# SUPERVISORY FIELD–ORIENTED CONTROL OF INDUCTION MOTORS WITH UNCERTAIN ROTOR RESISTANCE

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**Abstract:** It is well known that the performance of the (industry standard) field–oriented control (FOC) for induction motors is highly sensitive to uncertainties in the rotor resistance. In this paper we describe how to use the supervisory control ideas of Morse to obtain an adaptive implementation of FOC for current–fed machines. The unknown rotor resistance is assumed to belong to a discrete set, while the uncertain load torque ranges in a closed interval. Even though no restrictions are *a priori* imposed on the size of these sets, its definition reflects the prior knowledge of the designer, which is effectively incorporated in supervisory control designs. The supervisor selects from these sets the value to be applied to the FOC, a choice that is made by continuously comparing some suitably defined performance signals. We prove that the proposed supervisor achieves *global stabilization* of the system. To the best of our knowledge, this is the first globally convergent adaptive scheme for current–fed machines –which, by the way, largely dominate in practical applications. Some simulation results illustrate the properties of the scheme.

**Keywords:** Supervisory Control, Indirect Field-Oriented Control, Induction motors.

## 1 Introduction and problem formulation

In most practical applications induction motors are operated in the so–called current–fed mode. The behaviour of the machine in this operation mode is described by a third order model which expresses the rotor flux $\lambda \in \mathcal{R}^2$ and the stator currents $u \in \mathcal{R}^2$ in a reference frame rotating at the rotor angular speed $\omega$ as

$$\mathcal{P}: \quad \left\{ \begin{array}{rcl} \dot{\lambda} & = & -R\lambda + Ru \\ \dot{\omega} & = & \tau - \tau_L \\ \tau & = & u^T \mathcal{J} \lambda \\ \beta & = & |\lambda| \end{array} \right. \tag{1.1}$$

where $\tau$ is the generated torque, $R \in \mathcal{R}$ is the rotor resistance, which ranges in $R \in [R_M, R_m]$, with $R_m > 0$, the load torque $\tau_L$ takes values in the interval $\mathcal{T} \triangleq [\tau_{LM}, \tau_{Lm}]$, and $\mathcal{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$.

The outputs to be regulated are $\omega$ and the rotor flux norm $\beta$, which should be driven to some *constant* values $\omega_*$ and $\beta_* > 0$, respectively, while $\omega$ is the *only*

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*measurable signal.*

Notice that, without loss of generality (see e.g. [2], [9]), we have set all parameters to one except $R$ and $\tau_L$, which we assume constant and unknown. We assume known, however, the interval in which they range. See [9] for a detailed derivation of this model from the textbook standard.

Field–oriented control (FOC) is the *de–facto* industry standard for high performance application induction motors. In its indirect formulation FOC is a nonlinear dynamic output feedback controller with a cascaded structure where the inner loop control consists of a rotation and the outer loop is typically defined via a PI regulator around the velocity error as

$$\mathcal{C}(\hat{R}): \quad \left\{ \begin{array}{rcl} u & = & \mathbf{e}^{\mathcal{J}\rho} \left[ \begin{array}{c} \beta_* \\ \frac{\tau_d}{\beta_*} \end{array} \right] \\ & = & \left[ \begin{array}{cc} \cos(\rho) & -\sin(\rho) \\ \sin(\rho) & \cos(\rho) \end{array} \right] \left[ \begin{array}{c} \beta_* \\ \frac{\tau_d}{\beta_*} \end{array} \right] \\ \dot{\rho} & = & \frac{\hat{R}}{\beta_*^2} \tau_d \\ \tau_d & = & -\left( K_P + \frac{K_I}{p} \right) e_\omega \\ e_\omega & = & \omega - \omega_* \end{array} \right. \tag{1.2}$$

Here $p = \frac{d}{dt}$, $\hat{R} > 0$ is the *constant estimated* rotor resistance, and $K_P, K_I > 0$ are some tuning gains. We use the notation $\mathcal{C}(\hat{R})$ to underscore the dependence of the controller on the estimated rotor resistance. It is important to remark that, even though $\tau_L$ is unknown, the controller does not attempt to estimate it, since its effect is countered by the integral action, at least as long as it remains constant.

The following remark concerning the practical implementation of FOC is in order: the angle $\rho$, which plays the role of an estimate of the rotor flux angle, is generated as the output of an integrator whose input $\tau_d$ converges to a nonzero constant, therefore it grows unbounded. Since $\rho$ is subsequently used as the argument of periodic functions, the windup problem is avoided by simply resetting the integrator.

In [2] (see also [9]) we have shown that the closed-loop system (1.1), (1.2) has a unique equilibrium point if and only if $0 < \hat{R} \leq 3R$, which is satisfied in most practical applications. Furthermore, we prove this equilibrium is *globally exponentially stable* provided $|R - \hat{R}|$ is sufficiently small.[1] This establishes, via total stability arguments, that the scheme is robustly stable *vis–à–vis* variations in the rotor resistance, which are unavoidable in practical applications. However, extensive simulation and experimental evidence, e.g., [5], [11], [3], [9] have shown that *performance* and power efficiency are significantly degraded when there are large errors on the rotor resistance estimate. This stems from the fact that the main objective of field orientation is not achieved in this case [9].

A natural approach to solve this problem is to make the FOC adaptive by defining an update law for $\hat{R}$. In this paper we achieve this end applying the *supervisory control* ideas of Morse [7], [8]. To this end, we define a discrete set of candidate resistance values

$$\mathbf{R} \stackrel{\triangle}{=} \{R_1,\ R_2, \cdots, R_N\} \subset [R_M,\ R_m] \tag{1.3}$$

with $N \geq 2$, and *assume* that the actual rotor resistance belongs to this set,[2] i.e.,

$$\exists\ i_* \in \mathcal{N} \stackrel{\triangle}{=} \{1, 2, \cdots, N\} : R_{i_*} = R \tag{1.4}$$

A supervisor, which selects the value to be applied to the FOC, is then set in place. The supervisor i) continuously compares some suitably defined performance signals and ii) uses in the FOC the estimated value whose corresponding performance signal is the smallest. The rationale underlying the supervisors operation is very simple: the nominal model whose associated performance signal is the smallest, "best" approximates the process behaviour and thus the corresponding controller ought to be able to control the process better. The origin of this idea is the concept of certainty equivalence. This is a well known heuristic idea central to the whole adaptive control literature whose role has been formally established for linear plants in [6] and extended to nonlinear systems in the recent paper [4]. See also [1].

The performance signals in supervisory control [7] are generated by designing an estimator for each member of $\mathbf{R}$ and evaluating their norm–squared output estimation error. This task is complicated in the present problem because, besides the uncertainty in $R$, the load torque $\tau_L$ is also unknown. Furthermore, not all state variables are available for measurement. To overcome these difficulties we need to implement a flux observer and simultaneously estimate $R$ and $\tau_L$. The main result of the paper is the proof that this new globally convergent adaptive observer, which is of interest on its own, together with the proposed supervisor achieves *global stabilization* of the system. To the best of our knowledge, this is the first globally convergent adaptive scheme for current–fed machines, which is, moreover, an "add–up" to the widely popular FOC, and not a radically new complicated controller that will hardly be adopted by practitioners.

[1] Bounds on the allowable estimation error in terms of $K_P, K_I$ and $\tau_L$ are also given in that paper.

[2] For all practical purposes we can relax this assumption to "$R$ sufficiently close to a set member". This can, of course, be ensured taking a finer grid, at the price of increased computational burden.

The remaining of the paper is organized as follows. In Section 2 we present the supervisory control scheme. The main result is presented in Section 3. In Section 4 we show some simulation results which illustrate the properties of the scheme. We wrap–up the paper with some concluding remarks in Section 5.

## 2 Estimator–based supervision

A block diagram describing the overall supervisory control system is depicted in Fig. 1. It consists of the induction motor model $\mathcal{P} : (u, \tau_L) \mapsto \omega$ (described by (1.1)), in closed–loop with the parametrized FOC $\mathcal{C}(\hat{R}) : (\omega, \omega_*, \beta_*) \mapsto u$ (with dynamics (1.2)), whose estimated rotor resistance $\hat{R}$ is generated by the estimator–based *supervisor* $\Sigma : (u, \omega) \mapsto \hat{R}$. We proceed now to derive the elements entering in the definition of $\Sigma$. To motivate our developments we will consider first in the next section a hypothetical case of known parameters. The supervisor is derived in Subsection 2.2.

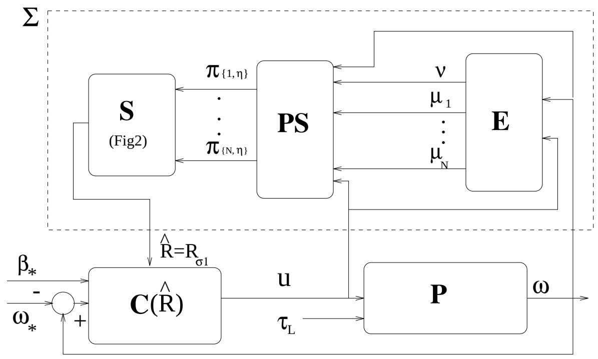


Figure 1: Configuration of the supervisory control system

### 2.1 Observer design for the known parameter case

Assume for the moment that $R$ and $\tau_L$ were known. In this case one could construct a nonlinear state-observer for (1.1) using the equations[3]

$$\begin{aligned} \dot{\hat{\lambda}} &= -R\hat{\lambda} + Ru, & (2.1)\\ \dot{\hat{\omega}} &= u^T \mathcal{J}\hat{\lambda} - \tau_L - \kappa(1+|u|^2)(\hat{\omega} - \omega), & (2.2) \end{aligned}$$

[3]Notice that we have introduced a weighting factor $(1 + |u|^2)$ in the correction term of the observers. The role of this term will be clarified in the next section.

where $\kappa$ is any constant larger than $\frac{1}{2}$. In fact, with $\hat{\lambda}$ and $\hat{\omega}$ so defined, one can show that the estimation errors

$$\tilde{\lambda} \triangleq \hat{\lambda} - \lambda, \quad \tilde{\omega} \triangleq \hat{\omega} - \omega, \qquad (2.3)$$

converge to zero exponentially fast for any piecewise continuous (possibly unbounded) input signal $u$. To see that this is so consider an arbitrary piecewise continuous input signal $u$. From (2.3) one concludes that

$$\dot{\tilde{\lambda}} = -R\tilde{\lambda}, \quad \dot{\tilde{\omega}} = u^T \mathcal{J}\tilde{\lambda} - \kappa(1+|u|^2)\tilde{\omega},$$

along solutions to (1.1), (2.1)–(2.2). Thus, defining the exponentially weighted Lyapunov-like function

$$V = e^{\gamma t}\left(\frac{1}{2R}|\tilde{\lambda}|^2 + \frac{1}{2}\tilde{\omega}^2\right)$$

where $\gamma$ is a positive constant, one concludes that along solutions to (1.1), (2.1)–(2.2),

$$\begin{aligned} \dot{V} &\leq \gamma V + e^{\gamma t}\left(-|\tilde{\lambda}|^2 + |\tilde{\omega} u|\,|\tilde{\lambda}| - \kappa(1+|u|^2)\tilde{\omega}^2\right)\\ &\leq \gamma V + e^{\gamma t}\left(-\frac{1}{2}|\tilde{\lambda}|^2 - \kappa\tilde{\omega}^2 - \left(\kappa - \frac{1}{2}\right)|u|^2\tilde{\omega}^2\right) \end{aligned}$$

where we have used the Schwartz inequality. Therefore, one can conclude that

$$\dot{V} \leq -e^{\gamma t}\left(\kappa - \frac{1}{2}\right)|u|^2\tilde{\omega}^2 \qquad (2.4)$$

for any positive constant $\gamma$ such that $\gamma \leq \min\{R, 2\kappa\}$.

For such a $\gamma$, $V$ must then be bounded and therefore both $\tilde{\lambda}$ and $\tilde{\omega}$ converge to zero as fast as $e^{-\frac{\gamma}{2}t}$. Moreover, integrating both sides of (2.4), one further concludes that

$$\int_0^t e^{\gamma\tau}|u(\tau)|^2\tilde{\omega}^2(\tau)d\tau \;\leq \tfrac{2}{2\kappa-1}V(0), \quad t \geq 0 \quad (2.5)$$

Now, for each piecewise continuous signal $u$ (2.2) can be regarded as a linear time-varying system with inputs $u^T\mathcal{J}\hat{\lambda} + \kappa(1+|u|^2)\omega$ and $-\tau_L$. Thus the same estimate $\hat{\omega}$ could also be generated by the 2-dimensional system

$$\begin{aligned} \dot{\mu} &= -\kappa(1+|u|^2)\mu + u^T\mathcal{J}\hat{\lambda} + \kappa(1+|u|^2)\omega & (2.6)\\ \dot{\nu} &= -\kappa(1+|u|^2)\nu - 1 & (2.7)\\ \hat{\omega} &= \mu + \tau_L \nu & (2.8) \end{aligned}$$

We will see shortly that generating $\hat{\omega}$ as above is more convenient for our purposes. The following has been proved:

**Proposition 2.1.** *Let $\gamma$ be a positive constant no larger than $\min\{R, 2\kappa\}$. For any piecewise continuous signal $u$ and any initial conditions there exist* *positive constants $c_1, c_2, c_3$ such that*

$$\int_0^t e^{\gamma\tau}(1+|u(\tau)|^2)\tilde{\omega}^2(\tau)d\tau \le c_1, \quad |\tilde{\lambda}| \le e^{-\frac{\gamma}{2}t}c_2,$$
$$|\tilde{\omega}| \le e^{-\frac{\gamma}{2}t}c_3, \qquad t \ge 0$$

*along solutions to (1.1), (2.1), (2.3), (2.6)-(2.8).*

## 2.2 Derivation of the supervisor

The previous proposition motivates the following *multi-estimator*

$$\begin{cases} \dot{\lambda}_i = -R_i\lambda_i + R_i u \\ \dot{\mu}_i = -\kappa(1+|u|^2)\mu_i + u^T\mathcal{J}\lambda_i + \kappa(1+|u|^2)\omega \\ \dot{\nu} = -\kappa(1+|u|^2)\nu - 1 \end{cases} \tag{2.9}$$

and *performance signal generator*[4]

$$T_\pi \dot{w}_i = -w_i + (1+|u|^2)\begin{bmatrix} \nu^2 \\ 2\nu(\mu_i-\omega) \\ (\mu_i-\omega)^2 \end{bmatrix} \tag{2.10}$$

where $T_\pi$ is a positive constant no smaller than $1/\min\{R, 2\kappa\}$. The time constant $T_\pi$ plays the role of a forgetting factor of standard adaptive control [10].

For each pair $\{i,\eta\} \in \mathcal{N}\times\mathcal{T}$ we can then define a *performance signal*

$$\pi_{\{i,\eta\}} \triangleq \Pi(w_i,\eta) \tag{2.11}$$

where $\Pi : \mathbb{R}^3 \times \mathcal{T} \to \mathbb{R}$ denotes the *performance function* defined by $\Pi(w,\eta) = \begin{bmatrix}\eta^2 & \eta & 1\end{bmatrix} w_i$.

The above definitions of the performance signal generator and performance function are prompted by the observation that, with the $\pi_{\{i,\eta\}}$ given by (2.11),

$$T_\pi \dot{\pi}_{\{i,\eta\}} = -\pi_{\{i,\eta\}} + (1+|u|^2)(\mu_i + \eta\nu - \omega)^2. \tag{2.12}$$

and that from (2.8), $(\mu_{i*} + \tau_L\nu - \omega)^2 = \tilde{w}^2$. Therefore, since $1/T_\pi \le \min\{R, 2\kappa\}$, Proposition 2.1 guarantees that for $\{i,\eta\} = \{i_*, \tau_L\}$, $\pi_{\{i,\eta\}}$ converges to zero as fast as $e^{-t/T_\pi}$. Thus, each $\pi_{\{i,\eta\}}$ can be viewed as a measure of the expected performance of $i$ and $\eta$ as estimates of $i_*$ and $\tau_L$, respectively. In a supervisory control context it is then natural to regard the pair[5]

$$\begin{aligned} \{i_{\min}, \tau_{L_{\min}}\} &\triangleq \arg \min_{\{i,\eta\}\in\mathcal{N}\times\mathcal{T}} \pi_{\{i,\eta\}} \\ &= \arg \min_{\{i,\eta\}\in\mathcal{N}\times\mathcal{T}} \Pi(w_i,\eta) \end{aligned} \tag{2.13}$$

as an estimate of $\{i_{i_*}, \tau_L\}$. This is because the pair $\{i_{\min}, \tau_{L_{\min}}\}$ is at least "as good as" $\{i_{i_*}, \tau_L\}$ as far as the values of the corresponding performance signals are concerned.

The algorithm used to generate $\hat{R}$ is the *scale-independent hysteresis switching logic* [1] and can be regarded as the hybrid dynamical system, with state $\sigma \triangleq \{\sigma_1, \sigma_2\} \in \mathcal{N}\times\mathcal{T}$ and output

$$\hat{R} = R_{\sigma_1}, \tag{2.14}$$

defined by the computer diagram in Figure 2. Here $h$ is a pre-specified positive constant called the *hysteresis constant*, the $\pi_p$ are defined by (2.11), and the pair $\{i_{\min}, \tau_{L_{\min}}\}$ is defined by (2.13).

We shall require that the performance signal generator be initialized so that[6]

$$\pi_{\{i,\eta\}}(0) > 0, \qquad \forall i \in \mathcal{N},\ \eta \in \mathcal{T} \tag{2.15}$$

Because of (2.12), this guarantees that all the $\pi_{\{i,\eta\}}$ remain strictly positive for all future times. This is used in the sequel to exclude the possibility of chattering.

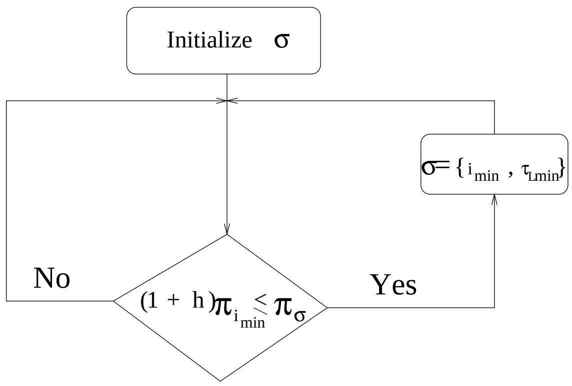


Figure 2: Scale-independent hysteresis switching logic.

# 3 Main Result

**Theorem 3.1.** [7] *Consider the induction motor model (1.1) in closed-loop with the multi-controller (1.2), the multi-estimator (2.9), the performance signal generator (2.10) and the switching logic in Figure 2 with output given by (2.14).*

[4] The first component of each of the $w_i$ is generated by the same differential equation so the performance signal generator could be implemented more efficiently using a $2N+1$ dimensional system, instead of the $3N$ dimensional system in (2.10).

[5] The optimization in (2.13) can be trivially computed in a closed form because, for each value of $i$, $\Pi(w_i,\eta)$ is a quadratic function of $\eta$.

[6] This can be achieved, for example, by setting $w_i(0) = [a, 2b, c]^T$, $i \in \mathcal{N}$, for some $a, b, c \in \mathbb{R}$ so that $a > 0$ and $b^2 - ac < 0$.

[7] For the complete version of the paper with the proof of this theorem please address to the authors.

*For any initialization of the closed-loop system such that (2.15) holds, the solution exists in $[0, \infty)$ and the signals $\lambda, \omega, v, \nu, \lambda_i, \mu_i, w_i$, $i \in \mathcal{N}$ are uniformly bounded on $[0, \infty)$. Moreover, $\rho$ grows at most linearly with time and $\omega \to \omega_*$ as $t \to \infty$* [8].

# 4 Simulations

With the goal of verifying the performance of the supervisor FOC described above several simulation tests were carried out. We consider the academic example reported in [3] where the (fixed parameter) FOC operates very close to the stability boundary predicted in proposition 4 of [2], and a small change in the rotor resistance drives the system to instability. This is illustrated in Fig. 3 where we have set $K_P = 0.1$, $K_I = 1$, $\beta_* = 1$, $\omega_* = 10$, $\hat{R} = 10$, the initial conditions are all set equal to zero except $\omega(0) = 10.1$ and the motor operates without load, i.e., $\tau_L = 0$. The rotor resistance changes from its initial value $R = 6$, for which the closed-loop is stable, to the instability region of $R = 4$ at $t = 40$. The theoretical stability–instability boundary in this case is $R = 4.9$. Fig. 4 shows the same experiment but with the supervisory FOC with $N = 6$, $\mathbf{R} = \{2, 4, \cdots, 12\}$, $\sigma_2(0) = 0.5$ (note: $\sigma_2(0)$ is the initial estimate for $\tau_L$) , $\hat{R}(0) = 10$ and $\kappa = 5, h = 0.02$, $T_\pi = 1/3.5$. For the extreme points of the interval, to which the load torque $\tau_L$ belongs, we have fixed $\tau_{Lm} = 0$ and $\tau_{LM} = 5$. The initial conditions of $w_i$ were chosen so that (2.15) holds. Their initial values were $w_i(0) = [2, -2, 2]^T$ for $i \in \mathcal{N}$. Notice that, after a very brief transient, the supervisor correctly estimates the resistance value and stabilizes the motor.

In a second test, we considered a situation where both the rotor resistance and the load torque change. The rotor resistance changes from its initial value $R = 6$ to $R = 8$ at $t = 60$ and the load torque changes from its initial value $\tau_L = 2$ to $\tau_L = 3$ at $t = 20$ and changes again to $\tau_L = 4$ at $t = 40$. From Fig. 5, one can observe that the tracking as well as the correct estimation of the rotor resistance and the load torque are achieved with only brief burstings at the jump instants.

Finally, we investigated the sensitivity of the scheme *vis à vis* the filter time constant $T_\pi$. The simulations showed that, as expected due to a longer memory in the performance signals, when the value of $T_\pi$ is increased, the transient becomes slower. On the other hand, if we set $T_\pi$ to a very small value the switching is faster but exhibits significant dither.

Other simulations with various values of $\kappa$ and $h$ confirmed that performance is less sensitive to these parameters.

# 5 Conclusions

We have presented in this paper an application of Morse's supervisory control to induction motors with uncertainty in the rotor resistance. This is a problem of great practical importance which, in the authors' opinion, had not found a satisfactory solution in the literature. Motivated by industrial practice we consider the case of current–fed induction motors and propose to adjust on line one parameter of the existing FOC. The overall scheme is shown to be globally convergent under the assumption that the actual rotor resistance belongs to a given discrete set and that the load torque ranges in some known finite set. Both assumptions are reasonable in applications. In spite of its apparent complexity the supervisor involves very simple operations, which can be easily implemented in modern DSPs with numerically robust algorithms. The performance of the scheme, as well as its sensitivity to the various tuning parameters, were tested via simulations. In a future paper we will report the application of this algorithm to the experimental set-up of the benchmark problem recently proposed in the literature.[9]

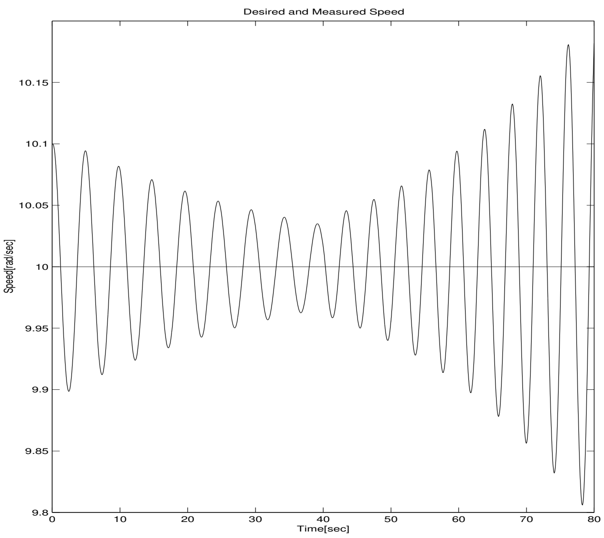


Figure 3: Instability in the nonadaptive FOC due to a change in the rotor resistance.

[8] One would also like to prove that $|\lambda| \to \beta_*$ as $t \to \infty$ but this seems unlikely unless one can show that $\hat{R} \to R$.

[9] See the web site: http://www.supelec.fr/invi/lss/fr /personnels/ortega/benchmi/benchmi.html.

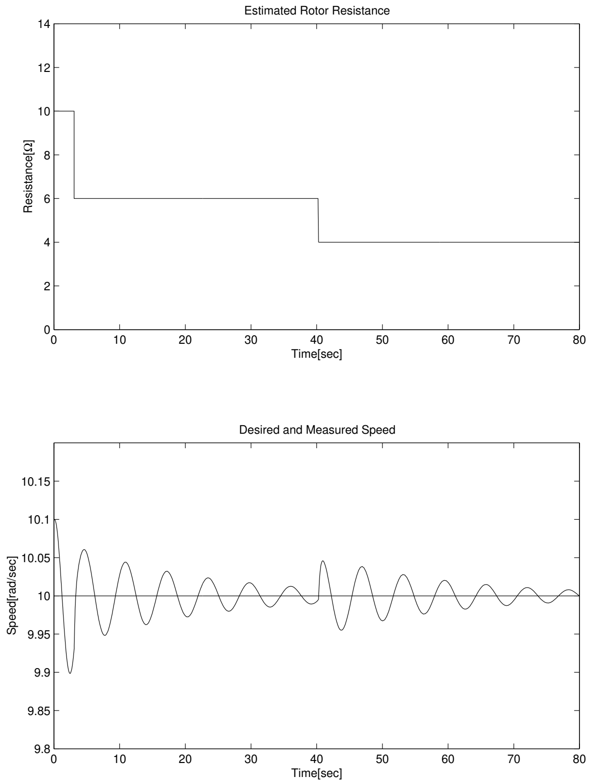


Figure 4: Stabilization with supervisory FOC

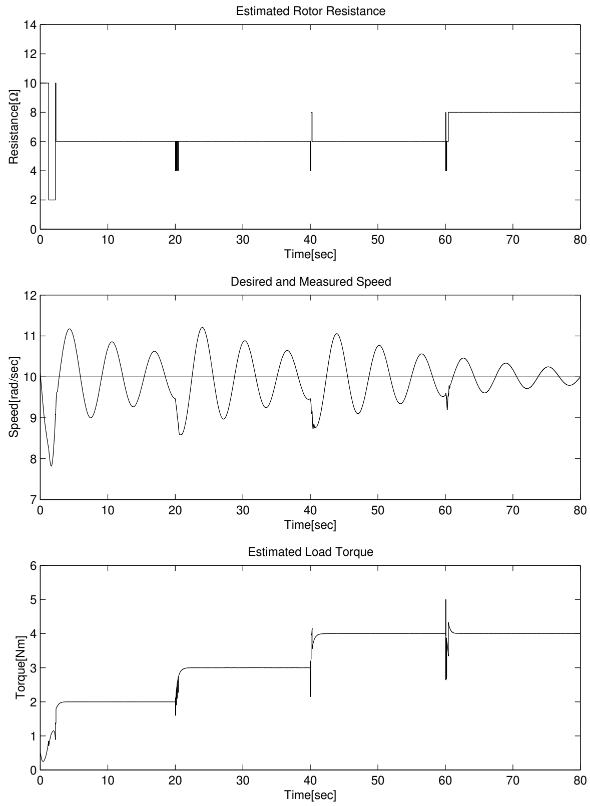


Figure 5: Simultaneous change of rotor resistance and load torque

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