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Numerical Method for Power Losses Minimization of Vector-Controlled Induction Motor

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ABSTRACT

The paper devoted to energy efficiency maximizing problem of the induction motor under part-load conditions. The problem is formulated as the minimization of ohmic losses power as a function from flux-producing current in field-oriented motor operation. Control input prefiltering which transforms the dynamic time-varying optimization problem to stationary one is introduced. Update rule for control variable is proposed which speeds-up the method convergence in comparison with linear variation of input. Finally a new continuous-time search algorithm for solving the problem of minimizing power consumption was given. The statements on method behavior were formulated and convergence to local minimum was proved. The method verified in simulation and in hardware experimental setup.

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1. INTRODUCTION

Currently dominating approach to the control of asynchronous motors is the vector control, including field oriented control (FOC) and direct torque control (DTC). Important feature of the FOC induction motor control [1, 2] is the possibility of an independent manipulation of quadrature stator current i_{qs} which linearly affects the motor torque and control of rotor flux ϕ_r. Independent control of current i_{qs} and flux ϕ_r transforms the asynchronous machine to a DC motor with independent excitation.

In the literature [3, 4, 5] there are large number of different strategies to improve the efficiency of induction motors, which can be divided into two groups: control based on motor energy models (loss model control, LMC) and minimizing the measured power consumption on the basis of numerical optimization algorithms (search control, SC). Most of the known strategies of energy optimization manipulate of rotor magnetic flux ϕ_r setpoint in FOC or DTC algorithm. LMC model-based control can quickly calculate the optimal value of flux-producing current i_{sd} based on motor mechanical load estimation, shaft speed and motor parameters. Major drawback of LMC control is a sensitivity to motor model parameters variation.

The search control (SC) is another technique that does not relies on motor model and parameters. It consists in algorithmic search for minimum of the measured input power consumption P_{in}. This is easy to implement and effective method. A major shortcoming of SC control is the need for artificial perturbation of i_{sd} for the obtaining of the input power derivative $\partial P_{in}/\partial i_{sd}$, as well as relatively slow convergence to the optimum and torque ripple due to i_{sd} step changes.

Many scientific papers were devoted to development and improvement of search control techniques for motor power losses minimization. We will count most cited of them and relevant to current work.

In papers [6,7] three methods were studied: method based on the power-flux gradient, linear stepwise (ramp) change of flux setpoint and combination of loss model and search control to speed up the convergence, where the loss model provides initial point for search controller. In next section we will refer to one of method described there.

The paper [8] proposes algorithm based on the golden section technique in the process of searching the optimal value of rotor flux current reference, for which the electrical input power of the system is minimal. The algorithm is fast and effective, however it produces discrete sequence of magnetizing current values, which requires low-pass filtering of algorithm output. Very closely related is method from [9] where losses function locally approximated by quadratic polynomial on every iteration and the next search point selected based on analytically calculated minimum of approximation.

In paper [10] a flux search controller is proposed to increase the efficiency of a direct torque-controlled induction motor. The amplitude of stator current is used as the objective function. Also adaptive strategy implemented to determine the proper flux step. Related results are published in [11] where adaptive gradient descent method used for power optimization in direct torque control of a six-phase induction machine.

Another search method proposed in [12] based on particle swarm optimization for loss model estimation which produces initial point for search controller. Unfortunately only simulation results are given without hardware tests. Classical search method of extremum seeking is used in [13] for power losses minimization, however the convergence to optimum is rather slow. Another related technique is ripple-correlation control, which uses inherent ripple in power converters to achieve the optimum of objective function [14]. However, in induction machine there is no inherent ripple with desired frequency range, and this method reduces to a variation of extremum seeking control [15].

The purpose of presented paper is to make further developments of search control direct optimization methods. Proposed method produce smooth trajectory of i_{sd} and faster than ramp-based techniques. The method has following ingredients:

- The calculated value of power losses P_{loss} is used instead of measured input power P_{in},
- Input precompensation is provided which transforms dynamic optimization problem to static one,
- Dependence of $\dot{i}_{sd}$ from $\dot{P}_{loss}$ is added that makes proposed algorithm considerably faster than ramp-based method,
- Method operates in continuous time and produces smooth trajectory of i_{sd}, thus the torque ripples are completely eliminated without any smoothing filters.

2. BACKGROUND

2.1 Motor Model

The motor model used in this paper is the Γ-inverse model [16] illustrated in Figure 1 where u_s is the stator voltage phasor, i_s and i_r are the stator and rotor current phasors, respectively R_s and R_r are the stator and rotor resistances, respectively. Also L_σ denotes the stray inductance and L_M is the main inductance.

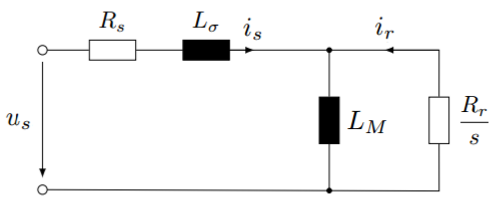

Figure 1. Γ-inverse equivalent circuit of an induction machine

With the orientation of the rotor flux vector ϕ_r along the d-axis of synchronously rotating orthogonal dq-coordinate system, the state-space motor model can be realized by the fourth order system of differential equations [17]:

$$\begin{aligned}
\frac{d}{dt}\phi_r &= -\frac{R_R}{L_M}\phi_r + i_{sd}R_R \\
\frac{d}{dt}i_{sq} &= -\frac{\omega}{L_\sigma}\phi_r - \frac{R_s}{L_\sigma}i_{sq} - \frac{R_R}{L_\sigma}i_{sq} - i_{sd}\omega_s + \frac{u_{sq}}{L_\sigma} \\
\frac{d}{dt}i_{sd} &= \frac{R_R}{L_M L_\sigma}\phi_r - \frac{R_R}{L_\sigma}i_{sd} - \frac{R_s}{L_\sigma}i_{sd} + i_{sq}\omega_s + \frac{u_{sd}}{L_\sigma} \\
\frac{d}{dt}\omega &= p\frac{p\phi_r i_{sq} - T_m}{J}
\end{aligned} \tag{1}$$

where $\omega_s = \omega + \frac{R_R i_{sq}}{\phi_r}$ is a synchronous speed, ω is electrical shaft rotation speed, $T_e = p\phi_r i_{sq}$ is an electromagnetic torque produced by the motor.

Note, that the currents and voltages in model (1) are measured using power-invariant scaling of Park-Clarke transforms.

During all material of the paper we will neglect the dynamics of i_{sd} and i_{sq} stator currents with assumption that in FOC control the performance of PI current controllers are much faster than flux and speed dynamics. In this case, we can write the reduced motor model:

$$\begin{aligned}
\frac{d\phi_r}{dt} &= -\frac{R_R}{L_M}\phi_r + i_{sd}R_R \\
\frac{d\omega}{dt} &= p\frac{p\phi_r i_{sq} - T_m}{J}
\end{aligned} \tag{2}$$

which is subject of study in present work.

2.2. Power Losses and Optimal Regime

For given constant mechanical torque T_m it is possible to calculate steady-state power losses as function of steady-state magnetizing current i_{sd} :

$$P_{loss}^{ss}(i_{sd}) = \left(\frac{T_m}{pL_M i_{sd}}\right)^2 (R_s + R_R) + i_{sd}^2 R_s \tag{3}$$

where $T_m/(pL_M i_{sd})$ is a steady-state value of quadrature current i_{sq} for fixed i_{sd} and T_m .

It is known [1-3], that optimal magnetizing current that minimizes (3) can be calculated as follows

$$i_{sd}^{opt}(T_m) = \sqrt{\frac{T_m}{L_M p}}\sqrt[4]{\frac{R_R + R_s}{R_s}} \tag{4}$$

2.3. Simple Ramp Method

The ramp-based method [6] is a simplest type of search controller. Suppose the direction of the optimum search relative to the present value of magnetizing current i_{sd} is known. Such information could be provided from the analysis of $i_{sq}(t)$ transient: if new steady-state value of i_{sq} is higher than previous one, then the load torque T_m is increased and new optimum of i_{sd}^{opt} is higher than previous one as well (because $i_{sd}^{opt} \cong \sqrt{T_m}$), and vice-versa.

In original description [6] ramp method consists of sequential changes of i_{sd} by small steps until measured input power P_{in} starting to increase. In continuous time the step changes could be replaced to integration of a constant:

$$\frac{d}{dt}i_{sd} = c \tag{5}$$

until the input power P_{in} stops changing near the point of minimum: $|\dot{P}_{in}| < \varepsilon$, where $c = const$ and the sign of c depends on the direction of search, $\varepsilon > 0$ is an arbitrary small value.

The selection of constant value c could be done from the two following simple ideas: if a value of c is too small, then the method converges slowly; if the c is too big, then the instant value of $P_{in}(t)$ is considerable different from steady-state value for given i_{sd} due to inheriting dynamics of power losses, which leads to optimization error.

3. OPTIMIZATION PROBLEM FORMULATION

3.1. Objective Function

Here and after instead of using the input power $P_{in} = i_{sq}u_{sq} + i_{sd}u_{sd}$ as optimization criterion we will use the ohmic power losses P_{loss}, calculated from measured values of i_{sq} and i_{sd}:

$$P_{loss}(t) = i_{sq}^2(t)(R_s + R_R) + i_{sd}^2(t)R_s \qquad (6)$$

It's introduces some modeling uncertainty, but usually the measurement noise of P_{loss} is much lower than in P_{in}.

3.2. Control Input Prefiltering

For search control methods it is essential to know steady-state power $P_{loss}^{ss}(i_{sd})$ for given i_{sd} value. But changing i_{sd} according to some search trajectory $i_{sd}(t)$ we will get only instant value $P_{loss}(t)$, which is obviously different from $P_{loss}^{ss}(i_{sd})$. The solution is to change and fix i_{sd} and then wait some time until steady-state and only then measure P_{loss}, which limits the speed and accuracy of methods. Here we propose pre-compensation scheme with which is possible to estimate the steady-state value $P_{loss}^{ss}(i_{sd})$ on-the-fly, without waiting for the steady-state.

Suppose the speed controller is fast enough to accommodate the change of torque load and the speed drop is close to zero for torque T_m and flux ϕ_r variation. Then it is possible to neglect the transient processes in speed PI-controller and assume that the regulator always maintains appropriate value of qudrature current to ensure constant output torque:

$$i_{sq}(t) = \frac{T_m}{p\phi_r(t)} \qquad (7)$$

Thus the major source of inherent dynamics of P_{loss} is the flux dynamics of motor.

Let's introduce a new manipulable variable $\xi' = d\xi/dt$, which determines the trajectory of $i_{sd}(t)$ as follows:

$$i_{sd}(t) = \xi'(t)\cdot\tau_r + \int_0^t \xi'(t)dt = \xi'(t)\cdot\tau_r + \xi(t) \qquad (8)$$

The same can be rewritten in Laplace s-domain:

$$I_{sd}(s) = \frac{\tau_R s + 1}{s}\cdot\Xi'(s) \qquad (9)$$

where $I_{sd}(s)$ and $\Xi'(s)$ are Laplace transforms of the $i_{sd}(t)$ and $\xi'(t)$.

Then we can construct new estimation for power losses in following form:

$$P_{loss}^{ss}(\xi) = i_{sq}^2(t)(R_s + R_R) + \xi(t)^2 R_s \qquad (10)$$

We will show that (10) has a very nice property that it doesn't dependant from flux dynamics. It is allows convert the optimization problem with time-varying function (6) to simple minimization problem for one-to-one static function (10) with neglecting flux dynamics. Our main result can be formulated as a simple theorem.

Theorem 1 . *For any trajectory* $i_{sd}(t)$ *determined by* ξ' *when initial conditions* $\xi(0) = i_{sd}(0)$ *and* $\xi'(0) = 0$ *are satisfied the following are true:*

1. $\phi_r(t) = L_M \xi(t)$
2. $\xi^{opt} = i_{sd}^{opt}$

where ξ^{opt} is a minimum point of (10), i.e. $P_{loss}^{ss}(\xi^{opt}) \le P_{loss}^{ss}(\xi)$.

Proof. Substituting (9) to flux equation from motor model (2) gives

$$\Phi_r(s) = \frac{L_M}{\tau_R s + 1} \cdot \frac{\tau_R s + 1}{s} \cdot s\Xi(s) = L_M \Xi(s) \tag{11}$$

For converting to time domain note, that $\xi(0) = i_{sd}(0)$ and then $\phi_r(0) = L_M \xi(0)$ from the flux equation of the motor model (2). Thus, the first statement of theorem comes obviously.

For the proof of second statement, let's substitute the speed controller dynamics (7) to (10) and take to account the first statement of theorem $\phi_r(t) = L_M \xi(t)$:

$$P_{loss}^{ss}(\xi) = \left(\frac{T_m}{p\phi_r(t)}\right)^2 (R_s + R_R) + \xi(t)^2 R_s = \left(\frac{T_m}{pL_M \xi(t)}\right)^2 (R_s + R_R) + \xi(t)^2 R_s \tag{12}$$

From the last equation one can note that the $P_{loss}^{ss}(\xi)$ is in fact equation for steady-state losses (3) where i_{sd} is formally replaced to ξ. Thus, both functions are identical and have the same range and the same minimum point $\xi^{opt} = i_{sd}^{opt}$. **Q.E.D.**

To demonstrate the difference between methods (10), (3) and (6) for power losses estimation we simulated the motor model under linear increasing of i_{sd} (Figure 2).

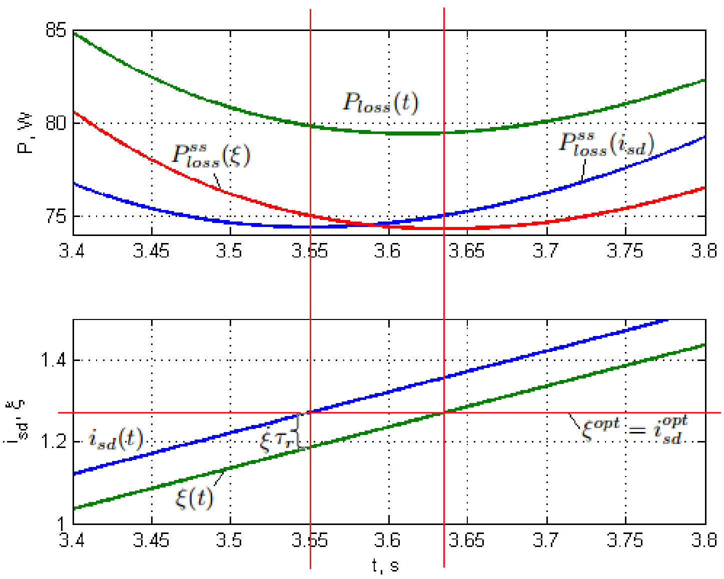

Figure 2. Difference between $P_{loss}^{ss}(\xi)$ by (10), $P_{loss}^{ss}(i_{sd})$ by (3) and $P_{loss}(t)$ by (6)

4. OPTIMIZATION ALGORITHM

4.1. Termination Criteria and Accuracy

In this section we will change the notation by considering the abstract minimization problem of convex scalar function $y = f(x)$. The connection to problem above is: $x = \xi$, $y = f(x) = P_{loss}^{ss}(\xi)$.

Let's x^* is a minimum point of f, and x_0 is initial guess.

The algorithm described in section **2.3** is formulated in the new notation as follows:

$$\text{while} \,|\,\dot{y}\,| = |\,df(x)/dt\,| > \varepsilon \text{ do } \dot{x} = c \tag{13}$$

where $\operatorname{sign} c = \operatorname{sign}(x^* - x_0)$, $x(0) = x_0$.

Let us study how the value of ε affects the accuracy of search algorithm. If ε sufficiently small, then it is possible to expand the $f(x)$ into power series near the neighborhood of x^*:

$$f(x) = f(x^*) + \frac{1}{2} f''(x^*)(x - x^*)^2 + O(x - x^*)^3 \tag{14}$$

For further analysis, without loss of generality, we can assume $x^* = 0$ and use quadratic approximation near the x^*:

$$f(x) = \frac{1}{2} f''(x^*) x^2 \tag{15}$$

Hence the time derivative is

$$\dot{y} = f''(x^*) x \dot{x} = c f''(x^*) x \tag{16}$$

Since $x(t) = x_0 + ct$, then $\dot{y} = f''(x^*) c (x_0 + ct)$.

Let's denote $\hat{\dot{y}}$ as a numerical estimation of $\dot{y}$ obtained by digital differentiation. The easiest way to obtain $\hat{\dot{y}}$ by using first-order filter in the operator form;

$$\hat{\dot{Y}}(s) = \frac{s}{\tau s + 1} Y(s) = \frac{1}{\tau s + 1} \dot{Y}(s) \tag{17}$$

where $\hat{\dot{Y}}(s)$ is Laplace transform of $\hat{\dot{y}}(t)$, $\dot{Y}(s)$ is a Laplace transform of $\dot{y}(t)$, and τ is a filter time constant.

From [18] known, that the response of first order system to the ramp $u(t) = \dot{y} = f''(x^*) c (x_0 + ct)$ is

$$\hat{\dot{y}}(t) = c f''(x^*) e^{-t/\tau} \cdot (c\tau - x_0) - c f''(x^*) \cdot (-ct + c\tau - x_0) \tag{18}$$

When τ is sufficiently small the exponential term in (18) rapidly converges to zero. Thus it is possible to write an expression for the steady-state $t >> 0$:

$$\hat{\dot{y}}(t) \to c f''(x^*) \cdot (x_0 + ct - c\tau) = c f''(x^*) \cdot (x(t) - c\tau) \tag{19}$$

The algorithm terminates when $|\,\hat{\dot{y}}\,| = \varepsilon$ or

$$c f''(x^*) \cdot (x(t) - c\tau) = \varepsilon \tag{20}$$

When using the high-pass filter to estimate the derivative $\hat{\dot{y}}$, there is a delay between the actual value $\dot{y}$ and estimation $\hat{\dot{y}}$. As a result the search is stopped with a delay $c\tau$. Hence, in the absolute accuracy Δx of search procedure the error associated with finite precision ε and band-limited filter should be taken with a different signs:

$$\Delta x = \left| \frac{\varepsilon}{f''(x^*)c} - c\tau \right| \tag{21}$$

4.2. Convergence Speed-Up

To accelerate the search it is possible to use the time derivative of y. Thus, we have updated rule:

$$\dot{x} = -k \cdot \hat{\dot{y}} \tag{22}$$

where $k > 0$ is positive constant.

Since the accuracy minimum setpoint (21) depends from the argument x rate of change, to ensure that the specified accuracy is necessary to limit the value $\dot{x}$, i.e.:

$$\dot{x} = \min\{-k \cdot \hat{\dot{y}}, \gamma \cdot c\} \tag{23}$$

where $\gamma > 1$ is ratio of the maximum rate of change of x to initial c. Note that this formula is written for the case $c > 0$, otherwise, obviously, the $\min$ operation needs to be replaced to $\max$.

To ensure the unconditional improvement of convergence rate, it is necessary to exclude cases when $|k \cdot \hat{\dot{y}}| < |c|$. Hence, we obtain the final expression for the argument dynamics:

$$\dot{x} = \max\{c, \min\{-k \cdot \hat{\dot{y}}, \gamma \cdot c\}\} \tag{24}$$

4.3. Final Algorithm

In this subsection we are going to formulate the final form of search algorithm procedure according to all discussions above in original notation for power losses optimization problem.

Let's denote: $c > 0, k > 0, \gamma > 1, \varepsilon > 0$ are the algorithm parameters as it described before. Let's introduce additional parameter t_0 for duration of unconditional change of x for initial estimation of $\hat{\dot{y}}$. And temporary variable $d \in \{-1, 1\}$ is used for indication of search direction. Here is pseudocode of algorithm:

1. **if** $x^* > x_0$ **then** $d := 1$**, else** $d := -1$**.**
2. **while** $t < t_0$ **do** $\dot{x} = d \cdot c$
3. **while** $|\hat{\dot{y}}| > \varepsilon$ **do**
3.1 **if** $-k \cdot \hat{\dot{y}} > c$ **then**
3.1.1 **if** $-k \cdot \hat{\dot{y}} < \gamma \cdot c$ **then** $\dot{x} = -d \cdot k \cdot \hat{\dot{y}}$ **else** $\dot{x} = d \cdot \gamma \cdot c$
3.2 **else** $\dot{x} = d \cdot c$

Value of $\hat{\dot{y}}$ is being estimated in parallel to algorithm execution by high pass filter (17).

Algorithm called in mechanical steady-state condition when transient after torque change is finished. The condition $x^* > x_0$ is equivalent to $i_{sq}^* > i_{sq}(0)$ where $i_{sq}(0)$ is initial values of magnetizing and quadrature currents respectively (before the torque change), i_{sq}^* is a steady-state quadrature current for new load torque.

4.4. Convergence Analysys

The behavior of the algorithm can be characterized by the following theorem.

Theorem 2 *If the following conditions are true:*

$$|c| \cdot t_0 < |x^* - x_0| \tag{25}$$

$t_0 >> \tau$ (26)

*the algorithm from section **4.3** finds a local minimum of the function* $f(x)$ *with accuracy* (21).

Proof. The first condition $|c| \cdot t_0 < |x^* - x_0|$ means that the minimum point x^* is not within the interval $[x_0, x_0 + c \cdot t_0]$, where the algorithm cannot terminate.

Due to the second condition $t_0 >> \tau$ at time t_0 transient process in the derivative estimator is finished and $\hat{y}(t) = cf''(x^*) \cdot (x(t) - c\tau)$ near the x^* with ramp dynamics of argument $x(t) = x_0 + ct$.

Because the $f(x)$ is convex, then the value of derivative $f'(x)$ decreases at interval $[x_0, x^*]$, and the value of time derivative $\dot{y} = f'(x)\dot{x}$ decreases as well in case of nonincreasing $\dot{x}$. Hence, after the transition to the accelerated dynamics $\dot{x} = -k \cdot \hat{y}$ there is exist moment of time where $c \geq -k \cdot \hat{y}$ and the search procedure always switches to the ramp change of argument $\dot{x} = c$ near minimum point. Thus, the statement of the theorem (21) in form of ramp search accuracy is always true in the final phase of the algorithm. **Q.E.D.**

From a practical viewpoint the condition (25) means that the initial approach of x_0 is far enough away from the desired x^* . Satisfactory interpretation of the condition (26) from an engineering viewpoint is a choice $t_0 \geq 3\tau$.

5. EXPERIMENTAL DATA

5.1. Simulation

For the verification of proposed algorithm the simulation was conducted. Structure of Simulink model is shown at Figure 3.

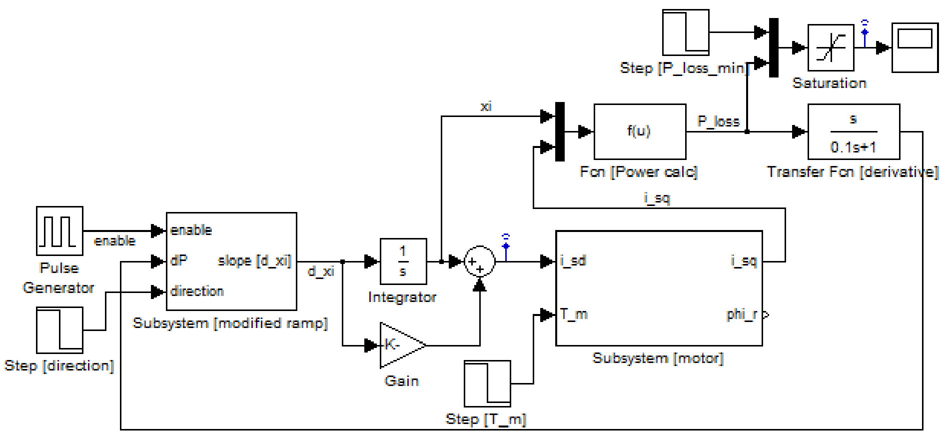

Figure 3. Model of optimization algorithm

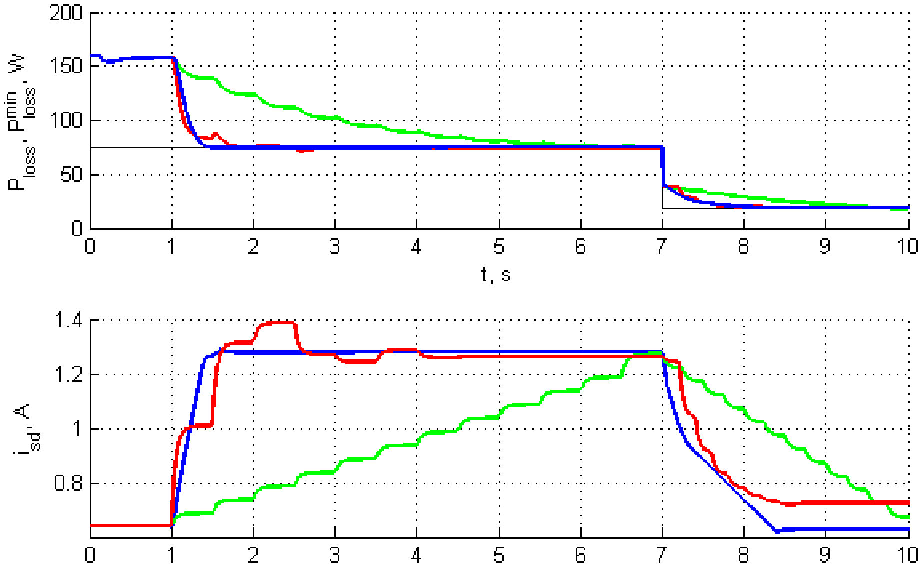

Figure 4. Simulation results for proposed method along with ramp and golden search methods

The model of motor (2) is implemented inside block Subsystem [motor]. Parameters of model are estimated from motor DRS71S4 by SEW-Eurodrive with 0.37 kW rated power. Algorithm of optimization implemented as discrete system with the blocks MATLAB Function and Unit Delay. Parameters of algorithm are chosen as follows: $c = 0.15$, $k = 0.02$, $\varepsilon = 0.5$, $t_0 = 0.2$.

During simulation two cases was considered: when $T_m = T_m^{nom}$ and then load torque dropped to $T_m = 0.25T_m^{nom}$, where T_m^{nom} – rated load torque (2.6 Nm). Initially the current i_{sd} was selected as optimal for lower load $T_m = 0.25T_m^{nom}$.

For the comparison of a proposed approach with other similar algorithms the pure ramp method [6,7] and golden section technique [8] were implemented in simulation.

The simulation results are presented at Figure 3. For the power losses analytically calculated minimum P_{loss}^{min} is shown as well as a black line. The green line is a trajectory for ramp method, and red line for golden search. The current step for ramp is chosen $\Delta I = 0.05$ A. The duration of current steps for ramp method was adjusted so that the transients have time to be completed before the next change. For increase of magnetizing current $\Delta T = 0.5$ s was used and for decrease of magnetizing current $\Delta T = 0.2$ s.

5.2. Hardware Implementation

As a platform for implementing control algorithms was used the controller dSPACE with DS5202 motor control board (Figure 5). The dSPACE platform is a system based on DSP and FPGA which is used as hardware target for automatic code generation and implementation of MATLAB Simulink models. For the motor power stage used a modified SEW-Eurodrive MoviAxis inverter. The PWM control signals for three-phase bridge comes directly from the dSPACE controller.

Experimental setup consist of DRS112M4 motor from SEW-Eurodrive with 26.6 Nm rated torque (4 kW) coupled with a load machine for testing various load conditions.

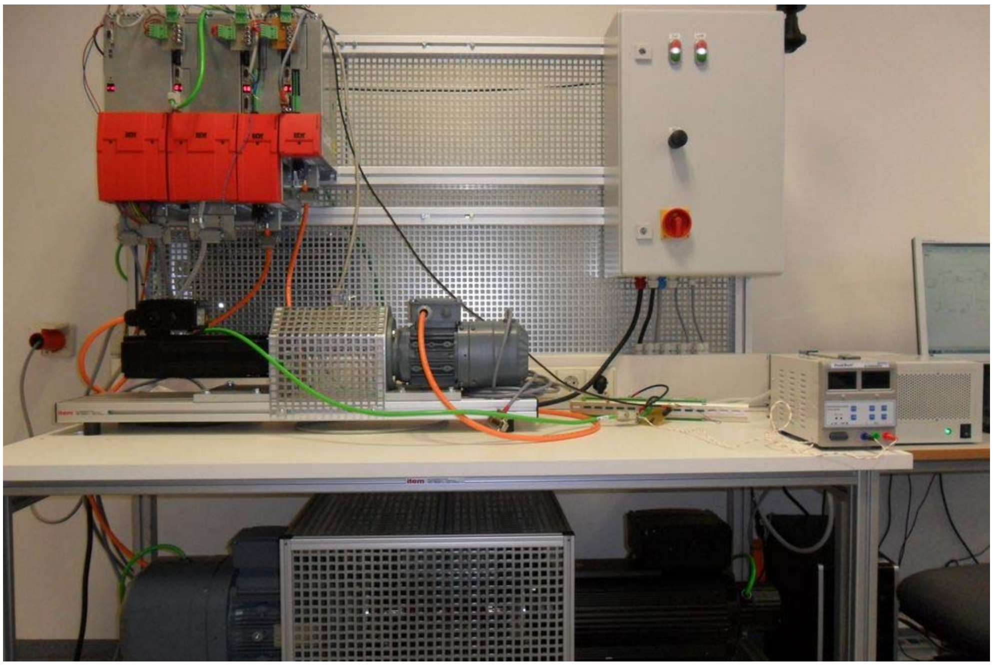

Figure 5. Experimental setup

Field-oriented vector control of stator currents in the rotating dq-coordinates was implemented. Following algorithm parameters was used: $c = 0.5$, $k = 0.015$, $\varepsilon = 2$, $t_0 = 0.5$. For the filtering of input power ripple the continuous time 3-rd order Butterworth filter with cutoff frequency $f_c = 2$ Hz was used.

The motor was put to continuous vector-controlled rotating mode with the speed $\omega = 100$ rad/sec and two values of mechanical load were tested $T_m = 13.6$ Nm (approx 50 % of rated torque) and $T_m = 6.8$ Nm (approx 25 % of rated torque).

The transients of power optimization obtained from gradient-based algorithm are presented at Figures 5-6. The power losses P_{loss} were calculated from measured currents by (6).

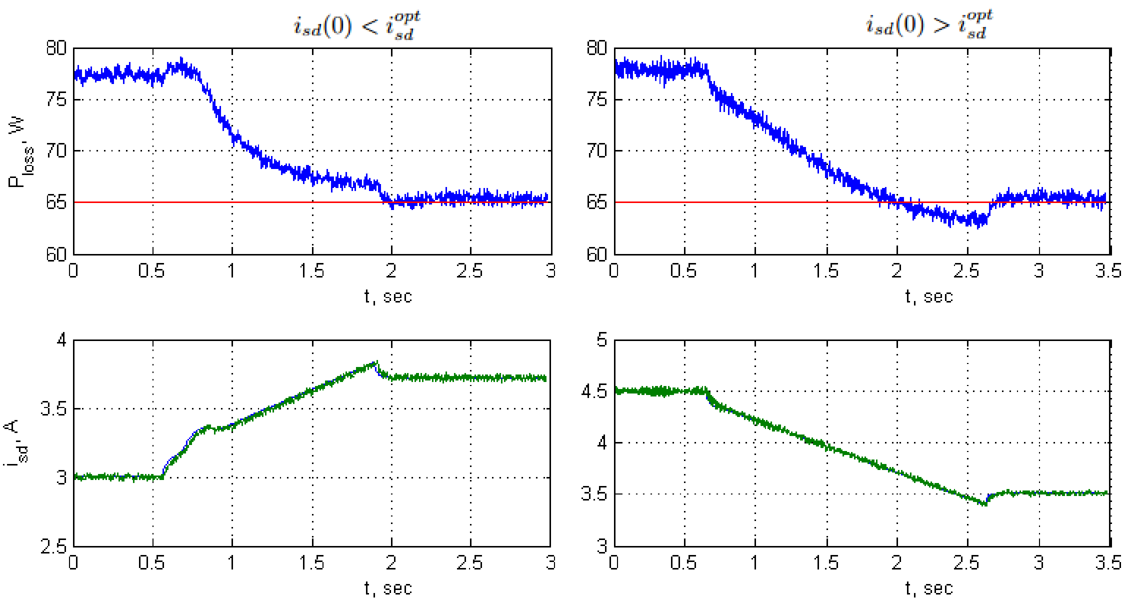

Figure 6. Power losses P_{loss} and magnetizing current i_{sd} dynamics for $T_m = 6.8$ Nm

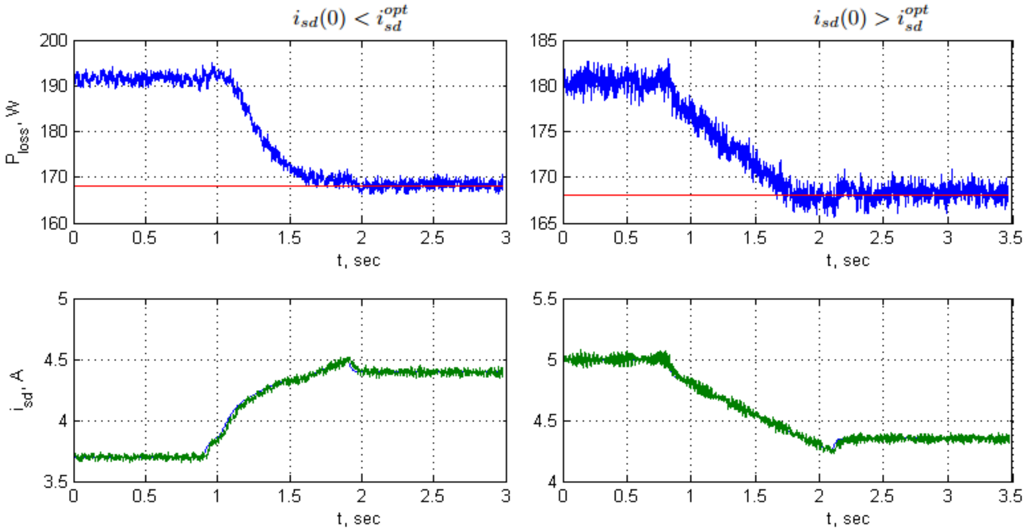

Figure 7. Power losses P_{loss} and magnetizing current i_{sd} dynamics for $T_m = 13.6$ Nm

6. RESULT AND DISCUSSION

Based on the simulation results it is possible to compare our method to other known approaches with the similar implementation complexity. The results are summarized in table 1.

Table 1. The comparison of methods

Method	Proposed	Ramp step change	Golden section
Transient time ($T_m = T_m^{nom}$)	0.5 s	5 s	1.5 s
Transient time ($T_m = T_m^{nom}/4$)	1.4 s	2.5 s	1.5 s
Continuous trajectory of i_{sd}	yes	possible	no
Overshoot possibility	no	no	yes
Torque ripple	no	yes, requires setpoint filtering	yes, requires setpoint filtering
Motor parameters required	τ_R	no	no

As one can see, the method converges faster or in the same rate in comparison to other tested approaches. However, method has also important qualitative features. It does not require flux setpoint filtering to prevent torque ripple because it produces continuous magnetizing current trajectory. Also an overshoot above or under the optimal point is impossible in opposite to golden search method.

Also it can be noted that the speed of convergence for proposed method dependant on how far the initial point is from power losses minimum. It shows much faster convergence when the gradient slope of losses function is steep in case when initial point is far from minimum. Also method is independent does not require discrete steps for flux setpoint change, and thus the adaptive step change developed in [11] is not required.

Described features come in cost of additional motor parameter τ_R. However, any implementation of FOC control requires value of τ_R as well.

Experimental implementation of the method also indicated its practical applicability. From the results obtained it is evident that method converges practically to optimal value of magnetizing current and the speed of convergence is a superior to the pure ramp method.

7. CONCLUSION

In this paper we proposed a strategy for optimizing the efficiency of the induction motor under FOC control, which is based on the regulation of the magnetizing current i_{sd} by estimating the ohmic power losses of the motor. The method relates to the direct search algorithm optimization (search controller) and is characterized in that it is not dependent on the motor parameters variations. The algorithm makes practically no disturbance on output electromagnetic torque. It is shown that the method resistant to random noise power measurement. Convergence of the algorithm is comparable to methods based on the loss model (LMC).

Further work will focus on the implementation and laboratory testing of developed strategies to optimize the power consumption by the means of vector control algorithms library ACIM IFOC for STM32 microcontrollers.

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