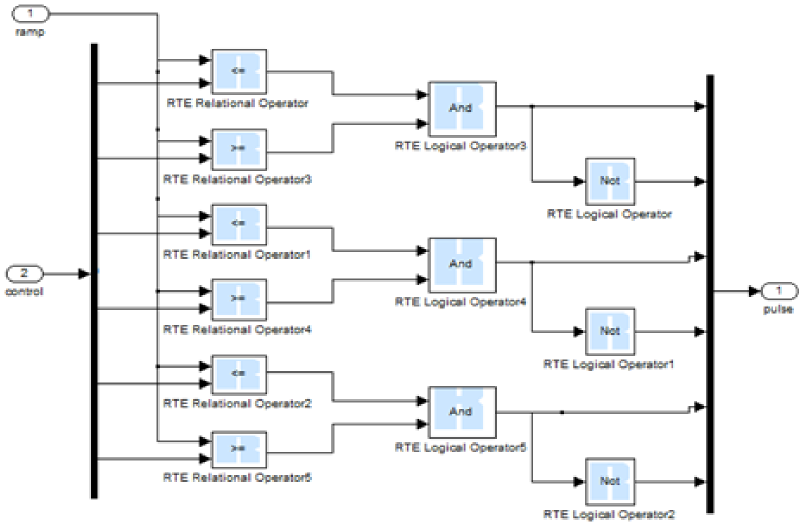


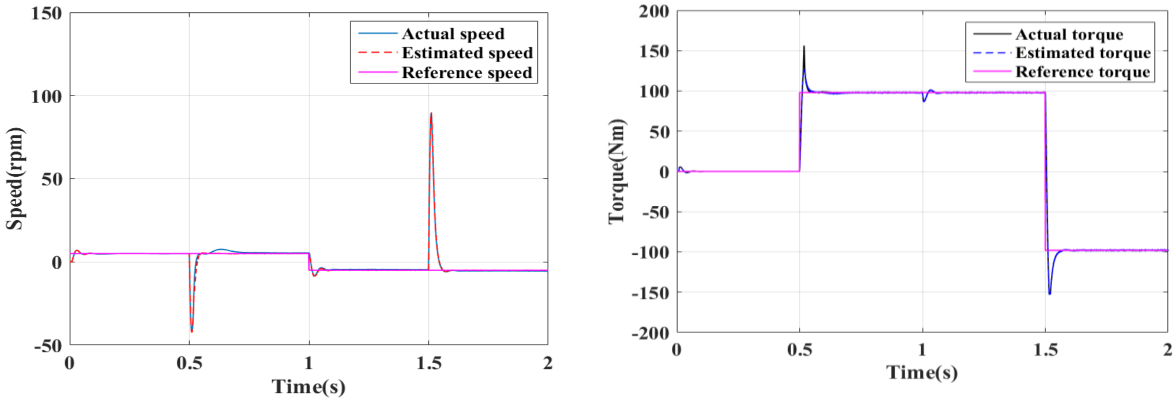
Figure 6. Pulse generation using RT-events

6. REAL TIME PROCESSOR-IN-THE LOOP SIMULATION RESULTS & ANALYSIS OF EKF CONTROLLER

The real time performance validation of the new load profile input feed EKF estimator for sensorless DTC IMD for low speed estimation was performed in Real-Time Processor- In- The-Loop (RT-PIL) using Opal-RT digital simulator. In this approach both plant and controller are running in the same simulator and they exchange real time signals via loop back cables (hardwired) through the I/Os of the simulator. Real Time - PIL results are presented here to prove the effectiveness of new EKF estimator for low speed estimation in DTC IMD. To validate the effectiveness of the new EKF algorithm during steady state and transient state, the speed and torque reversal are tested for all ranges of speeds from rated speed to very low speed including zero speed.

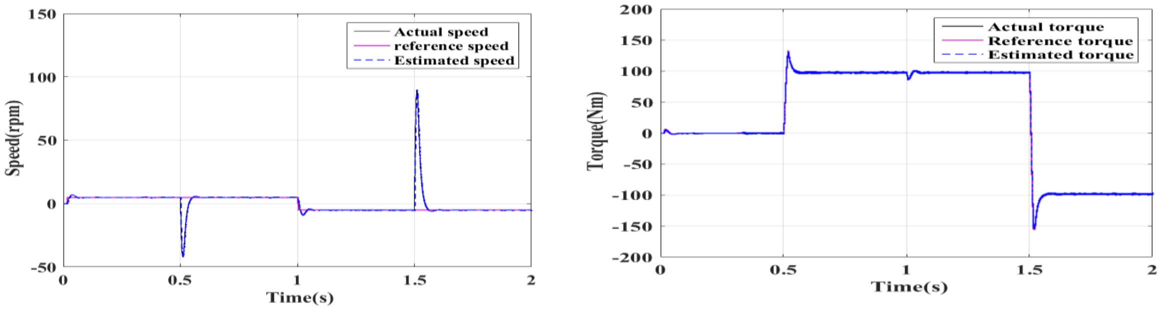
Table 2. Profile of Reference Speed and Applied Load

Time(s)	0	1	Time(s)	0	0.5	1.5
Speed(rpm)	5	-5	Torque(Nm)	0	98	-98



(a) (b)

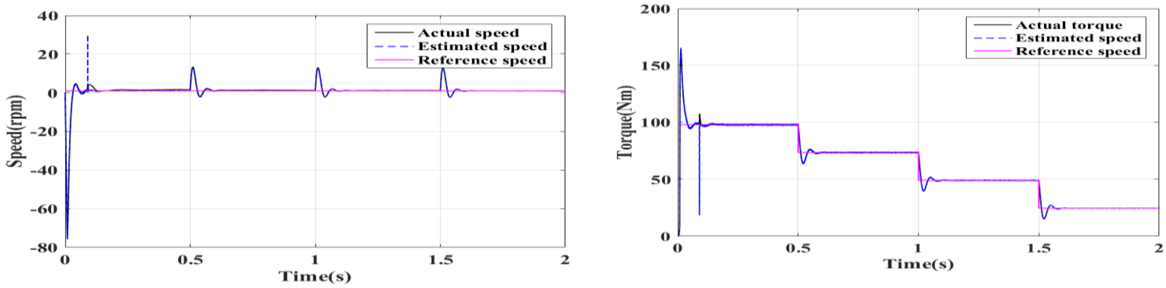
Figure 7. Plots taken through opwrite file of real time simulator at 5 rpm subjected to full load torque of 98 Nm with speed and torque reversal a) Speed plots b) Torque plots



(a) (b)

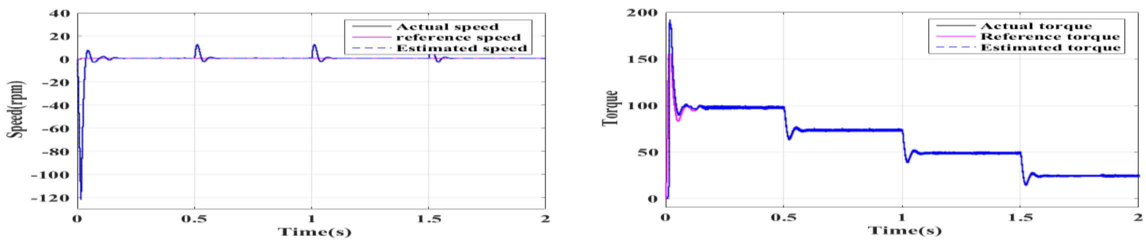
Figure 8. MATLAB-simulink simulation plots of speeds at 5 rpm subjected to full load torque of 98 Nm with speed and torque reversal a) Speed plots b) Torque plots

From Figure 7 and Figure 8 clearly proves that the load profile input feed EKF estimator provides quick response, accurate speed and torque estimation at very low speeds at rated torque with speed and torque reversal. The speed and torque estimated by EKF is closely following the reference speed and torque. This proves the effectiveness of EKF estimator for speed estimation from rated speed to very low speed. To validate the performance of the drive under varying load conditions, the drive is subjected to run at full load torque, 3/4th load, 1/2th load and 1/4th load and speed and torque estimation is observed to be satisfactory for the entire ranges of speeds. Figure 8 and Figure 9 shows the operation of the drive at 1 rpm and subjected to variable torques. The test set speed and torque values are shown in Table. 3.



(a) (b)

Figure 9. Plots taken through opwrite file of real time simulator (a) Speeds and (b) Torques at 1 rpm subjected to varying load conditions



(a) (b)

Figure 10. MATLAB-simulink simulation plots (a) Speeds and (b) Torques at 1 rpm subjected to varying load conditions

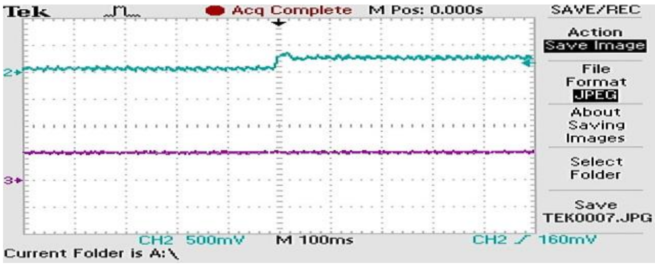
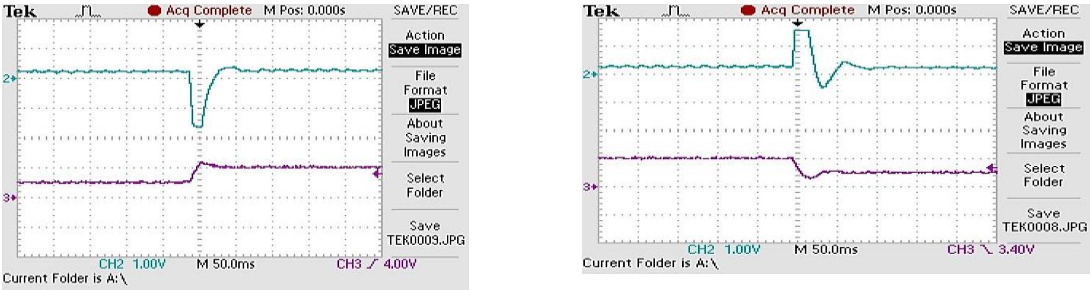


Figure 11. Real time Simulator output displayed in DSO with an applied constant torque of 98 Nm(scale:1division=100Nm) and speed varies from 2 rpm to 5 rpm (scale: 1 division= 10 rpm)



(a) (b)

Figure 12. Real time Simulator output displayed in DSO with a 2 rpm speed subjected to a torque change a) from 49Nm to 98Nm (half load to full load torque) b) from 98 Nm to 49Nm (speed scale:1 div=10 rpm and torque scale: 1div =100Nm)

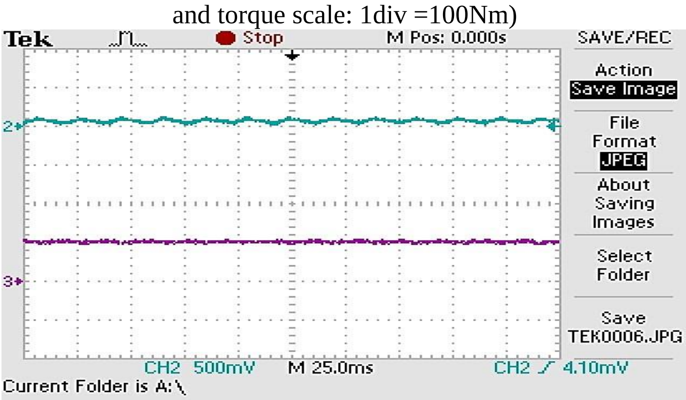


Figure 13. Real time Simulator output displayed in DSO at 0rpm subjected to full load torque of 98Nm (speed scale: 1 div = 10 rpm, Torque scale 1 div=98Nm)

The real time output seen in the DSO validates the excellent performance of the drive with EKF estimator with Load profile fed to EKF as an input for estimation.

7. CONCLUSION

To improvise the performance of the sensorless DTC IM drive during low speed operation an EKF estimator with load torque required for speed estimation is fed to the EKF model is simulated in OPAL-RT real time simulator using the Processor-In-The Loop technique to evaluate the real time performance of the EKF estimator for low speed estimation. The output results obtained from real time simulator shows the effectives of the EKF for low speed estimation at various torque and speed conditions. The steady state and transient state performance at rated full load torque and varying load conditions are verified and observed the EKF estimator gives excellent performance from rated speed to very low speed including zero speed. The Processor-In-The -Loop (PIL) validation scheme helps to analyze the performance of EKF estimator to realistic conditions using a real time simulator. The real time simulator relates the analysis to realistic problems associated communication and exchange of data between embedded processor and sensorless DTC controller. The future work is to validate the controller in Hardware-In-The -Loop real time validation technique using OPAL-RT real time simulator.

ACKNOWLEDGEMENTS

We express our gratitude to Dr. Ilam Parithi and Mr. Amit Kumar K.S of OPAL-RT, Bangalore for their support, valuable guidance and providing access to real time simulator facility for validating our EKF controller.

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