Investigation of the Process Parameters Influence on the Energy Efficiency of an Induction Motor under Model Predictive Control GRAMPC

G.G. Diachenko[1, a], O.O. Aziukovskyi[1, b]

1 – State Higher Educational Institution "National Mining University", Dnipro, Ukraine

a – diachenko.g@nmu.one

b – azalex@nmu.one

DOI **10.2412/mmse.5.86.76** provided by Seo4U.link

Keywords: induction motor drives, model predictive control, field oriented control, energy efficiency.

ABSTRACT. This paper presents the implementation of the nonlinear gradient based model predictive control (MPC) software GRAMPC (GRAdient based MPC) for the energy efficient control of three-phase induction motor drives. GRAMPC is appropriate for controlling nonlinear systems with input constraints in the (sub)millisecond range and is based on real-time solution strategy. The effect of the model algorithmic parameters: prediction horizon, the maximum number of iterations and number of data points is considered and default values in terms of real-time demands are determined. Additionally, some comparison results with conventional methods are provided, which demonstrate the advantages and performance of GRAMPC. The analysis for appropriate choice of the algorithmic parameters is based on simulation results for three different induction motors with different rated powers.

Introduction. The question of increasing the energy efficiency of asynchronous machines is a topic that is widely discussed is research and development nowadays. Induction motors are the most frequently used type of asynchronous machine for variety of industrial applications due to their robustness, low cost and simple structure. The two main reasons for solving the energy efficiency issues of this type of motors is, on one hand, an eager desire to make an induction motors more attractive compared to the synchronous machines and, on the other hand, applications which require a higher energy efficiency as well as users who want as energy-saving function in real-time for various reasons. As can be seen from the overview [1] and the references cited therein, numerous methods exist for energy efficient operation management both for field-oriented control methods and other methods like *V/f* control methods. These methods are mainly appropriate for applications in which the asynchronous machine operates in stationary operating points over considerable time intervals. Thus, in applications where load torque changes occur, these methods lead to total power consumption increase. Only a comparatively small number of papers are devoted to energy-efficiency improvement in dynamic mode of operation due to changing load torque. One of the first treatment of this problem is presented in [2]. This solution gave a significant improvement compared to the operation under constant flux reference. However, the proposed offline optimization is not feasible in many applications, because precalculated offline optimal trajectories are valid only for one specific application under certain conditions. In [3] a brief review of the previous optimization procedures for dynamics is given and a new online implementable approach is proposed using parametrized curve with a good approximation for dynamic transitions. Another recent work that is also based on online optimization is presented in [4]. It is shown that high field-generating current values due to step change in load torque could be avoided by filtering magnetic flux linkage reference. An appropriate choice of the filtering coefficients was numerically investigated in [5].

The present paper takes a different approach. In this context a methodology described in [6] is used. It is suited for dynamic systems and uses predictive solution approach. The algorithm and its properties are investigated in [7]. The efficiency of the gradient based model predictive control scheme and time requirements are also presented. In this paper it will be used to solve the problem of the energy efficient operation of an induction motor in transient behaviour when load conditions are changing. The selection of process parameters in the application is discussed and simulation results are provided.

Background. Consider the Γ-inverse equivalent circuit of an induction motor (IM) given in Figure 1.

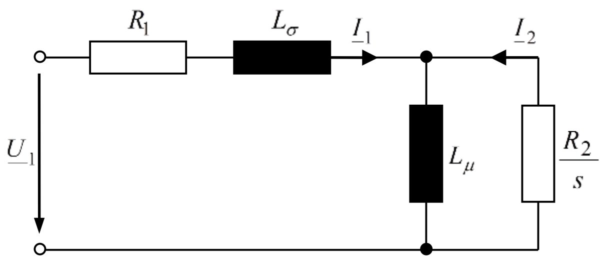

Fig. 1. Γ-inverse equivalent circuit of IM.

It is assumed that the speed and current regulators of the field-oriented control have high enough performance to ensure the control characteristic close to perfectly rigid that is, the dynamics of the speed and current controllers can be disregarded. All variables are transformed from the three-phase system (abc) to an orthogonal amplitude invariant (dq) reference frame. The differential equations of the reduced motor model can be written as follows:

$$\dot{\psi}_2 = -\frac{R_2}{L_\mu}\psi_2 + R_2 I_{1d}, \tag{1}$$

$$M_M = \frac{3}{2} Z_p \psi_2 I_{1q}, \tag{2}$$

where ψ_2 – is the rotor flux linkage;

Z_p – is the number of pole pairs;

L_μ – is the mutual inductance;

I_{1d} – is the field-generating current;

I_{1q} – is the torque-generating current;

M_M – is the motor torque.

It is also assumed that all the necessary preparations for solving the optimal control problem are made, e.g. the first-order optimality conditions following from the Pontryagin's Maximum Principle as well as the Hamiltonian are defined using simplified system of differential equations of the induction motor above.

The influence of the process parameters. The algorithms for particular process stages have been already implemented in GRAMPC. However, it is required from the user to set the algorithmic options regarding the numerical integrations in the gradient algorithm (this question was addressed in [6]), the line search implementation the number of gradient iterations per model predictive control (MPC) step, the prediction horizon, the number of discretization points for the numerical integration, vectors with initial and desired states, constraints as well as further settings. In this paper, the attention is given to the following settings affecting the time of the whole calculation procedure:

• The prediction horizon T_{hor};

• Maximum number of gradient iterations $N_{maxIter}$ per MPC step to adjust the rate of convergence and improve the solution of the optimization problem;

• The number of discretization points N_{hor} for the numerical integration, which are calculated at the first step of the basic algorithm, to predict the optimal trajectory for the rotor flux linkage and the backward time integration.

To make a reasonable choice of the parameter for the prediction horizon lets proceed from the following reasoning. The functional principle of the predictive control is actually not far from our real life and it represents a kind of "natural" predictive control. One of the most convenient examples to demonstrate this principle is the situation when driving the car. Millions and billions of people get behind the wheel of their cars every day. And most of them do it at the same time, because a car remains the most popular type of transport. When driving, you endanger not only yourself, but also the others. You have to watch the movement in general and anticipate the actions of the other drives. You have to monitor the situation on several cars in advance and use your peripheral vision to observe the behaviour of pedestrians and cars. Thus, you do not look immediately in front of your car, but you look far enough ahead and change the actuating variables, e.g. the steering, the gas pedal and brake before you approach for instance a red traffic light, a curve or some hindrance on the road. You as a driver precalculate the behaviour of the car for a certain distance in front of you up to a finite horizon taking future values of the actuating variables into account, and moreover, you optimize the amount of acceleration or braking according to your own optimization criteria for this distance and make a decision how to act every moment perhaps without even noticing it to such extent. As many men, so many opinions, e.g. many optimization criteria are possible, leading to various results. If you do not want to waste your time for a long duration trips, most likely you will increase the rate of acceleration and braking in this case if a reduction of fuel/energy consumption is an optimization criterion.

Due to the precalculation of the system behaviour up to the prediction horizon, MPC inevitably leads to a high computation demands. Hence, a reasonable value for the selection of the prediction horizon is obviously:

$$T_{hor} = 3T_2 = 3\frac{L_\mu}{R_2}. \tag{3}$$

Since the rotor flux linkage ψ_2 and thus the power losses P_V reach their stationary values after three rotor time constants T_2 corresponding to (1). The optimum value for the field-generating current I_{1d} in steady state with respect to power losses can be calculated using the known methods from the paper [5].

For the analysis of the parameters left within the list $N_{maxIter}$ and N_{hor}, firstly, a value as small as possible is chosen for the two parameters. Afterwards, these values are increased until the visible improvement is observed. For the calculation of the field-generating current I_{1d} two methods are used for comparison purposes:

• Method 1. Steady state optimal value for magnetic flux ψ_2 is calculated according to the next formula

$$\psi_{2,stationary} = \sqrt{\frac{2}{3}\frac{M_M L_\mu}{Z_p}\sqrt{\frac{R_1 + R_2}{R_1}}}. \tag{4}$$

This reference value is set via flux regulator and the controlled variable of the regulator is the flux-generating current I_{1d}. The given method as was discussed in [4] and [5] leads to high instantaneous power loss overshoot during a load torque, because with the step change in the magnetic flux linkage, a rapid change in current I_{1d} is observed.

• Method 2. Gradient based model predictive control according to [6].

For both methods, the integral of power loss is determined by method 1, W_{M1} and predictive method 2, W_{M2} respectively, during transients according to the next formula:

$$J = \int_0^T \left(\frac{3}{2}(R_1 + R_2)I_{1d}^2 + \frac{2}{3}(R_1 + R_2)\frac{M_M^2}{Z_p^2\psi_2^2} + \frac{3}{2}\frac{R_2}{L_\mu^2}\psi_2^2 - 3\frac{R_2}{L_\mu}\psi_2 I_{1d} \right) dt . \tag{5}$$

The comparison of $\Delta W_{M12} = W_{M1} - W_{M2}$ for the case when both $N_{maxIter}$ and N_{hor} are changed is shown in Figure 2. This study is based on a very simple model of an asynchronous machine in Figure 1 with a rated power output of 370W, where only rotor flux dynamics $\dot{\psi}_2$ corresponding to (1) is considered. The torque-generating current I_{1q} is determined from the rotor flux linkage and the torque with (2). A torque jump from 25% to 100% of the motor rated torque is used as the load jump. The left plot shows trajectories for the case when the number of discretization points changes and the number of maximum iterations equals 2. On the right-hand side, the plot shows trajectories for the case when the number of maximum iterations changes and the number of discretization points equals 9.

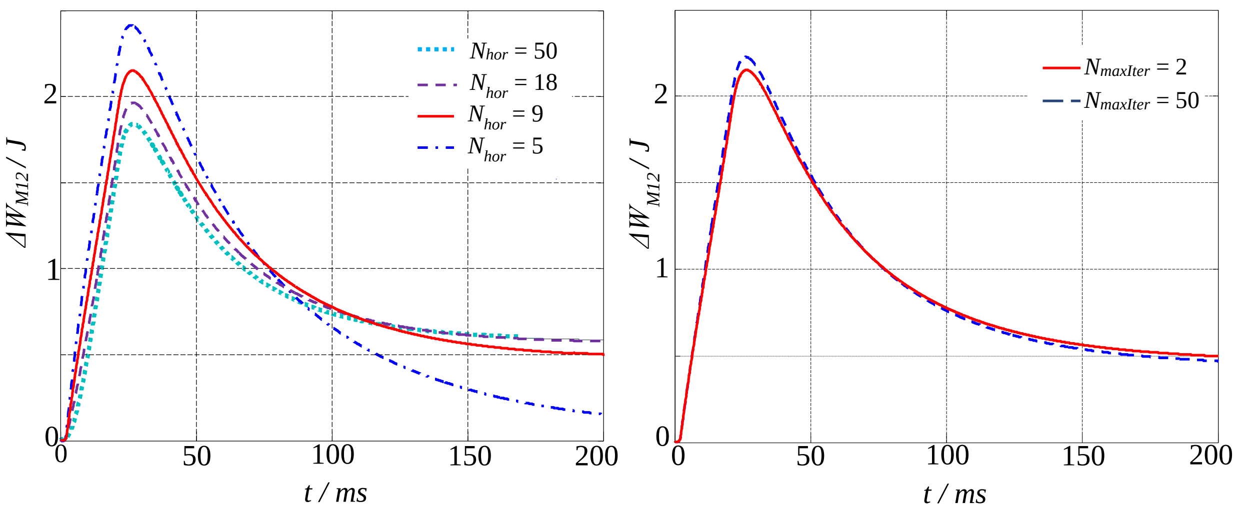

Fig. 2. Change of N_{hor} (left) and $N_{maxIter}$(right) at a load step change from 25% to 100%.

By analogy the same test is made for the case of load torque step change from 100% to 25%. The trajectories are shown in Figure 3. The results show that in all cases the W_{M2} is lower than when using method 1 compared to W_{M1}. Also, it can clearly be seen that a very good result can be achieved with the number of gradient iterations $N_{maxIter} = 2$. In addition, the number of discretization points for the numerical integration used for prediction can be relatively small $N_{hor} \geq 9$. These applies both for the cases of load step up and load step down. The difference between the results for $N_{hor} = 9$ and $N_{hor} = 18$ is clearly visible, but still acceptable. The number of iterations has no significant effect in this case.

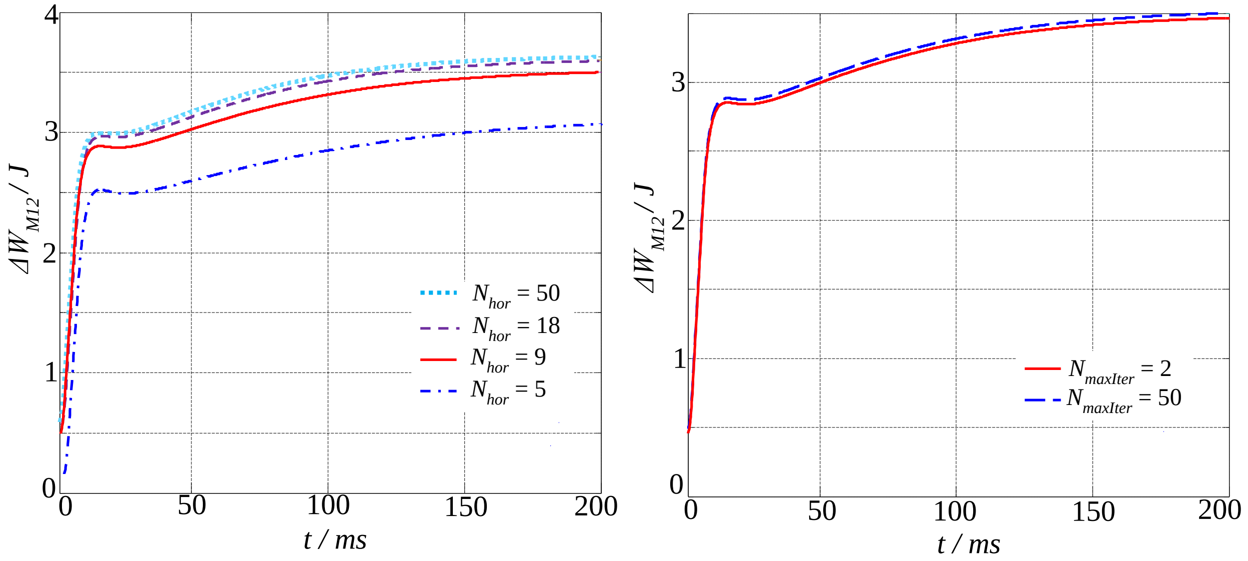

Fig. 3. Change of N_{hor}(left) and $N_{maxIter}$(right) at a load step change from 100% to 25%.

The same analysis is carried out with the data of two more asynchronous motors with rated powers of 4 kW and 11 kW. For all three motors, comparable results are obtained with respect to the choice of the two parameters. Thus, the optimal choice is

$$N_{maxIter} = 2, \, N_{hor} = 9.$$

To keep the integrity of the choice, let us take a look at curves obtained using these two values of the field-generating current and torque-generating current for the case of load step from 100% to 25% of the motor rated torque that are shown in Figure 4.

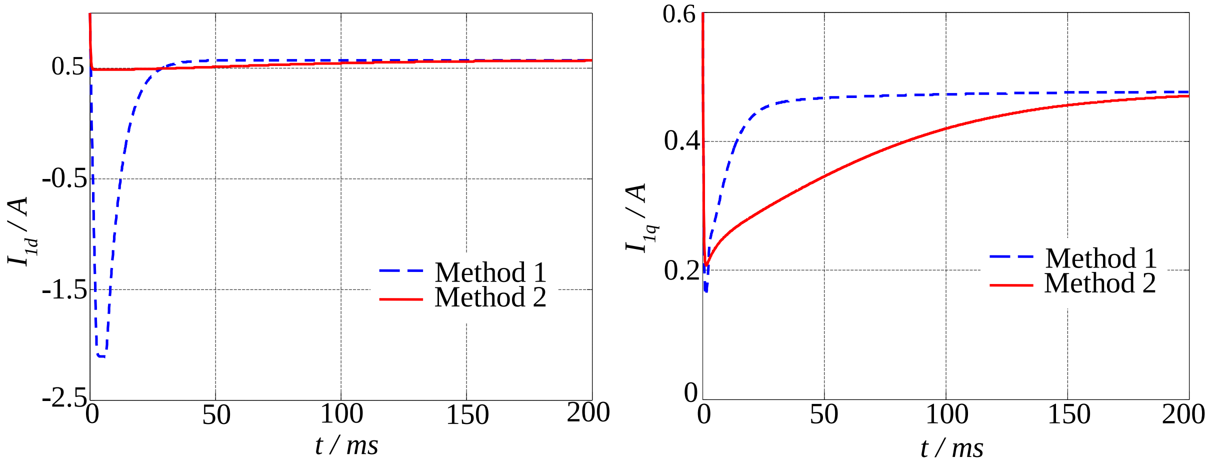

Fig. 4. Comparison of the stator current components

Comparison of the currents obtained by method 1 and method 2 shows why the model prediction control yields better results: the field regulator attempts to establish a new steady-state optimal value for the rotor flux linkage as quickly as possible and as a result uses a high magnitude of the field-generating current and reaches its output almost in no time. This is the main contribution to short-term high losses according to method 1. This fact means that it is not profitable to use the conventional flux controller in dynamic mode of operation due to high instantaneous power loss overshoots during a load torque steps.

Simulation of speed control closed loop. For the verification of the proposed approach a simulation with a motor with the current and speed control loops is performed in MATLAB/Simulink environment. The optimal parameters choice defined in the previous section is used as default in algorithmic options. The motor data of the induction motor with 370W rated power is used in the investigation. The simulation results for a speed ramp are shown in Figure 5. A load torque of 25% of the rated value is applied to the motor shaft initially. The speed ramp is selected such that acceleration process takes place in the period $t \in [0\ 200]$ms. A load torque step change from 25% to 100% is done at $t = 0$. In addition to method 1 and method 2, another method is used for comparison purposes:

- Method 3 Constant reference of ψ_2 for optimal operation under 100% load condition.

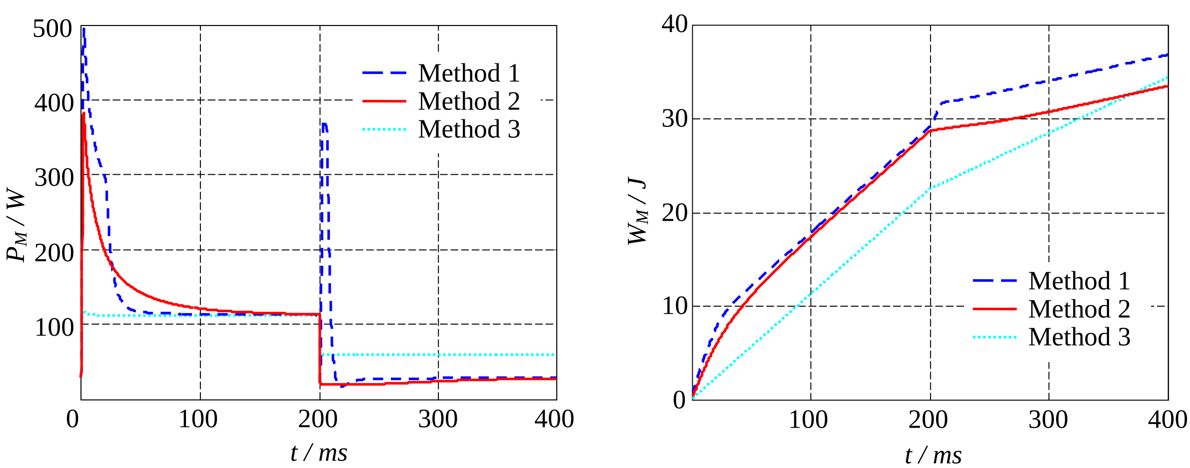

Fig. 5. Power and energy consumption

The comparison of loss energies calculated from the power loss shows that at the time period $t \in$ [0 200]ms the loss energy obtained by method 3 is lower than is the other cases. Such a result was expected as the level of magnetic flux linkage of the methods 1 and 2 is lower at the time range $t \in$ [0 100]ms. The trajectories of energies calculated by methods 1 and 2 are very close in range $t \in$ [100 200]ms. A detailed analysis shows that the latest gives slightly better results than method 1.

At $t = 200$ms, the speed setpoint is reached due to ramp-shaped speed reference signal and load torque drops stepwise from 100% to 25% of the rated motor torque. From power and energy trajectories shown in Figure 5 it can be clearly seen that from this point onwards methods 1 and 2 have much better behaviour compared to method 3. Moreover, predictive method 2 leads to the best possible results throughout the given operation range.

Concerning the comparison results throughout the entire operation range of the induction motor, it can be concluded that loss energy obtained by method 3 is significantly higher, since in part-loaded mode of operation the efficiency of the motor dramatically decreases due to over-excitation and redundant power dissipation in contradistinction to method 1 and method 2.

The curves of the stator current components, e.g. field-generating current and torque-generating current are shown in Figure 6.

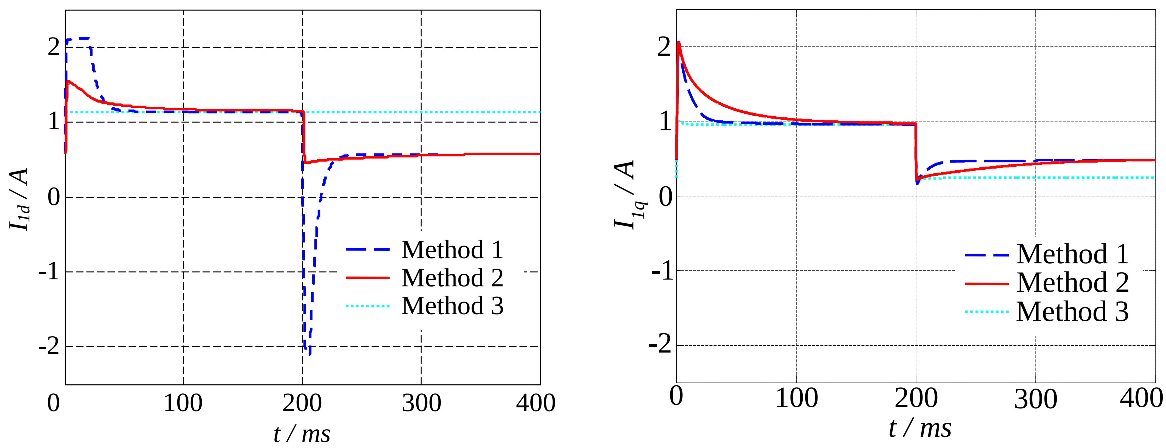

Fig. 6. Simulation results for I_{1q} and I_{1d}

The same behaviour of the trajectories is obtained for the methods 1 and 2, as in the previous section for the simplified model. It means that assumption concerning the neglect of the dynamics of the speed and current controllers stated at the beginning of the paper appears to be justified.

Summary. This paper has described how a known control method with a gradient-based predictive algorithm can be used to optimize the energy efficiency of an asynchronous motor in dynamic mode of operation. The effect of the model algorithmic parameters: prediction horizon, the maximum number of iterations to improve the solution of the optimization problem and number of data points for the control trajectory is considered and default values for optimal control in terms of real-time demands are determined. It allows for a reliable operation of the drive throughout its whole operation range. Comparison with other methods without optimization, e.g. when the magnetic flux linkage is kept at the nominal level throughout the entire load range and when it is set to its new optimum value for each new load step change, shows the advantages of the gradient-based model predictive control which is well suited to control nonlinear and input constrained systems. GRAMPC is licensed under the GNU Lesser General Public License (version 3) and can be downloaded from http://sourceforge.net/projects/grampc.

References

[1] Bazzi, A. M., Krein, P. T. (2010). Review of Methods for Real-Time Loss Minimization in Induction Machines. IEEE Transactions on Industry Applications, 46(6), 2319-2328. DOI 10.1109/tia.2010.2070475

[2] Klenke, F., Hofmann, W. (2011). Energy–Efficient Control of Induction Motor Servo Drives With Optimized Motion and Flux Trajectories. Proceedings of the 14th European Conference on Power Electronics and Applications (pp. 1-7).

[3] Stumper, J., Dotlinger, A., Kennel, R. (2013). Loss Minimization of Induction Machines in Dynamic Operation. IEEE Transactions on Energy Conversion,28(3), 726-735. DOI 10.1109/tec.2013.2262048

[4] Qu, Z., Ranta, M., Hinkkanen, M., Luomi, J. (2011). Loss-minimizing flux level control of induction motor drives. 2011 IEEE International Electric Machines & Drives Conference (IEMDC). DOI 10.1109/iemdc.2011.5994597

[5] Diachenko, G., Schullerus, G. (2015). Simple dynamic energy efficient field oriented control in induction motors. In Proceeding of the 18th International Symposium on Power Electronics. Novi Sad.

[6] Kapernick, B., Graichen, K. (2014). The gradient based nonlinear model predictive control software GRAMPC. 2014 European Control Conference (ECC), 1170-1175. DOI 10.1109/ecc.2014.6862353

[7] Graichen, K., Kapernick, B. (2012). A Real-Time Gradient Method for Nonlinear Model Predictive Control. Frontiers of Model Predictive Control, 9-28. DOI 10.5772/37638