INTELLIGENT SENSORS BASED ON ESTIMATORS AND INTERPOLATING IMPLEMENTATION FOR FLUX AND TORQUE MEASUREMENTS

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Abstract - *The paper develops and compares intelligent sensors for flux and torque estimation in permanent magnet synchronous motors (PMSM) based on combined voltage-current flux estimators and interpolating implementation. Typical applications are in the direct torque and flux control (DTFC) and in the field-oriented vector control of ac drives. Simulation results using a PMSM drive system prove good dynamic performances of the flux and torque sensors to parameter deviations in wide speed range.*

Keywords - Intelligent sensor, State estimator, Interpolating implementation, Flux and Torque measurements in ac drive, Digital simulation.

1. INTRODUCTION

The intelligent sensor definition includes: i.) a reduced level intelligence, i.e., the synthesis of required information from partial information that present a reduced information significance when they are independently considered, and ii.) a high level intelligence, i.e., the rising of the information content using specific tools. The desired signal is obtained by using indirect measurements. An intelligent sensor with digital processing has as main tasks: control of measurement process, processing of measured values, error correction, and external communication to integrate the applications [1].

The design of the intelligent sensor concept, for steady state and dynamic measurements, requires to use also the principles from the state observer theory [2-3] and dynamic sensitivity theory[4]. Their implementations engage different structures, including interpolating structures (fuzzy, neural network, RIP) frequently used in intelligence elements.

The direct torque and flux control (DTFC) and the field oriented vector control (FOC) are modern control methods for high-dynamic performance ac drives [5-6]. They require fast estimations of the electromagnetic flux and torque vector that can be performed by using the terminal variables: stator currents and voltages, and eventually the rotor position. In recent years, flux estimators using combined voltage-current models are presented in [7-9] - for induction motors, in [5], [10] - for synchronous reluctance motors and in [11-12] - for PMSM. If the flux vector is correctly estimated, then the electromagnetic torque is simple to calculate from the estimated flux vector and measured stator current vector.

This paper is focused on the PMSM flux estimators, the problem being recently systematised in [12]. The main goal of present paper is to develop new aspects of flux estimators based on combined voltage-current models and to propose interpolating implementation as tool to rise performances.

2. INTELLIGENT SENSOR PRINCIPLE

2.1. Observer-based approach

The principle of the state observer-based intelligent sensors (SO-IS) is illustrated in the structures from fig.1a, b. All the variables are vectors. The dynamic subsystem (S) has the state vector $\boldsymbol{x}$ and the parameter vector ρ. The desired output vector $\boldsymbol{y}_i$ is not directly measured. Direct measured signals from S are $\boldsymbol{u}$ - input vector and $\boldsymbol{y}$ - output vector.

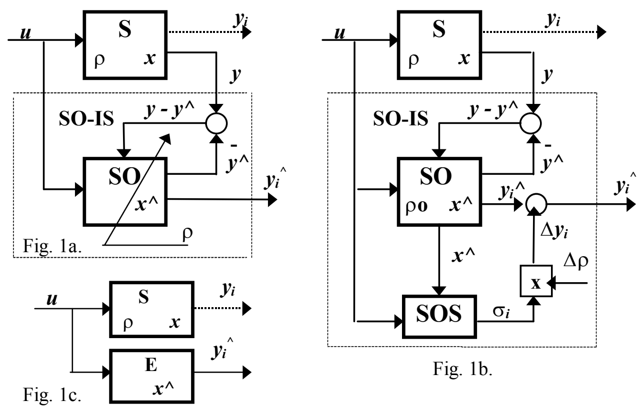


Fig.1 - Structures of state observers for intelligent sensors.

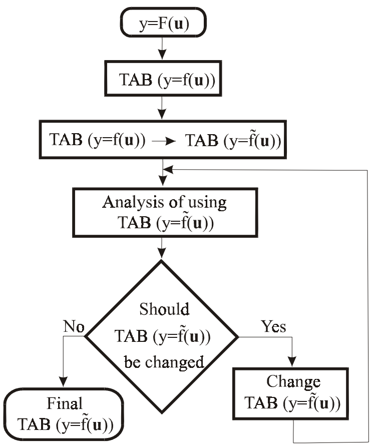
The main goal of the SO-IS structure is to obtain the vector $\hat{\boldsymbol{y}}_i$, which estimates $\boldsymbol{y}_i$, using the direct measurements $\boldsymbol{u}$ and $\boldsymbol{y}$. The superscript " ^ " means estimated variables. The state observer (SO) contains a model of the subsystem S given by structure and nominal parameters ρ_0. It has the same input $\boldsymbol{u}$ and a dynamic correction error $\boldsymbol{y} - \hat{\boldsymbol{y}}$ to estimate the state vector $\hat{\boldsymbol{x}}$, thus the desired output vector $\hat{\boldsymbol{y}}_i$. This is an asymptotic estimation, i.e., $\hat{\boldsymbol{x}}(t) - \boldsymbol{x}(t) \to 0$ in shorter time t.

Usually, the S-model is not accurately known regarding the ρ parameters. Because the SO design considers constant parameters, there are two approach to follow in parameter adaptations: i.) adaptive SO using estimated parameter ρ (fig.1a), and ii.) SO with an associated sensitivity system (SOS) (fig.1b). In the second case, σ_i represents the sensitivity function of the $\boldsymbol{y_i}$^ vector; $\Delta\rho = \rho - \rho_0$ is the parameter error related to the rated parameter ρ_0; $\Delta\boldsymbol{y_i}$^ is the dynamic correction applied to $\boldsymbol{y_i}$^. The correction error $\boldsymbol{y} - \hat{\boldsymbol{y}}$ is used to provide the loop stability for the asymptotic estimation. However, the correction is not always necessary. This is the case of direct measurements, or more general, the case when the estimation errors without this correction could be in an acceptable tolerance area regarding $\boldsymbol{y_i}$^ (fig.1c).

2.2. Interpolating implementation approach

Frequently, in measurement or control applications, arise the task to implement non-linear functions as $y = f(\boldsymbol{u})$, $\boldsymbol{u} \in \boldsymbol{R}^n$. These functions mainly represent processing algorithms given by the design of estimation or control laws. The $y=f(\boldsymbol{u})$ implementation could wake up different problems. Usually, the practice shows that the initial designed function $y = f(\boldsymbol{u})$ is necessary to be changed in the implementation process, resulting a modified function $y = \tilde{f}(\boldsymbol{u})$. The changes can have the following characters: i.) local - in the vicinity of the current point ($\boldsymbol{u}$, $f(\boldsymbol{u})$), ii.) partial - e.g., imposing some limitations, iii.) general - in the whole function domain. Therefore, the implementation of $y = \tilde{f}(\boldsymbol{u})$ finally becomes complicated, even in digital realisation.

In this context, an alternative solution seams to be the interpolating (or tabular-interpolating) implementation. The procedure used for first time by authors in [13] to generalise the RIP method [14] is suggested by the flowchart.



The TAB ($y = f(\boldsymbol{u})$) and TAB ($y = \tilde{f}(\boldsymbol{u})$) indicate the tables associated to the functions $y = f(\boldsymbol{u})$ and $y = \tilde{f}(\boldsymbol{u})$. Only the last function is implemented in tabular form to realise the application. In practice, there are used programs that have the same behaviour as the Lookup Table 2D, Lookup Table 3D from Matlab-Simulink package. The operation in this TAB takes into account the following explanation: determine current values of $\boldsymbol{u}$ as co-ordinates; vectors $\boldsymbol{u}$ from table are addresses; $y = \tilde{f}(\boldsymbol{u})$ from table are the values between them the interpolation performs the y value for the $\boldsymbol{u}$ current value.

The analysis of the application means to do relevant tests to suggest to the designer iterative local changes in TAB ($y = \tilde{f}(\boldsymbol{u})$). The changes is performed by the designer according to the design goal $y = f(\boldsymbol{u})$. It has a subjective character (most of optimisation criteria are subjectively!).

Finally, it remarks that the interpolating implementation represents not only an implementation method but also a synthesis method characterised by the following features: i) the starting point is the function $y = f(\boldsymbol{u})$ obtained as a design result from other methods; ii) the goal is to optimise the application by synthesis of the new function $y = \tilde{f}(\boldsymbol{u})$ tabular implemented; it does not direct use the design data; iii) the degree of freedom, used by designer, are: - the table structure TAB ($y = \tilde{f}(\boldsymbol{u})$), - each point ($\boldsymbol{u}$, $\tilde{f}(\boldsymbol{u})$) from the table, - the interpolation method, i.e., linear or non-linear [15]; iv) the functions $y = f(\boldsymbol{u})$ is non-inertial, without dynamic.

As a particular case of the intelligent sensor based on estimators and interpolating implementation, the next part develops the flux and torque estimation for PMSM drives.

3. FLUX AND TORQUE MEASUREMENT

The flux vector can be estimated by *estimators without corrections* from the voltage model (Eu) or from the current model (Ei), in $\alpha\beta$ stator reference (s) or in *dq* rotor reference (r). A critical evaluation regarding the sensitivity to parameter variation [12] recommends that the most suitable estimator to be: the Eu^s (1) estimator for medium-high speed and the Ei^r (2) estimator for low speed, even zero speed.

$$Eu^s: \quad d\hat{\lambda}/dt = -R_o\,\boldsymbol{i} + \boldsymbol{u}, \quad \hat{\lambda}(0) = \hat{\lambda}_0 \qquad (1)$$

$$Ei^r: \quad \hat{\lambda} = (L_{do}\,i_d + \lambda_{0o}) + j\,L_{qo}\,i_q, \quad \boldsymbol{i}(i_d, i_q), \qquad (2)$$

where $\hat{\lambda}$, $\boldsymbol{i}$, $\boldsymbol{u}$ - flux, stator current and stator voltage vectors, R_o - stator phase resistance, λ_{0o} - permanent magnet flux, L_{do}, L_{qo} - *d, q* axis inductance („*o*" - means estimated parameters). It is assumed that the air-gap magnetic flux is sinusoidal distributed, there are no damper windings, and the iron losses are neglected.

The torque (T_e) is directly computed from the estimated flux vector and the measured current vector.

$$\hat{T}_e = 3/2p\,(\hat{\lambda}_\alpha i_\beta + \hat{\lambda}_\beta i_\alpha), \quad \boldsymbol{i}\,(i_\alpha, i_\beta), \quad \hat{\lambda}\,(\hat{\lambda}_\alpha, \hat{\lambda}_\beta) \qquad (3)$$

The Eu^s estimator (1) is a pure integrator depending only on the stator phase resistance R_o. On the other hand, there are problems with the offset errors at the integrator input. It estimates the flux $\hat{\lambda}(\boldsymbol{e})$ depending on the induced voltage $\boldsymbol{e} = \boldsymbol{u} - R_o\,\boldsymbol{i}$. Eu^s is recommended at medium-high speed range.

The Ei^r estimator (2), without dynamic, strongly depends on the estimated magnetic parameters, i.e., λ_{0o}, L_{do}, L_{qo} and it requires rotator operator $e^{\pm j\theta}$. It estimates the flux $\hat{\lambda}(\boldsymbol{i})$ depending on the stator current $\boldsymbol{i}$. Ei^r is recommended at low speed range, even zero speed. The inverse operator Ei^{r-1} estimates $\hat{\boldsymbol{i}}$ from $\hat{\lambda}$.

The Eu^s and Ei^r estimators are speed invariant.

3.1. Estimator-based flux sensors

Based on the flux estimator features, there are proposed estimator-based intelligent sensors for PMSM flux and torque measurement *in wide speed range* using combined voltage-current models. The main goal is to select the Ei estimator at low speed, including zero speed, respectively the Eu estimator at medium-high speed, with a smooth and monotone transition between them depending on ω speed.

The solution consist on a Luenberger observer topology [2] as in fig.1a, but the usual linear $\boldsymbol{K}$ compensator is replaced at scalar level by a PI compensator $K = kp\,(1 + ki\,/\,s)$. The dynamic transition between Ei^r and Eu^s estimators depending on ω speed is fixed by the observer frequency bandwidth [ω_1, ω_2]. The correction is placed at the Eu^s estimator level that contains a pure integrator to have a good stability and to reduce the possible input dc offset. The compensator parameters are given by

$$kp = \omega_1 + \omega_2\,, \qquad ki = \omega_1\,\omega_2. \tag{4}$$

The recommend range for ω_1, ω_2 is: ω_1 = 2...10 rad/s, and ω_2 = (3...10) ω_1 [11].

From the voltage-current model combination [12], two solutions are selected to be the most suitable in practical implementations: i.) $E\lambda\lambda^s$ - parallel flux estimator with flux correction in stator reference (fig.2), ii.) $E\lambda i^s$ - serial flux estimator with current correction in stator reference (fig.3). These structures improve the stability of the pure integrator voltage model. The negative effect of integrator saturation, given by the *dc offset* that could be present in measurement circuits of the stator current and voltage, is avoided due to the integral term of $\boldsymbol{K}$.

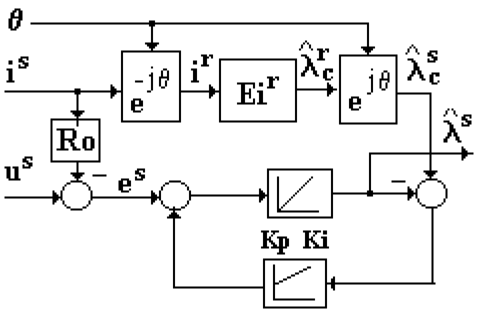


Fig.2 - Flux estimator vector structure $E\lambda\lambda^s$.

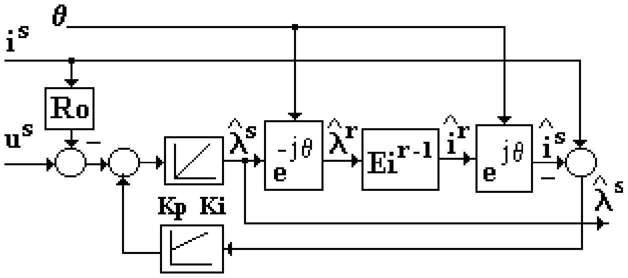


Fig.3 - Flux estimator vector structure $E\lambda i^s$.

3.2. Interpolating implementation-based flux sensor

The flux estimation, in the interpolating implementation approach (EλII), is based on the structures presented in fig.4.

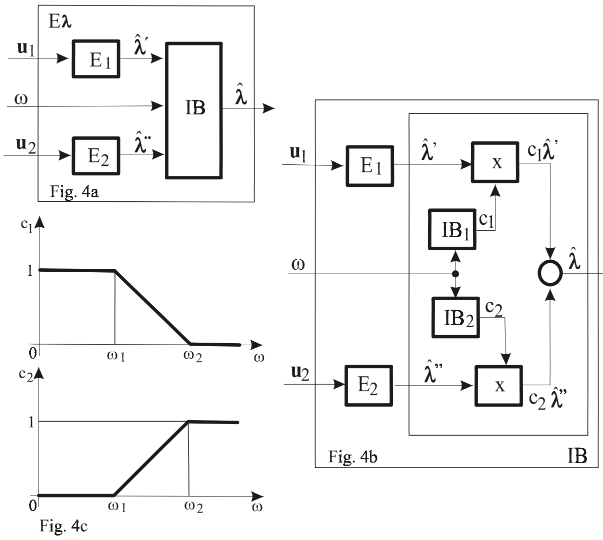


Fig.4 - Interpolating implementation of flux estimation EλII.

The flux λ is estimated in parallel by two estimators (see also fig.1c): $\hat{\lambda}'$ by the E1 estimator (Ei^r model), and $\hat{\lambda}''$ by the E2 estimator (modified Eu^s model as first order lag (5)).

$$Eu^s m: \; d\hat{\lambda}/dt + k\hat{\lambda} = -R_o\,\boldsymbol{i} + \boldsymbol{u}\,, \qquad \hat{\lambda}(0) = \hat{\lambda}_0 \tag{5}$$

The inputs are the vectors $\mathbf{u_1}$ ($\mathbf{i}^s$, θ), respective $\mathbf{u_2}$ ($\mathbf{u}^s$, $\mathbf{i}^s$). The interpolation block (IB) gives the estimated flux $\hat{\lambda}$ using as inputs $\hat{\lambda}'$, $\hat{\lambda}''$ and the speed ω, based on estimator features.

Both solutions from fig.4a, b are based on a function $\hat{\lambda} = \boldsymbol{f}(\hat{\lambda}', \hat{\lambda}'', \omega)$. The goals are: i.) recurrent optimisation of the function $\hat{\lambda} = \tilde{\boldsymbol{f}}(\hat{\lambda}', \hat{\lambda}'', \omega)$ to be more closed of λ in the entire speed range, and ii.) implementation of this function in a tabular manner using interpolation. The changes in the tables are performed as a result of the process analysis suggested in fig.5. This is based on a critical comparison between the real flux λ and the estimated flux $\hat{\lambda}$ which both are obtained by digital simulation of the electrical drive system, including the measurement procedure.

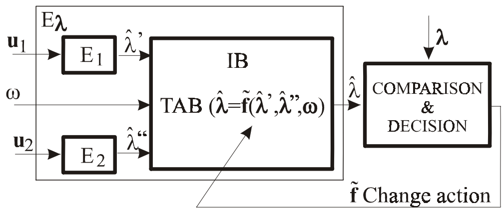


Fig. 5 – Changing process in the interpolating table.

The IB detailed in fig.4b is based on a simple relation:

$$\hat{\lambda} = c_1(\omega)\,\hat{\lambda}' + c_2(\omega)\,\hat{\lambda}'' \qquad (6)$$

Initially, according to fig.4c, the $c_1(\omega)$ and $c_2(\omega)$ terms was considered to have positive unit-complement values

$$c_1(\omega) + c_2(\omega) = 1 . \qquad (7)$$

If $\omega \in [\omega_1, \omega_2]$ then $\hat{\lambda}$ is obtained from (6) as a linear combination of $\hat{\lambda}'$ and $\hat{\lambda}''$ to realise the transition between them. If $\omega \le \omega_1$ then $\hat{\lambda} = \hat{\lambda}'$, else if $\omega \ge \omega_2$ then $\hat{\lambda} = \hat{\lambda}''$.

The functions $c_1(\omega)$ and $c_2(\omega)$ are implemented by tabular interpolation in the IB_1 and IB_2 blocks from fig.4b. The table TAB($c_1 = c_1(\omega')$) contains the $c_1(\omega)$ values corresponding to ω values $\omega'_1 = \omega_1 < \omega'_2 < ... < \omega'_{k1} = \omega_2$, while the table TAB($c_2 = c_2(\omega'')$) contains the $c_2(\omega)$ values for other ω values $\omega''_1 = \omega_1 < \omega''_2 < ... < \omega''_{k2} = \omega_2$. In particular case, the values for ω' and ω'' can be the same.

According to fig.5, the actions to change the TABs could modify $c_1(\omega'_i)$, $i = \overline{1, k_1}$ and $c_2(\omega''_j)$, $j = \overline{1, k_2}$ values, and/or the table lengths. Finally, there is the possibility that the relation (7) to be not satisfied because the compensation of the systematic errors, especially in the E_2 estimator (5), i.e., the amplitude and phase corrections. Note that the IB_1 and IB_2 blocks realise a scalar interpolation.

Other solution to implement the flux estimator (fig.4b) uses a three-dimension interpolation block, which associates the hyper-surface $\hat{\lambda} = \alpha_i \hat{\lambda}' + \beta_i \hat{\lambda}''$, $i = \overline{1, k_3}$ for each ω from $\omega'''_1 = \omega_1 < \omega'''_2 < ... < \omega'''_{k3} = \omega_2$ values. Initially, $\alpha_i + \beta_i = 1$, but this will be modified during the recursive optimisation.

At last, it remarks that the technique to modify the table TAB($y = \tilde{f}(\boldsymbol{u})$) has an empirical character. The result is a sub-optimal solution for multi-criteria optimisation problem.

3. SIMULATION RESULTS

The proposed flux intelligent sensors are incorporated in a DTFC system for PMSM drives [11] (fig.6).

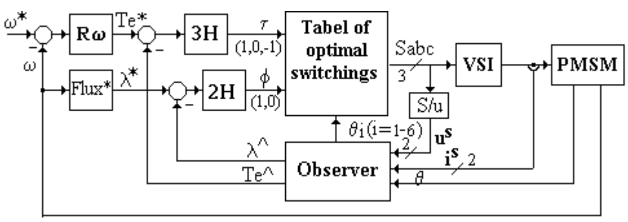


Fig.6 - DTFC structure for PMSM.

The PMSM rated parameters are p = 4 pole pair, λ_{0o} = 0.1 Wb, L_{qo} = 0.02 H, L_{do} = 0.012 H, R_o = 1.8 Ohm, J_o = 0.004 kgm^2, B_o = 0.001 Nms/rad, ω_o = 100 rad/s, T_{eo} = 2 Nm, I_{ao} = 3 A, V_{dco} = 100 V, ω_1 = 2 rad/s, ω_2 = 10 rad/s.

If the stator temperature increases with 80°C, then the stator resistance linear increases with 30%, while the PM flux linear decreases with 15%. This is called the *detuned case* with $R = 1.3\ R_o$ and $\lambda o = 0.85\ \lambda_{0o}$.

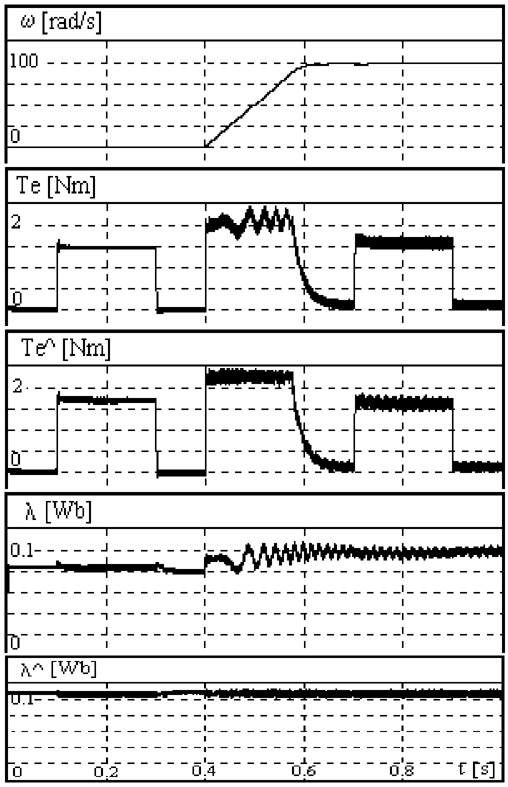


Fig.7b - Eλi^s estimator. Dynamic estimations λ^, Te^.

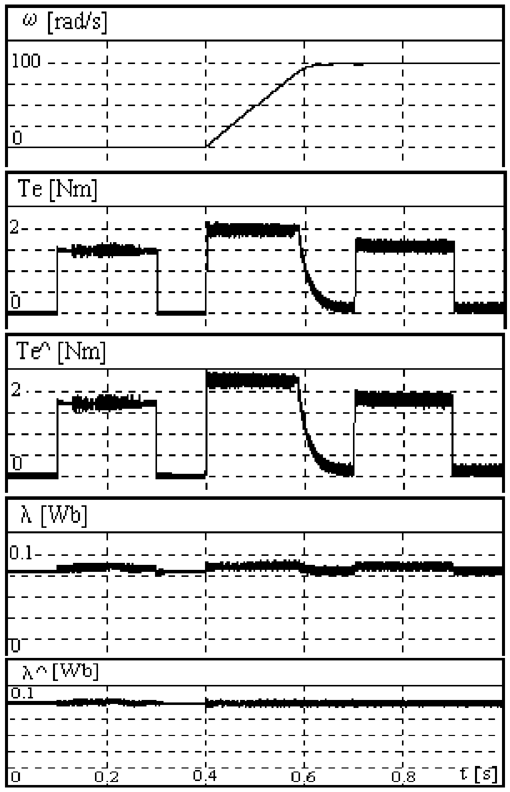


Fig.8a - Eλλ^s estimator. Dynamic estimations λ^, Te^.

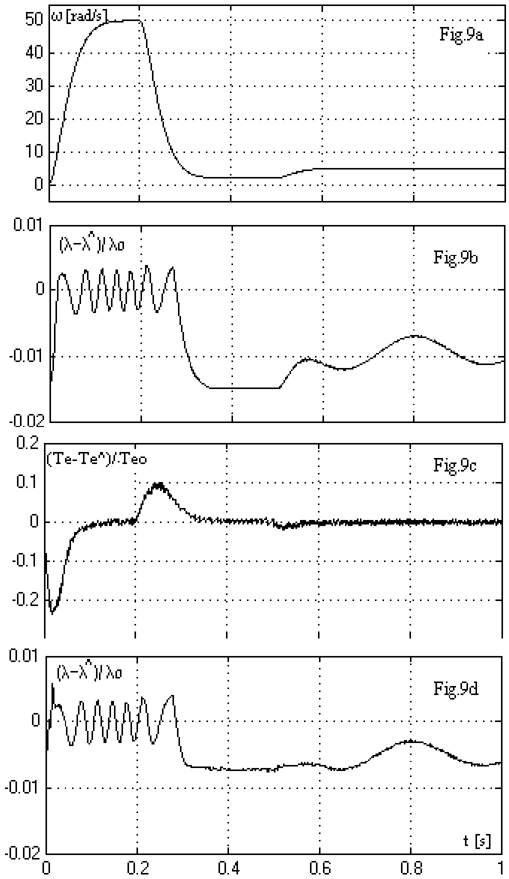


Fig.9 - EλII estimator - dynamic estimations.

The Matlab-Simulink package with Runge-Kutta 4 method having the sampling rate h = 100 μs is used. The simulation case studies presented in fig.7 - for Eλi^s estimator, and in fig.8 - for E$\lambda\lambda^s$ estimator, give the transient step responses for $\omega, T_e, \hat{T}_e, \lambda, \hat{\lambda}$. Comparative simulation results demonstrate the flux and torque estimator convergence and the robustness to large parameter variations (de-tuned case) and to load torque (T_L*=1.5 Nm), in wide speed range (0 - 100 rad/s). They also prove high-dynamic performances and global robustness of the DTFC.

To point out the functionality and the performances of the EλII (fig.4b), it is conceived the scenario from fig.9a, taking into account that the EλII parameters are k = 1 rad/s, ω_1 = 2 rad/s, ω_2 = 10 rad/s. For the case λo = 0.85 λ_{0o}, there are presented the normalized flux error $(\lambda - \hat{\lambda}) / \lambda_{0o}$ (fig.9b) and torque error $(T_e\text{-}\hat{T}_e) / T_{eo}$ (fig.9c) using variation of $c_1(\omega)$ and $c_2(\omega)$ from fig.4c. Fig.9d shows the case when $c_2(\omega)$ is modified. The scenario allows the evaluation of the estimation error that highlights the contribution of the E1 and E2 estimators depending on speed. The estimation errors are reduced even for linear variation of $c_1(\omega)$ and $c_2(\omega)$. The example from fig.9d indicates that the error could be reduced adjusting the interpolation characteristics.

4. CONCLUSIONS

The main conclusions and remarks are the following:

- The proposed PMSM intelligent sensors for flux and torque estimation in PMSM are based on combined voltage-current flux estimators and interpolating implementation. They combine advantages of the current model at low speed with the voltage model at medium-high speed using a dynamic compensator speed depending.
- The flux sensors based on estimator with compensator offer functional flexibility for usual applications. The interpolating implementation confers an additional facility for experimental tuning on application.
- These sensors solve the problem of the voltage model dc-offset from the current and voltage measurement circuits.
- The simulation results show good dynamic performances of the flux and torque sensors to parameter deviations in wide speed range.

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