Peculiarities of Construction of Electromechanical Converters' Macromodels with the Use of Optimization Process

Petro Stakhiv, Yuriy Kozak, Ivanna Vasylchyshyn

Abstract – **in this paper the new approach to the simplification of optimization problem of macromodels construction is suggested. The approach is based on a slight deviation from the black box principle and taking into consideration physics processes that occur in the object of modeling.**

Keywords – **macromodels, optimization approach.**

I. Introduction

The use of optimization approach for the construction of electromechanical converters' macromodels (MM) faces the difficulties, in the first place caused by a different physical nature of electric and mechanical processes. Electrical processes run much faster than mechanical ones, and cause a high frequency of transition processes' discretization in such objects, and as a result of sustainability of mechanical processes it leads to a large number of discretes in the outlet data on the basis of which macromodels of such objects are constructed.

Another reason for the complexity of the construction of electromechanical converters' macromodels is the significant influence of nonlinearity, which is caused by ferromagnetic processes occurring in electromechanical converters.

This paper describes the ways of solving the current problem and provides appropriate approaches to construction of electromechanical converters' macromodels.

II. The Essence of the Optimization Construction of Macromodels

Without limiting the generality the construction of macromodels will be considered in the form of discrete state equations [2]:

$$\begin{cases} \vec{x}^{(k+1)} = F\vec{x}^{(k)} + G\vec{v}^{(k)} + \vec{\Phi}\left(\vec{x}^{(k)}, \vec{v}^{(k)}\right) \\ \vec{y}^{(k+1)} = C\vec{x}^{(k+1)} + D\vec{v}^{(k+1)} \end{cases}, \qquad (1)$$

where $\vec{v}$ is the vector of input values; $\vec{y}$ is the vector of output values; $\vec{x}$ is the Vector of variables, describing the state of the object; F, G, C, D are matrices of macromodel's coefficients; Φ is nonlinear vector function; k is a discrete number.

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Let us consider some object for which the macromodel in the form (1) is constructed and which is described by a particular set of unknown parameters $\vec{l}$. It should be noted that the $\vec{l}$ will include the elements of matrices F, G, C, D and coefficients of the function Φ. The background information for the macromodel is a discrete set of transient responses of the modeled object $\left\{v_i^{(k)}; y_i^{(k)}\right\}$, where k is discrete number, i is the number of characteristics. We introduce the goal function which reflects the error with the help of which the constructed macromodel reproduces the behavior of the modeled object. In the simplest case it could be the mean square deviation:

$$Q\left(\vec{l}\right) = \sum_i \sum_k \left(\vec{\tilde{y}}_i^{(k)} - \vec{y}_i^{(k)}\right)^2, \qquad (2)$$

where $\vec{\tilde{y}}_i^{(k)}$ is the object's response, calculated with the help of the macromodel. The optimal set of macromodel's coefficients is a set of $\vec{l}^*$, in which the function (2) reaches its minimum. Thus, identification of macromodel's coefficients reduces to finding the minimum point of function (2) in the space of variables $\vec{l}$.

Taking into consideration the complexity of the optimization problem, which in our case is essentially nonlinear with a large number of unknown coefficients, one should pay attention to the choice of optimization algorithm. Practice shows that for such problems the best solution is the usage of stochastic optimization algorithms [5], which in particular are much less sensitive to a large number of local minima arising from rounding errors and large numbers of calculations. The authors used an algorithm of Rastrigin's directing cone [3, 4] with step length adaptation of the search and opening angle of the cone.

III. Ways of the Simplification of the Optimization Problem

As it was already mentioned, the main disadvantage of the optimization approach is the complexity of the optimization problem. This is particularly typical in case of necessity when the processes of different physical nature are taken into account. For example, it concerns the construction of the MM of electric motors, in which mechanical and electromagnetic processes should be considered.

Different nature of physical processes leads to different time scales that are inherent in them. In the case of electric motors, mechanical processes are much slower than electromagnetic processes. The feature, mentioned above, predetermines the complexity of the construction of macromodels of electromechanical converters, because it requires the use of high frequency discretization for sufficiently accurate description of electromagnetic processes along with continuous transient characteristics, caused by the slowness of mechanical processes. As a result, the output data for macromodel's construction of electromechanical converter will contain a large number of discretes, which leads to large computational costs to calculate the objective function.

An effective way to solve this problem is the division of the process of macromodel's construction on the phases caused by the distribution of the output variables into groups [1, 3]. Such partitioning is effective because some output variables (currents) are determined mainly by electromagnetic processes in the motor and the other (frequency of rotation of the rotor) – primarily by the mechanical processes.

Another reason for the essential complication of the optimization problem in the case of MM construction of motors is essential nonlinearities, inherent in them. If you construct a macromodel without taking into account physical nature of the relevant processes, in order to describe the nonlinearities you have to use polynomials with many coefficients. This in its turn not only complicates the optimization problem but also reduces the chances of obtaining an adequate macromodel.

To solve the given problem let us describe the main processes that occur in asynchronous motor in the following way:

We write the equation of electric equilibrium of the asynchronous machine:

$$u = Ri + L(j)\frac{d}{d(t)}i + w\left[\frac{\partial L(j)}{\partial (j)}\right]i \qquad (3)$$

where R, L are active resistance and inductance of the stator windings respectively, i, u are stator current and voltage respectively, ω is rotor rotational speed. Note that further this expression will allow us to minimize the set of coefficients, which describes the macromodel.

To describe the mechanical characteristics let us use the following ratio for capacities:

$$P_2 = P_1 - \Delta P_{el1} - \Delta P_{mg1} - \Delta P_{el2} - \Delta P_m - \Delta P_d \qquad (4)$$

where P_2 is mechanical power; P_1 is active engine power; ΔP_{el1} are electrical losses in the active resistance of stator windings; ΔP_{mg1} are magnetic losses in stator; ΔP_{el2} are electrical losses in the stator winding; ΔP_m, ΔP are friction losses and additional losses accordingly.

Assuming that:

$P1 = UI$; $P2 = Mw + J\frac{dw}{dt}\cdot w$; $\Delta Pm = M_m w$;

$\Delta P_{el1} : P_1$; $\Delta P_{el2} : P_1$; $\Delta P_d : P_1$

and hence $\Delta P_{el1} + \Delta P_{el2} + \Delta P_d = C_1 P_1$ where C1 is some coefficient and having neglected the magnetic losses $P_{мг}$ the following equation will be received:

$$J\frac{dw}{dt} = \frac{ui}{w}(1 - C_1) - M - M_m \qquad (5)$$

where *J* is a moment of inertia of the rotor, *M* is applied moment of mechanical load, M_m is mechanical moment caused by friction, ω – mechanical angle speed of rotation of the rotor.

For discrete form of macromodel's presentation equations (3) and (5) can be rewritten as follows:

$$i^{(k+1)} = \left(1 - \frac{R}{L(j)}\right)i^{(k)} + \frac{u^{(k)}}{L(j)} - \frac{\left(\frac{\partial L(j)}{\partial j}\right)w^{(k)}i^{(k)}}{L(j)} \qquad (6)$$

$$w^{(k+1)} = w^{(k)} + \frac{u^{(k)}i^{(k)}}{Iw^{(k)}}(1 - C_1) - \frac{M^{(k)}}{I} - \frac{M_m}{I} \qquad (7)$$

Since the coefficients' value will be determined on the basis of experimental data, having omitted some real physical quantities we can rewrite equations (6) and (7) with the help of the following abstract coefficients:

$$i^{(k+1)} = C_1 i^{(k)} + C_2 u^{(k)} + C_3 w^{(k)} i^{(k)} \qquad (8)$$

$$w^{(k+1)} = w^{(k)} + C_4 M^{(k)} + C_5 + C_6\left(\frac{u^{(k)}i^{(k)}}{w^{(k)}}\right) \qquad (9)$$

here C_j - coefficients of the constructed macromodel.

As we can see, the submodel (8) is a linear submodel because the process of its identification is quite simple. Submodel (9) is essentially nonlinear, but also its identification is not difficult, since in the equation (9) there are only 3 unknown coefficients.

The effectiveness of the proposed approach is predetermined by the possibility of determining the form of nonlinear dependence, represented in particular in the equation (9) by means of qualitative analysis of the relationships (3) between the physical quantities that describe the object of macromodeling. Knowledge of forms of nonlinear dependencies gives the possibility to reduce considerably the number of coefficients of the macromodel, and hence the complexity of its identification.

To verify the effectiveness of the proposed approach the macromodel of a single-phase asynchronous motor with the capacitor starting winding [2] was constructed. This macromodel was constructed in several ways:

1. Without the use of approaches to simplify the procedure of macromodel's identification. In this case the macromodel was constructed without intermediate submodels. All macromodel coefficients at once were under optimization. Nonlinearity was described by the schedule together with polynomial restriction by the cubic members.

2. Using common approaches to simplify the procedure of macromodel's identification within the "black box" approach [2, 4]. This partitioning was done with the excretion of the linear submodel. Nonlinearity was described by the power series with polynomial restriction by the cubic members.

3. Using common approaches to simplify the procedure of macromodel's identification within the "black box" approach [4]. This was done by splitting the original output variables. Namely the submodel for the frequency of rotor's rotation and for current's consumption, were built separately.

Nonlinearity was described by a number of limitations of polynomial degree by cubic members. The number of coefficients was limited on the basis of the analysis of transient characteristics (such a set of coefficients was selected, as would be consistent with the observed transient processes but real physical processes in the modeled object were not taken into account).

4. Using the suggested approach in this paper, i.e., macromodel was built with partitioning in the output variables as in the previous case, but the form of the description of nonlinearites was chosen on the basis of the processes' analysis in the simulated engine.

All macromodels were constructed on the basis of experimentally obtained transient processes during switching-on of the motor (Fig. 1).

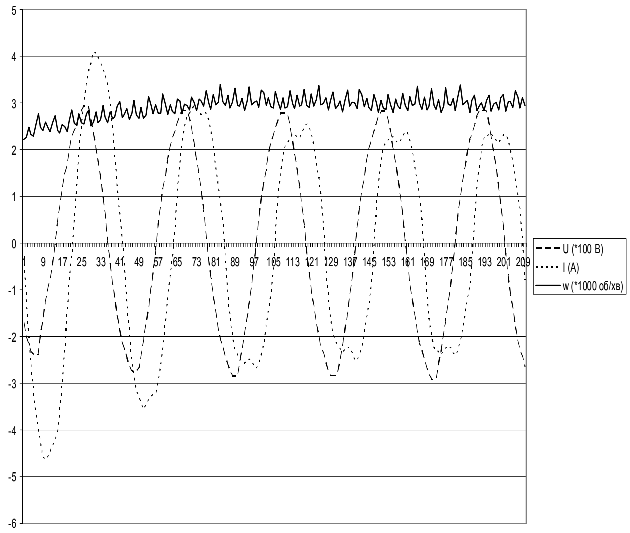

Fig. 1. Initial data used for macromodels' construction

As a result of macromodel's identification with the help of all the ways listed above, the following relations were obtained:

$$\begin{cases} \mathbf{x}_1^{(k+1)} = 0,90264 \cdot \mathbf{x}_1^{(k)} + 1,07155 \cdot \mathbf{v}^{(k)} - 0,27687 \cdot \mathbf{x}_2^{(k)} \cdot \mathbf{v}^{(k)} \\ \mathbf{x}_2^{(k+1)} = 0,9989 \cdot \mathbf{x}_2^{(k)} + 0,00191 \cdot \mathbf{x}_1^{(k)} \cdot \mathbf{v}^{(k)} \\ \mathbf{y}_1^{(k+1)} = \mathbf{x}_1^{(k+1)} - 0,05678 \cdot (\mathbf{x}_1^{(k+1)})^3 \cdot \mathbf{x}_2^{(k+1)} + 0,14657(\mathbf{x}_1^{(k+1)})^3 \\ \mathbf{y}_2^{(k+1)} = \mathbf{x}_2^{(k+1)} \end{cases} \quad (10)$$

where $\vec{x}^{(0)} = (0, \quad 2.5646)^T$.

Without the use of approaches to simplify the procedure of macromodel's identification, optimization algorithm was proved to be unable to solve the given optimization problems. Optimization algorithm stopped far from the optimal solution (error amounted to 98%!) having done only about 250 iterations. This experiment was conducted 10 times and the result has always been approximately the same.

In the second case the macromodel's structure and a set of coefficients was identical to the first case. However, the construction was done in 2 stages. At the first stage the linear submodel was based, and during the second a general specification of all factors was made. In this case the optimization algorithm still found a solution but to do this a very large number of iterations was needed - about 4 • 106. Mean square error for the obtained model was equal to 8.8%. The model included 55 non-nonzero coefficients.

In the third method of the macromodel's construction the quantity of coefficients were reduced to 29 through analysis of transient characteristics. This accelerated the identification process (algorithm completed its work after ~ 1,5 • 105 iterations). However, the accuracy of the obtained model has slightly decreased and amounted to 11%.

The best results, in terms of computer time costs, were obtained in the final variant using the approach, considered in the paper, i.e. a form of the description of nonlinearity was chosen on the basis of processes' analysis in the simulated motor and was used the partition according to the original variables on the electrical and mechanical submodels. In this case, the algorithm completed its work after ~ 4 • 104 iterations. The accuracy of the obtained model was 10.3%. This macromodel contained only 8 nonzero coefficients.

As we can see, taking into account information concerning physical phenomena occurring in the modeling object provides a considerable reduction of the number of coefficients describing the constructed macromodel. This in its turn leads to significant simplification of optimization problem, and thus to the acceleration the of macromodel's construction.

It should also be noted that reducing the number of macromodel's coefficients also improves its adequacy, provided the same accuracy achieved. This is particularly important for a correct assessment of correlation between stages 2 and 4. Better accuracy of the output data by a model obtained in the 2nd variant does not mean a better model because this model is less likely to adequately describe the other modes of the simulated object than the model obtained in the 4th variant.

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