Implementation of Predictive Current Control With State Space Model in the Sensor less Induction Motor Drive

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Abstract*- A Speed sensor less control system with state space model using with the predictive current control is presented. The whole control does not require measurements of the motor speed and flux. The state variables are calculated by the observer system using only the command value of stator voltage and the measured stator current and dc link voltage. In this paper we have presented a predictive control formulation that bridges the input-output and state-space approaches of predictive control. A key element in this bridge is the relationship between state-space and input-output models. Through a special interaction matrix which can be viewed as a generalization from the state-space perspective, it shows how the coefficients of various predictive models and the predictive controller gains are related to those of the original state-space model.

The obtained simulation and experimental results confirm the good properties of the proposed speed sensorless IM drive. The proposed IM drive works correctly without speed measurements even at very low speed. The problem is periodic disturbance cancellation without explicit disturbance or system identification. For each of these problems, an appropriate interaction matrix arises that helps provide a considerably concise solution.

NOMENCLATURE

IM – induction motor
FOC – field oriented control
PWM – pulse width modulation
PCC – predictive current controller
EMF – electromagnetic force (back EMF)
αβ– stationary frame of references
dq – rotating frame of references
p.u. – per unit system
com – superscript denotes commanded value
pred – superscript denotes predicted value
^ - denotes value calculated in the observer
bold style font denotes vector
CEMF, **C**2EMF – EMF transformation matrices
e – motor EMF
is, **i**r– stator and rotor current vector
J - inertia
k, k-1 – instants of calculation: actual, previous, etc.,
kab - observer gain
Lr, Ls, Lm – motor inductances
Rr, Rs – motor resistances
Timp - inverter switching period
T_L - load torque
$\mathbf{u}_S$– stator voltage vector

I.INTRODUCTION

Three-phase induction motors are the most widely used electrical motors, due to their ruggedness and low price. The induction motor can be operated directly from the mains, but variable speed and often better energy efficiency are achieved by means of a frequency converter between the mains and the motor. A typical frequency converter consists of a rectifier, a voltage-stiff dc link, and a pulse-width modulated (PWM) inverter. The inverters controlled using a digital signal processor.

A simple way of controlling the induction motor is to adjust the magnitude of the stator voltage proportionally to a reference frequency (Schonung and Stemmler, 1964). This open-loop method, known as the scalar control or the constant voltage-per-hertz control, is still used in low-cost frequency converters due to its important advantages. A speed sensor (which is expensive, fragile, and requires extra cabling) is not needed. The knowledge of motor parameters is not necessary either, implying that the method is robust. In addition, a scalar controlled frequency converter can feed several motors connected in parallel. However, the dynamic performance and the speed accuracy are poor, even if compensation for the stator resistance voltage drop and a slip compensation are used. Furthermore, oscillations at light loads may occur (Nelson et al., 1969).

The rotor flux orientation control by Blaschke (1972) made it possible to use induction motors in applications requiring high-performance torque and speed control. In the reference frame fixed to the direction of the rotor flux, the flux and torque-producing current components can be controlled separately, resembling the control of dc motors. The rotor flux, whose angle is needed for coordinate transformations between the stationary and rotor flux reference frames, can be estimated with good accuracy if a speed sensor is used (Bauer and Heining, 1989).

The controller's reference frame can also be fixed to the stator flux estimate (Xu and Novotny, 1991). The stator flux orientation control is more complicated than the rotor flux orientation control, but the flux estimation is slightly simpler if the estimator uses only the stator dynamics. In the direct torque control (DTC) proposed by Takahashi and Noguchi (1986) and Depen brock (1988), the switching functions are directly generated on the basis of the estimates of the stator flux and the electromagnetic torque.

The goal of this thesis is to develop a speed-sensorless flux estimator with the following properties:

• Usable with a standard off-the-shelf induction motor.
• Allows high dynamic performance of the system.
• Allows robust four-quadrant operation from zero speed up to very high speeds.
• Requires only the stator current and dc-link voltage measurements.
• Digital implementation is computationally efficient.

This thesis focuses on methods based on the standard motor model. The rotor flux orientation control, popular among both academic and industrial communities, is used. Methods using soft computing (e.g., neural networks or fuzzy systems) or Kalman filtering are beyond the scope of this thesis.

II PROPOSED SYSTEM

The structure of the proposed system is shown in Fig.1.

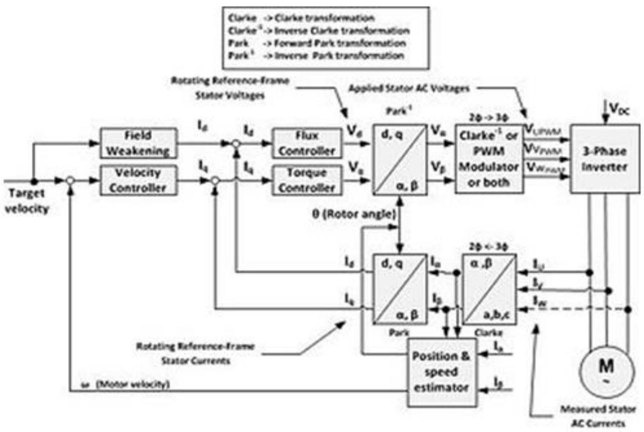

Fig 1 : Structure of the predictive current control with state space model in the sensorless induction motor drive.

The stator field oriented control method is used in the drive The superior PI controllers regulate the motor speed and rotor flux. The commanded motor current **i**scom is transformed from dq to αβ coordinates. The PCC controls the motor stator current in αβ coordinates. Calculations of the PCC are synchronized with PWM algorithm used for the inverter output voltage generation. The inverter with PWM and PCC works as controlled current source. The system works without speed sensor, while only the inverter input voltage and output currents are measured by hall-effect sensors. Other variables required by control system are calculated in closed-loop observer system.

1. FLUX OBSERVER SYSTEM

Suppose now it is desired to have a rotor flux estimation that converges faster than the real-time simulator given above. The philosophy underlying observer theory naturally suggests that a corrective signal derived from a prediction error should be added to the estimator in. So, this is essentially a closed loop observer. The companion equation which completes the idealized description of the electromagnetic variables, and which relates stator voltage $\boldsymbol{v}_s$(a two component vector) to stator current and rotor flux is

$$\boldsymbol{v}_s = (M/L_r)\,\boldsymbol{\lambda}_r' + (\sigma L_s)\,\boldsymbol{i}_s' + R_s\,\boldsymbol{i}_s \quad \ldots\ldots(1)$$

Where $\sigma = 1-(M^2/L_s L_r)$ is the leakage coefficient. Ls,Lr and Rs are stator and rotor self inductances, and the stator resistance, respectively. Rotor time constant, $T_r = L_r / R_r$, where R_r is the rotor resistance. If the stator voltage is measured, it can be compared with the stator voltage predicted on the basis of (7), but using $\hat{\lambda}_r'$ instead of λ_r'.

$$\hat{\boldsymbol{v}}_s = (M/L_r)\,\hat{\boldsymbol{\lambda}}_r' + (\sigma L_s)\,\boldsymbol{i}_s' + R_s\,\boldsymbol{i}_s \quad \ldots(2)$$

The resulting observer then takes the form

$$\hat{\boldsymbol{\lambda}}_r' = [(-1/T_r)\mathbf{I} + \omega_r \mathbf{J}]\,\hat{\boldsymbol{\lambda}}_r + (M/T_r)\,\boldsymbol{i}_s + \mathbf{G}(\hat{\boldsymbol{v}}_s - \boldsymbol{v}_s) \quad \ldots..(3)$$

Where $\boldsymbol{v}_s$ is measured stator voltage and $\hat{\boldsymbol{v}}_s$ is the stator voltage computed from (8). **G** is a 2×2 matrix of observer gains. A straight forward calculation shows that the system (5) that governed error dynamics of the real-time simulation is now replaced by

$$\boldsymbol{e}' = [(-1/T_r)\mathbf{I} + \omega_r\,\mathbf{J}]\,\boldsymbol{e} + (M/L_r)\,\mathbf{G}\,\boldsymbol{e}'$$

$$\text{or} \quad \boldsymbol{e}' = [\mathbf{I} - (M/L_r)\,\mathbf{G}]^{-1}[(-1/T_r)\mathbf{I} + \omega_r\,\mathbf{J}]\,\boldsymbol{e} \quad \ldots\ldots(4)$$

It is evident that different choices of the observer gain matrix **G** will lead to different error dynamics.
For illustration purpose, let us assume

G = g I…..(5)

where g is a scalar observer gain parameter. If the rotor speed ω_r is constant, then) is a time-invariant linear system, and the eigen values that govern it are:

$$(1 - g\,M/L_r)^{-1}\,((-1/T_r) \pm j\,\omega_r) \quad \ldots\ldots(6)$$

Thus the eigen values of the error dynamics are scaled up by the factor $(1 - g\,M/L_r)^{-1}$, i.e., the time constant that governs the error decay is scaled down from that of the real-time simulator by this factor, while the frequency of oscillation in the error decay waveform is scaled up by the same factor. For the more general time varying rotor speed case, we proceed as earlier to find that (6) is replaced by

$$(\boldsymbol{e}^*\boldsymbol{e})' = -2\,(1 - g\,M/L_r)^{-1}\,(1/T_r)\,(\boldsymbol{e}^*\boldsymbol{e}) \quad \ldots(7)$$

so that the error magnitude now decays with a time constant of

$$(1 - g\,M/L_r)\,T_r \quad \ldots\ldots..(8)$$

It is evident that g can be chosen to make this time constant considerably smaller that T_r .In implementing the closed loop flux observer given by (7) and (8), it is necessary to avoid taking derivatives. For this purpose, let us define the auxiliary variable

$$\boldsymbol{z} = [\mathbf{I} - (M/L_r)\,\mathbf{G}]\,\hat{\boldsymbol{\lambda}}_r - \mathbf{G}(\sigma L_s)\,\boldsymbol{i}_s \quad \ldots\ldots.(9)$$

Then Z^i is obtained by grouping together all the terms of (9) that contain derivatives (after substituting for $\hat{\boldsymbol{v}}_s$ (8)) so that

$$\boldsymbol{z}' = [(-1/T_r)\mathbf{I} + \omega_r \mathbf{J}]\hat{\lambda}_r + (M/T_r)\, i_s + \mathbf{G}(R_s i_s - v_s) \quad \text{…..(10)}$$

Now shows that

$$\hat{\lambda}_r = [\mathbf{I} - (M/L_r)\mathbf{G}]^{-1}[\boldsymbol{z} + \mathbf{G}(\sigma L_s)\, i_s] \quad \text{…(11)}$$

Expression for $\hat{\lambda}_r$ given by (18) is substituted in (17) to get a state equation for the vector $\boldsymbol{z}$, as follows:

$$\boldsymbol{z}' = \mathbf{F}\boldsymbol{z} + \mathbf{H}\, i_s - \mathbf{G}\, v_s \quad \text{….(12)}$$

Where

$$\mathbf{F} = [(-1/T_r)\mathbf{I} + \omega_r \mathbf{J}][\mathbf{I} - (M/L_r)\mathbf{G}]^{-1}$$

$$\mathbf{H} = \mathbf{F}\mathbf{G}(\sigma L_s) + (M/T_r)\mathbf{I} + \mathbf{G} R_s \quad \text{….(13)}$$

The differential equation (13) is solved forward from the initial condition $\boldsymbol{z}(0)$ obtained from (12), through the choice of $\hat{\lambda}_r(0)$. Then to find $\hat{\lambda}_r$ from $\boldsymbol{z}$, only (13) is used. Thus the observer is implemented without differentiating any signal.

2. EXTENSION OF THE CLOSED LOOP OBSERVER

The particular gain in (12) was chosen for ease of illustration. However, the case of a more general gain is

$$\mathbf{G} = g_1 \mathbf{I} + g_2 \mathbf{J}$$

If the rotor speed $r\omega$ is constant, the corresponding error dynamic system is again a time invariant linear system. By proper choice of g_1 and g_2 , the eigen values of the error dynamic system can be placed at any specified pair of conjugate locations. For example, if it is desired to have the Eigen values of the error dynamic system at $(a \pm bj)$ (i.e., the error components should display an oscillation at the frequency b rad/sec and damped with a time constant of $1/a$ sec), then the scalar gains g_1 and g_2 in the observer gain matrix must be:

$$g_1 = \frac{L_r}{M}\,\frac{(a - (1/T_r))(1/T_r) + (b - \omega_r)\,\omega_r}{\omega_r^2 + (1/T_r^2)}$$

$$g_2 = \frac{L_r}{M}\,\frac{(a - (1/T_r))\,\omega_r + (b - \omega_r)(1/T_r)}{\omega_r^2 + (1/T_r^2)}$$

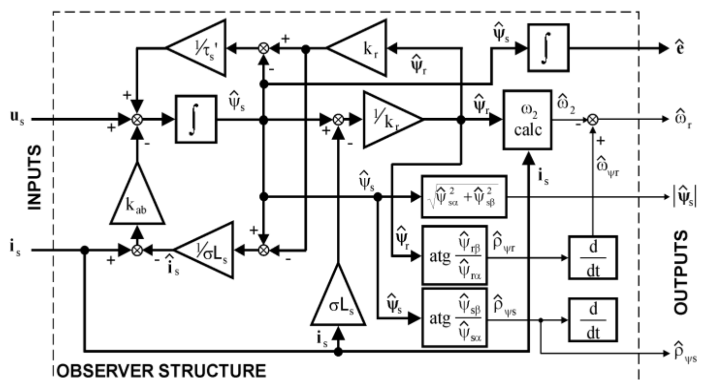

Fig 2 : Structure of the closed-loop observer.

When the rotor speed ω_r is varying slowly, g_1 and g_2 can also be varied as given above to control the variation of error dynamics.

III PREDICTIVE CONTROLLER

Model Predictive Control, or MPC, is an advanced method of process control that has been in use in the process industries such as chemical plants and oil refineries since the 1980s. Model predictive controllers rely on dynamic models of the process, most often linear empirical models obtained by system identification.

The models used in MPC are generally intended to represent the behaviour of complex dynamical systems. The additional complexity of the MPC control algorithm is not generally needed to provide adequate control of simple systems, which are often controlled well by generic PID controllers. Common dynamic characteristics that are difficult for PID controllers include large time delays and high-order dynamics.

MPC models predict the change in the dependent variables of the modelled system that will be caused by changes in the independent variables. In a chemical process, independent variables that can be adjusted by the controller are often either the set points of regulatory PID controllers (pressure, flow, temperature, etc.) or the final control element (valves, dampers, etc.). Independent variables that cannot be adjusted by the controller are used as disturbances. Dependent variables in these processes are other measurements that represent either control objectives or process constraints.

MPC uses the current plant measurements, the current dynamic state of the process, the MPC models, and the process variable targets and limits to calculate future changes in the dependent variables. These changes are calculated to hold the dependent variables close to target while honouring constraints on both independent and dependent variables. The MPC typically sends out only the first change in each independent variable to be implemented, and repeats the calculation when the next change is required.

While many real processes are not linear, they can often be considered to be approximately linear over a small operating range. Linear MPC approaches are used in the majority of applications with the feedback mechanism of the MPC compensating for prediction errors due to structural mismatch between the model and the process. In model predictive controllers that consist of only linear models, the superposition principle of linear algebra enables the effect of changes in multiple independent variables to be added together to predict the response of the dependent variables. This simplifies the control problem to a series of direct matrix algebra calculations that are fast and robust.

When linear models are not sufficiently accurate to represent the real process nonlinearities, several approaches can be used. In some cases, the process variables can be transformed before and/or after the linear MPC model to reduce the nonlinearity. The process can be controlled with nonlinear MPC that uses a nonlinear model directly in the control application. The nonlinear model may be in the form of an empirical data fit (e.g. artificial neural networks) or a high-fidelity dynamic model based on fundamental mass and energy balances. The nonlinear model may be liberalized to derive a Kalman filter or specify a model for linear MPC.

MPC is based on iterative, finite horizon optimization of a plant model. At time t the current plant state is sampled and a cost minimizing control strategy is computed (via a numerical minimization algorithm) for a relatively short time horizon in the future (t, t+T).

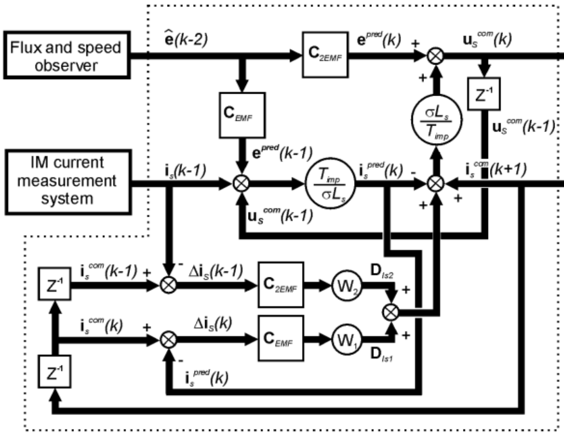

Fig 3 : Predictive current controller structure

Specifically, an online or on-the-fly calculation is used to explore state trajectories that emanate from the current state and find (via the solution of Euler-Lagrange equations) a cost-minimizing control strategy until time $t+T$. Only the first step of the control strategy is implemented, then the plant state is sampled again and the calculations are repeated starting from the now current state, yielding a new control and new predicted state path. The prediction horizon keeps being shifted forward and for this reason MPC is also called receding horizon control. Although this approach is not optimal, in practice it has given very good results. Much academic research has been done to find fast methods of solution of Euler-Lagrange type equations, to understand the global stability properties of MPC's local optimization, and in general to improve the MPC method. To some extent the theoreticians have been trying to catch up with the control engineers when it comes to MPC

IV EXPERIMENTAL RESULTS:

1. *Main circuit:*

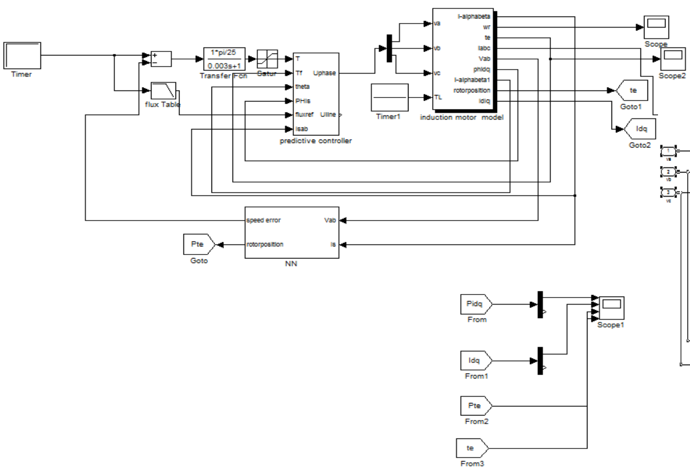

Fig 4 Main Circuit

Fig.4 Shows that the main circuit which represents the predictive current controller is based on the computation of back EMF by the observer. The whole control does not require measurements of the motor speed and flux. The state variables are calculated by the observer system using only the command value of stator voltage and the measured stator current and dc link voltage. The whole system is practically insensitive to inaccuracy of calculations and the deviation of motor parameters. In case of motor choke use, the choke parameters are added to PCC algorithm. It was shown that the choke inductance has to be taken into account in PCC calculations. The required rotor flux and motor speed by the controllers are calculated in the observer. Simultaneously, the motor EMF is calculated for a use in PCC feedback. The observer is based on the known voltage model of the induction motor with the combination of the rotor and stator fluxes. To improve the estimation properties, a feedback part was added. The rotor and stator fluxes are computed

2 Predictive current control:

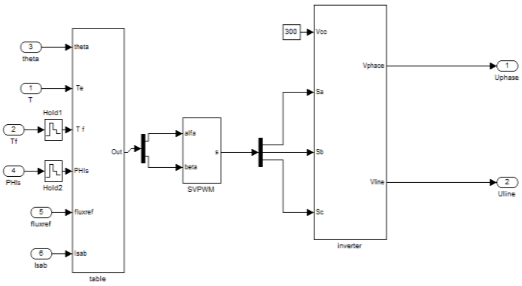

Fig 5: Predictive current control

The basic structure of the PCC implemented in the IM drive was previously presented in [6]. The relations of the PCC are based on the equations of the αβ model of the IM. For PCC derivation purposes the IM was modeled as an inductance and EMF connected in series, while the small motor resistance was neglected. In [6] the EMF was calculated using the simple equation of the IM model. In this paper, the accuracy of EMF calculation is improved. Better accuracy of EMF calculation is obtained using flux and speed closed-loop observer presented in the previous section. The observer structure is extended in order to calculate the EMF simultaneously with flux and speed computation. So in PCC the EMF calculation part is removed and substituted by the signals obtained directly from the observer system.

3 Induction motor:

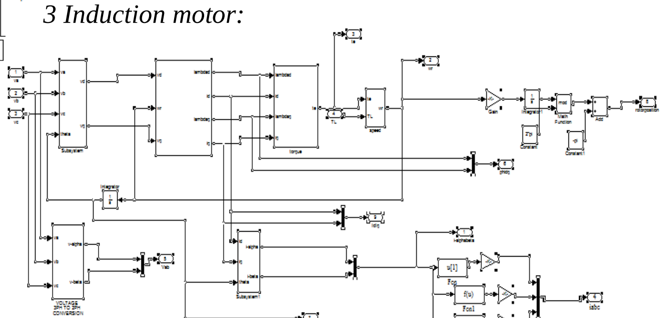

Fig 6: Induction motor

The 3 phase induction motor is modeled to accept the No-Load & Blocked rotor test results for determining the equivalent circuit parameters. The model is used to simulate various performance characteristics. these characteristics can be viewed using a scope This file calculates the equivalent circuit of a three phase induction motor from the data of open circuit test and blocked rotor test. It also calculates the thevenin equivalent circuit parameters, maximum torque induced, starting torque and slip for maximum power or torque. It finally plots torque speed characteristics of induction motor.

4 Inverter:

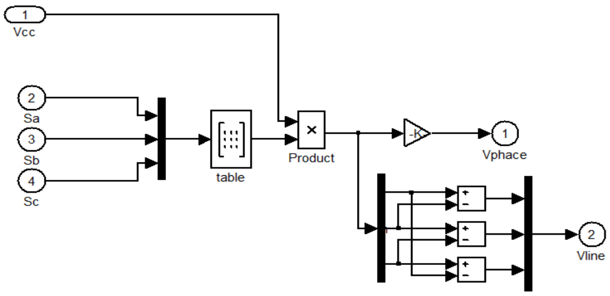

Fig 7 Inverter

This program analyzes the performance of a voltage source inverter with Sinusoidal-pulse-modulated output, under different loading conditions.

5 SVPWM:

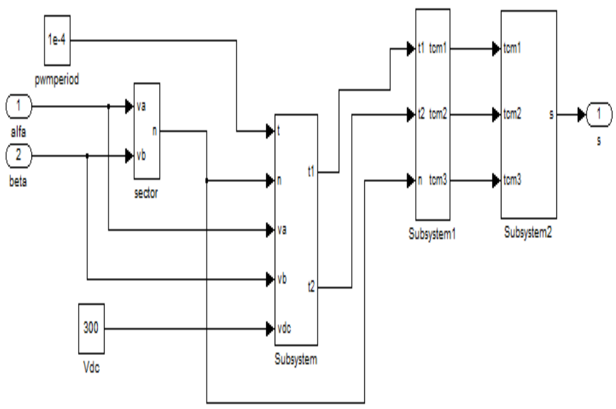

Fig 8: SVPWM

Space Vector PWM (SVPWM) is a more sophisticated technique for generating a fundamental sine wave that provides a higher voltage to the motor and lower total harmonic distortion, it is also compatible for use in vector control (Field orientation) of AC motors. This application note describes the theory of SVPWM and applies it to a practical example using a 56F803 16-bit digital signal processor

V OUTPUTS

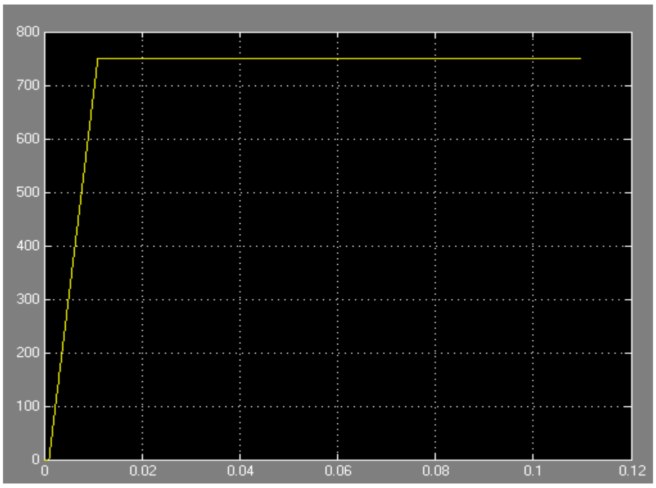

Fig.9: Step change of motor frequency related to ω_r 20% to 30% of the motor rated mechanical speed

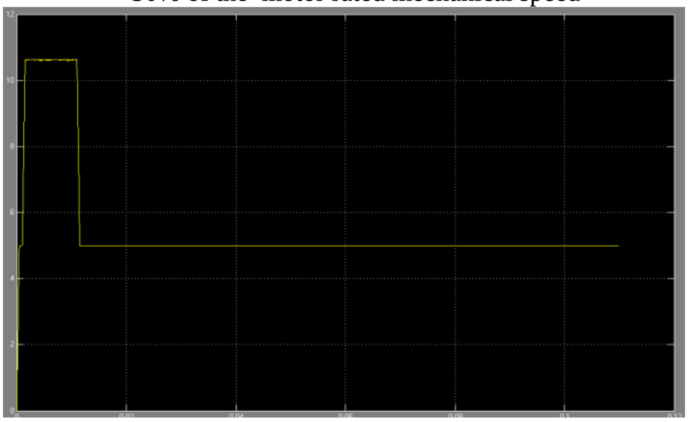

Fig10 : Motor reversing from 10% to -10% of rated speed under load.

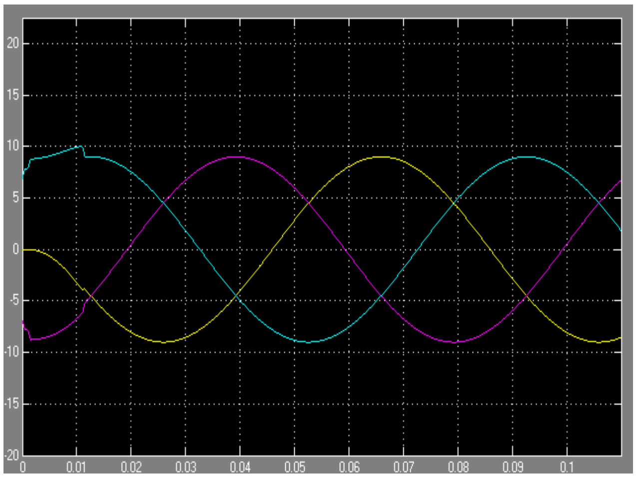

Fig 11: Three phase supply of induction motor

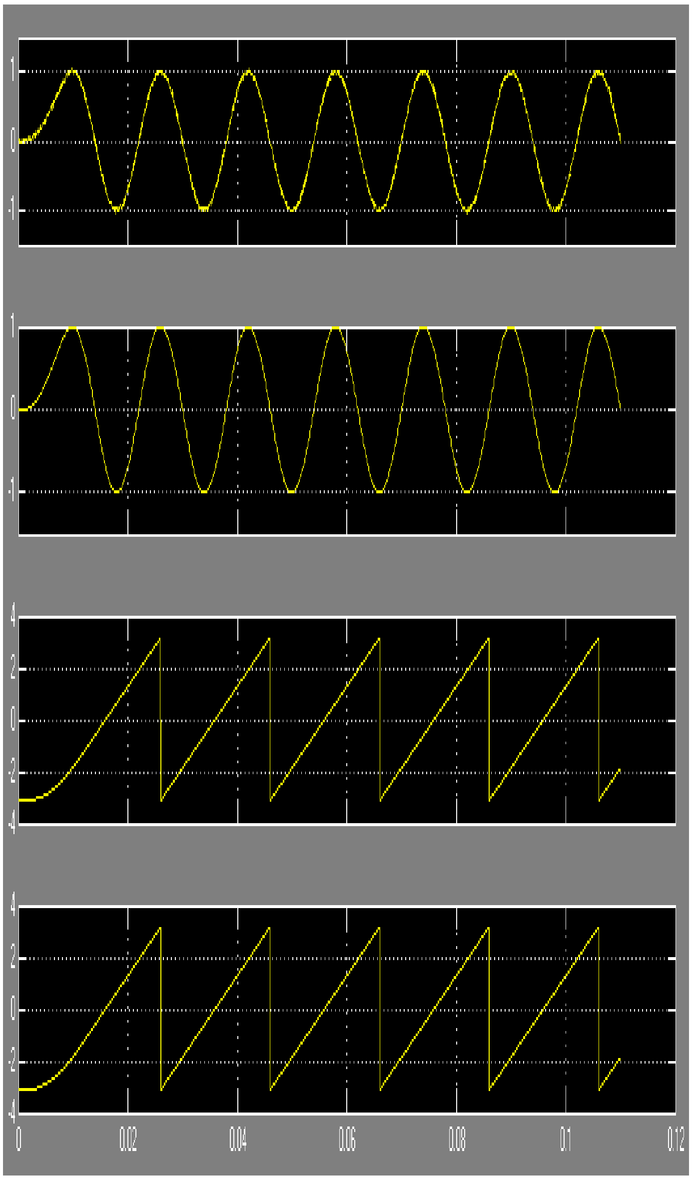

Fig.12: Response of the system for the simultaneously changes of motor parameters

VI CONCLUSIONS

The predictive current controller is based on the computation of back EMF by the observer. The whole control does not require measurements of the motor speed and flux. The state variables are calculated by the observer system using only the command value of stator voltage and the measured stator current and dc link voltage. In this paper we have presented a predictive control formulation that bridges the input-output and state-space approaches of predictive control. A key element in this bridge is the relationship between state-space and input-output models. Through a special interaction matrix which can be viewed as a generalization from the state-space perspective, it shows how the coefficients of various predictive models and the predictive controller gains are related to those of the original state-space model.

The obtained simulation and experimental results confirm the good properties of the proposed speed sensorless IM drive. The proposed IM drive works correctly without speed measurements even at very low speed. The problem of periodic disturbance cancellation without explicit disturbance or system identification. For each of these problems, an appropriate interaction matrix arises that helps provide a considerably concise solution.

VII FUTURE SCENARIO

1. Stator phase currents are measured, converted to complex space vector in (a,b,c) coordinate system.

2. Current vector is converted to (α, β) coordinate system. transformed to a coordinate system rotating in rotor reference frame, rotor position being derived by integrating the speed by means of speed measurement sensor.

3. Rotor flux linkage vector is estimated by multiplying the stator current vector with magnetizing inductance L_m and low-pass filtering the result with the rotor no-load time constant L_r/R_r, namely, the rotor inductance to rotor resistance ratio.

4. Current vector is converted to (d,q) coordinate system.

5. d-axis component of the stator current vector is used to control the rotor flux linkage and the imaginary q-axis component is used to control the motor torque. While PI controllers can be used to control these currents, bang-bang type current control provides better dynamic performance.

6. PI controllers provide (d,q) coordinate voltage components. A decoupling term is sometimes added to the controller output to improve control performance to mitigate cross coupling or big and rapid changes in speed, current and flux linkage. PI-controller also sometimes need low-pass filtering at the input or output to prevent the current ripple due to transistor switching from being amplified excessively and destabilizing the control. However, such filtering also limits the dynamic control system performance. High switching frequency (typically more than 10 kHz) is typically required to minimize filtering requirements for high-performance drives such as servo drives.

7. Voltage components are transformed from (d,q) coordinate system to (α, β) coordinate system.

8. Voltage components are transformed from (α, β) coordinate system to (a,b,c) coordinate system or fed in Pulse Width Modulation (PWM) modulator, or both, for signalling to the power inverter section.

Significant aspects of vector control application:

- Speed or position measurement or some sort of estimation is needed.
- Torque and flux can be changed reasonably fast, in less than 5-10 milliseconds, by changing the references.

- The step response has some overshoot if PI control is used.
- The switching frequency of the transistors is usually constant and set by the modulator.
- The accuracy of the torque depends on the accuracy of the motor parameters used in the control. Thus large errors due to for example rotor temperature changes often are encountered.
- Reasonable processor performance is required, typically the control algorithm has to be calculated at least every millisecond.

Although the vector control algorithm is more complicated than the Direct Torque Control (DTC), the algorithm is not needed to be calculated as frequently as the DTC algorithm. Also the current sensors need not be the best in the market. Thus the cost of the processor and other control hardware is lower making it suitable for applications where the ultimate performance of DTC is not required.

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