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Scheme of Several Surrogate Models Interaction for Electrical Load Simulation

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Abstract: The use of surrogate models for simulating the electrical load of power plants is considered to improve the performance of the modeling process. Surrogate models are fast-acting models that reflect only the external behavior of the modeled system, i.e. approximate its external characteristics. It is shown that long-known simplified models obtained using the least-squares identification method can be used to construct such models. To obtain such models, it is proposed to use a new mathematical description, in contrast to the one considered earlier. The models are constructed directly in the form of differential equations represented by vector-matrix equations, rather than using a transition matrix as was done previously. New models not previously considered are also obtained and investigated. A mathematical description of a structurally complex model of the energy system is shown. This model is used to obtain initial transient processes for identifying surrogate models. The derivation of a mathematical description of a surrogate model is shown, its difference from previously obtained models is shown. A multi-model scheme for the joint use of several surrogate models is proposed. For this purpose, in contrast to previous works, it was proposed to use a special switching scheme, which made it possible to form the very concept of a multi-model scheme.

Keywords: mathematical modeling, electric power system, thermal power plant, electrical load, asynchronous motor, surrogate model

1. INTRODUCTION

In the electric power industry, the optimization of the production and consumption of electrical energy is a pressing issue [1]. An important condition for optimization is the correct consideration of the influence of consumers when modeling the energy system.

The main consumers of electricity are manufacturing enterprises. For example, in the production of mechanical engineering products, the main operation is cutting, in which the drive is mainly an electric motor [2, 3]. In addition, one of the types of electrical load at industrial enterprises are artificial lighting systems, which consume a significant portion of all generated electricity. [4]. Electrical load accounting is also an important component of energy consumption for commercial [5] and residential consumers [6, 7]. Accounting and load management is especially important in networks without a constant voltage source [6], for example, in power systems with renewable energy sources [8]. One way to account for electrical load is to forecast energy consumption [9, 10].

Therefore, improving the efficiency of power system modeling associated with taking into account the electrical load is a relevant and in-demand scientific direction, since the types of electrical load are quite diverse both in nature and in magnitude. At the same time, the implementation of artificial intelligence (in particular, neural networks [11]) is relevant and in demand to improve production efficiency [12, 13], predict structural disasters [10] and in relation to the electric power industry as a whole [1, 14 – 16]. For example, compensation for the lack of real experiments by simulating based on artificial intelligence. The use of artificial intelligence brings tangible economic effects [17]. At the same time, the

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development of artificial intelligence for many areas of society is accompanied by an ethical assessment of the possibility of using such technologies [18].

Existing research considers the use of artificial neural networks to develop surrogate models [19–21]. Surrogate models [20, 21] are simplified models that can be quickly developed by replacing a computationally expensive model with an approximating simplified model. The study of complex technological systems, such as a power system or a power plant, is associated with the use of complete computationally expensive models. Therefore, the use of surrogate models is relevant in this area [22–23]. As publications show, the possibilities of a multi-neural model approach are currently being actively studied for creating surrogate models. [24–26]. A neural model is usually understood as a trained neural network that has sufficient accuracy and acceptable operating speed. But the capabilities of traditional methods have not yet been exhausted. These traditional methods are important, among other things, in order to compare their effectiveness with the effectiveness of newly developed neural network models [22–26]. In this article we will consider the use of a traditional simplified model in the form of systems of differential equations as a surrogate model.

2. POWER SYSTEM MODEL

As noted above, the mathematical model of a multi-element electrical system requires a lot of calculation time, that is, it is computationally expensive. In fact, the model of even a small electric power system contains sources of electrical energy (models of the electrical part of a thermal power plant), overhead lines, distribution substations and electrical loads (Figure 1). This power system can operate either in autonomous mode or be connected to a powerful system via a power line with a certain capacity.

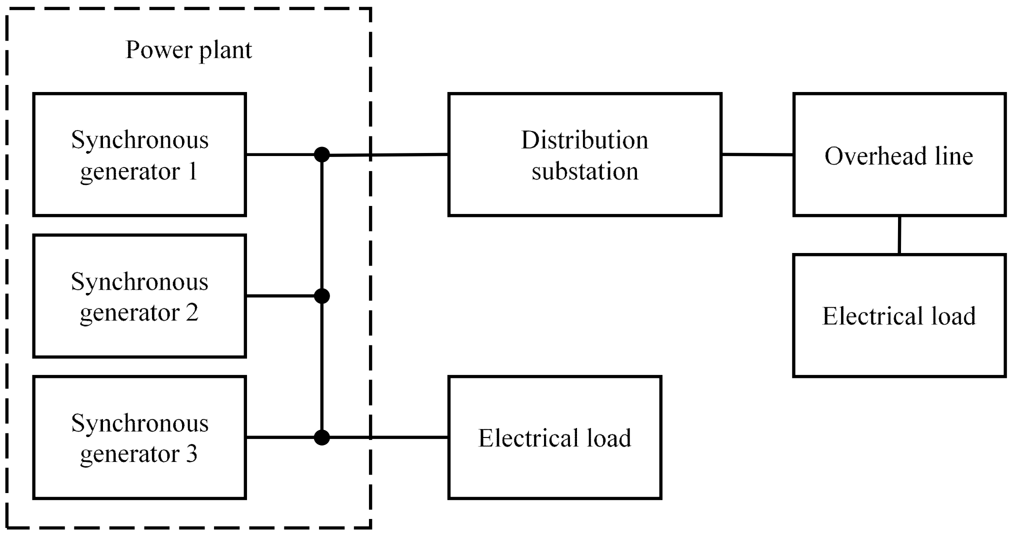

Fig. 1. Approximate structure of the energy system model

The electrical load block of the power system model (Figure 1) is itself a set of models: various electric motors; static load; transformers, etc. All submodels of a single complex model (Figure 1) influence each other. It is necessary to take into account the system load schedule, which should include the expected operating conditions [27]. A sharp change in the electrical load leads to a change in the magnitude of the voltage and frequency of the generated voltage and, as a consequence, to a change in the rotation frequency of the electric motors [28]. The latter is a violation of the technological process, which entails emergency shutdowns and equipment wear. Also, load accounting is important for simulation of emergency situations during the operation of the electric power system [29].

In addition to the structural complexity of the modeled system (Figure 1), it must be taken into account that each of its submodels is described in the general case by systems of high-order nonlinear differential equations. Therefore, the calculation step when integrating differential equations cannot be chosen to be large. Experience in operating proprietary software shows that the calculation step to ensure acceptable accuracy should be no more than 10^{-4} – 10^{-5}. As the number of submodels in the power system diagram increases (Figure 1), the calculation step should be further reduced. This significantly reduces the speed of calculations. And there is also the problem of organizing the interaction of these submodels with each other, such interaction is algorithmically expensive and tends to increase the instability of calculations. And the solution is again in reducing the calculation step and reducing the speed of simulation.

This shows how useful fast simplified surrogate models can be. They will allow multiple repetitive calculations to be performed to solve various research and optimization problems. The resulting solutions can then be tested on the original complex and computationally expensive model.

Let us consider the mathematical description of a complex model (Figure. 1) as a starting point for obtaining surrogate high-speed models.

A synchronous generator, taking into account the damper circuits in the *d*, *q* axes, can be represented as a system of differential equations:

$$\begin{cases} U_d = -\Psi_q\omega - \mathrm{d}\Psi_d / \mathrm{d}t - I_d r; \\ U_q = \Psi_d\omega - \mathrm{d}\Psi_q / \mathrm{d}t - I_q r; \\ U_f = \mathrm{d}\Psi_f / \mathrm{d}t + I_f r_f; \\ 0 = \mathrm{d}\Psi_D / \mathrm{d}t + I_D r_D; \\ 0 = \mathrm{d}\Psi_Q / \mathrm{d}t + I_Q r_Q; \\ \mathrm{d}\omega / \mathrm{d}t = \dfrac{1}{T_M}(M_T - M); \\ \mathrm{d}\gamma / \mathrm{d}t = \omega; \\ \mathrm{d}\delta / \mathrm{d}t = \omega - \omega_0; \end{cases} \tag{1}$$

where ω_0 – angular velocity of the stator field, ω – rotor angular velocity, δ – internal angle of the machine (load angle), γ – angle of rotation of the *d*-axis relative to the fixed axis *a*, M_T – torque of the prime mover (turbine), *M* – electromagnetic torque of the generator, Ψ_d, Ψ_q – stator flux linkage along the longitudinal and transverse axes, Ψ_D, Ψ_Q – flux linkage of damper circuits along the longitudinal and transverse axes, I_d, I_q – stator currents along the longitudinal and transverse axes, I_D, I_Q – currents of damper circuits along the longitudinal and transverse axes, *r* – active resistance of stator winding, r_D, r_Q – active resistances of damper circuits along the longitudinal and transverse axes, Ψ_f, i_f, r_f – flux linkage, current and active resistance of the excitation winding, T_M – electromechanical time constant of an electric machine, U_d, U_q – voltage on the stator winding along the longitudinal and transverse axes. The system of equations (1) is nonlinear, since the equations contain products of variables, and the parameters of the equations change depending on the saturation of the magnetic system. The system of differential equations (1) should be supplemented with a system of nonlinear algebraic equations, among them the equation of the electromagnetic moment: $M = \Psi_d I_q - \Psi_q I_d$.

The system of differential equations for an asynchronous motor has a similar form in the *d*, *q* axes:

$$\begin{cases} \mathrm{d}\Psi_d / \mathrm{d}t = -\omega\Psi_q - rI_d + U_d; \\ \mathrm{d}\Psi_q / \mathrm{d}t = \omega\Psi_d - rI_q + U_q; \\ \mathrm{d}\Psi_D / \mathrm{d}t = -r_2 I_D - (\omega - \omega_{AD})\Psi_Q; \\ \mathrm{d}\Psi_Q / \mathrm{d}t = -r_2 I_Q + (\omega - \omega_{AD})\Psi_D; \\ \mathrm{d}\omega_{AD} / \mathrm{d}t = \dfrac{1}{T_j}(M_C - M); \end{cases} \tag{2}$$

where ω_{AD} – angular velocity of an asynchronous motor, ω – angular velocity of the rotor of a synchronous generator, in the axes of which an asynchronous motor is modeled, M_C – load moment on the engine shaft, I_D, I_Q – rotor currents along the longitudinal and transverse axes.

Static load model in case of isolated neutral:

$$\begin{cases} \mathrm{d}I_d / \mathrm{d}t = \dfrac{r_l}{l_l} I_d + \omega I_q - \dfrac{1}{l_l} U_d; \\ \mathrm{d}I_d / \mathrm{d}t = \dfrac{r_l}{l_l} I_q - \omega I_d - \dfrac{1}{l_l} U_q; \end{cases} \tag{3}$$

where r_l, l_l – active resistance and load inductance, ω – angular velocity of the rotor of a synchronous generator, in the axes of which the load is modeled.

The situation is complicated by the fact that each synchronous generator (Figure 1) is modeled in its own axes d, q, which are rigidly connected to its rotor. Therefore, the power transmission line connecting two such generators will have the following model:

$$\begin{cases} \mathrm{d}I_d / \mathrm{d}t = \dfrac{1}{l} U_{dj} \cos\delta_{ij} - \dfrac{1}{l} U_{qj} \sin\delta_{ij} - \dfrac{1}{l} U_{di} - \dfrac{r}{l} I_d + \omega I_q, \\ \mathrm{d}I_q / \mathrm{d}t = \dfrac{1}{l} U_{dj} \sin\delta_{ij} + \dfrac{1}{l} U_{qj} \cos\delta_{ij} - \dfrac{1}{l} U_{qi} - r_{Л} I_{Лq} - \omega x_{Л} I_{Лd}, \end{cases} \tag{4}$$

where r, l – active resistance and inductance of power transmission, ω – angular velocity of the rotor of the i-th synchronous generator, $\delta_{i,j}$ – the angle of shift of the axes d, q of the i-th and j-th synchronous generator.

When simulating, equations (1) – (4) are integrated using a numerical method. At the same time, at each step of the calculation, the voltages of the nodes are updated; they are calculated on the basis of Kirchhoff equations using a system of algebraic equations, taking into account the topology of the modeled power supply system.

Thus, the simulating process itself is multi-stage, which further increases the time required to carry out the simulation.

Now, instead of a complex model described by equations (1) – (4), we obtain a surrogate model for one of the transient processes in the system in Figure 1.

3. ALGORITHM FOR CREATING A SURROGATE MODEL OF ELECTRICAL LOAD

The following algorithm for obtaining a surrogate model is proposed (Figure 2). The surrogate model is created in two stages: first, the model structure is selected, then the parameters for this structure are identified. The surrogate model is considered suitable based on the results of comparison with the complex model. In this case, the adequacy measures are assessed and the adequacy area of the surrogate model is determined. In this way, a bank of fast-acting surrogate models is formed. The final check of surrogate models is carried out when solving the main task for which they were created. For example, if the model is used to adjust the parameters of automatic controllers, then after a multi-iteration procedure of adjusting the controller on a surrogate model, the results of this adjustment are checked again on the complex model.

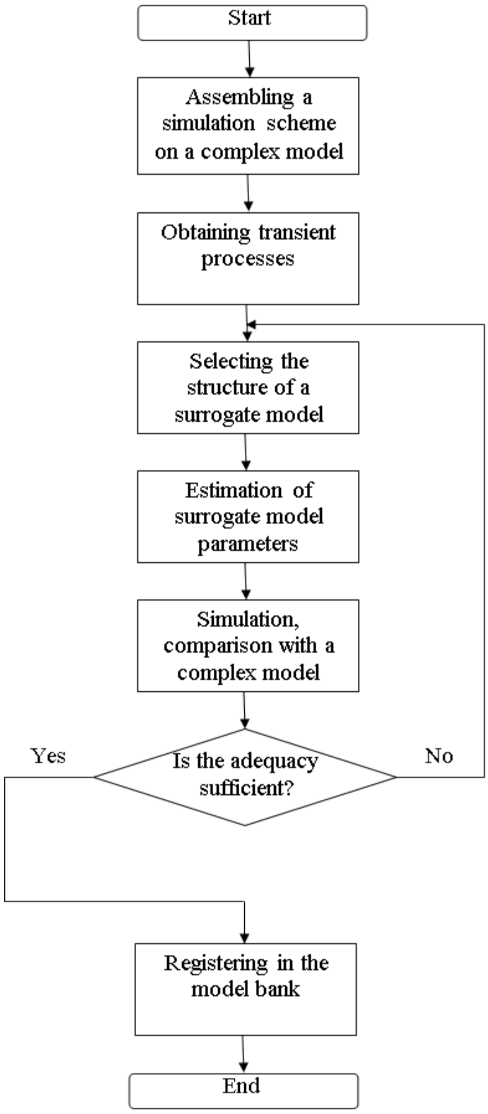

Fig. 2. Algorithm for obtaining a surrogate model

4. AN EXAMPLE OF OBTAINING A SURROGATE MODEL OF ELECTRICAL LOAD USING A MULTI-MODEL SCHEME

Let us consider for the system in Figure 1. the transient process of starting an asynchronous motor in idle mode from one synchronous generator, the remaining subsystems in Figure 1. are disconnected. In addition to the asynchronous motor (2), a static load (3) is supplied from the synchronous generator (1), the power of which is 0.1 of the nominal active power of the synchronous generator.

If the system of equations (2) is represented in vector-matrix form and the flux linkages are expressed through currents, we obtain the following equation:

$$\dot{\mathbf{I}}_s = \mathbf{AU} - \mathbf{BI}, \tag{5}$$

where $\dot{\mathbf{I}}_s$ – vector of derivatives of stator current, $\mathbf{I}$ – vector of stator and rotor currents of an asynchronous motor, $\mathbf{U}$ – voltage of the node from which the motor is powered, these vectors will have the following form:

$$\dot{\mathbf{I}}_S = \begin{pmatrix} \dot{I}_d \\ \dot{I}_q \end{pmatrix}; \quad \mathbf{I} = \begin{pmatrix} I_d \\ I_q \\ I_D \\ I_Q \end{pmatrix}; \quad \mathbf{U} = \begin{pmatrix} U_d \\ U_q \end{pmatrix};$$

in this case, matrix **A** will have the following form:

$$\mathbf{A} = \begin{pmatrix} \frac{1}{\alpha} & 0 & -\frac{r}{\alpha} & \frac{-\omega(l_s - S\frac{l_m^2}{l_r})}{\alpha} & \frac{l_m r_2}{\alpha l_r} & \frac{l_m \omega(S-1)}{\alpha} \\ 0 & \frac{1}{\alpha} & \frac{\omega(l_s - S\frac{l_m^2}{l_r})}{\alpha} & -\frac{r}{\alpha} & -\frac{l_m \omega(S-1)}{\alpha} & \frac{l_m r_2}{\alpha l_r} \\ -\frac{l_m}{l_r \beta} & 0 & \frac{l_m r}{\beta l_s} & -\frac{l_m \omega(S-1)}{\beta} & -\frac{r_2}{\beta} & -\frac{\omega(S l_r - \frac{l_m^2}{l_s})}{\beta} \\ 0 & -\frac{l_m}{l_r \beta} & \frac{l_m \omega(S-1)}{\beta} & \frac{l_m r}{\beta l_s} & \frac{\omega(S l_r - \frac{l_m^2}{l_s})}{\beta} & -\frac{r_2}{\beta} \end{pmatrix} \tag{6}$$

where $\alpha = l_s - l_m^2 / l_r$, $\beta = l_r - l_m^2 / l_s$, l_r – rotor inductance, l_s – stator inductance, l_m – mutual inductance, S – asynchronous motor slip.

It can be seen that some of the matrix elements **A** (6) – are not constant, they depend on S and ω. This complicates the requirements for the surrogate model. In addition, obtaining a surrogate model in the form of equation (5) with matrix (6) is not enough, since it is necessary to take into account the influence of the synchronous generator.

We will look for a surrogate model of electrical load in the following form:

$$\dot{\mathbf{X}} = \mathbf{A}\mathbf{X} \tag{7}$$

This type is convenient for the identification procedure. Identification is carried out by the least squares method. Here **X** vector of observed variables obtained from the original complex model (Figure 1), $\dot{\mathbf{X}}$ – vector of derivatives. Previously, similar models were obtained in [30], but in a different way, through the transition matrix **F** for the matrix equation $\mathbf{X}(k+1) = \mathbf{F}\mathbf{X}(k)$, here similar models are obtained again, but in a different mathematical description: through equation (7). A number of new models are also obtained.

Let $\mathbf{X} = \begin{pmatrix} U_d & U_q & I_d & I_q \end{pmatrix}^T$, then the surrogate model will have a significant error due to the above-mentioned reason: the dependence of the parameters of the matrix **A** on S and ω, as well as the absence of a clearly expressed influence of the synchronous generator (Figure 3).

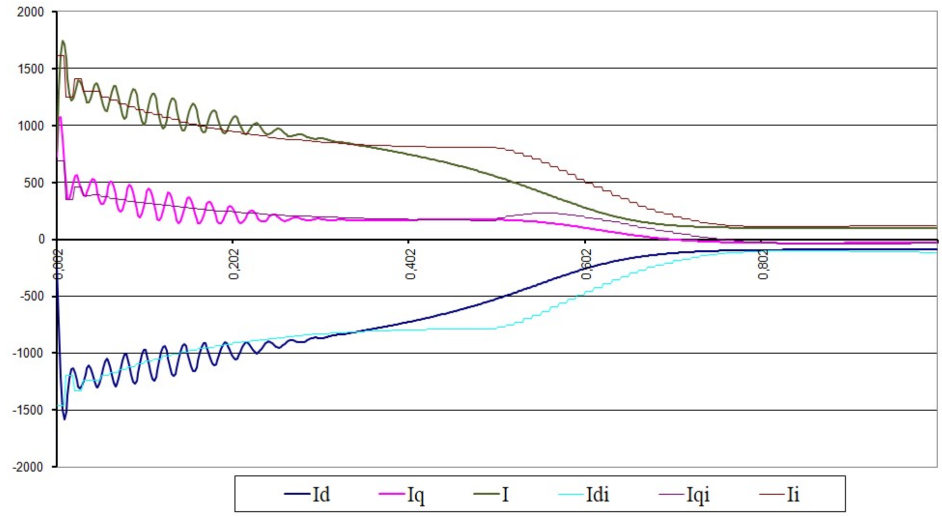

Fig. 3. Currents during starting of an asynchronous motor (diagram of interaction of two surrogate models)

In Figure 3 the currents obtained on the complex model are shown in bold lines, and on the surrogate model in thin lines. The figure shows the currents along the *d* and *q* axes and the effective current of the asynchronous motor. Since the parameters of the matrix **A** changed greatly during launch, the simulation error with one surrogate model turned out to be large. It is proposed to use a multi-model scheme of two surrogate models. One surrogate model is obtained for the beginning of the transition process. The other – for the end of the transition process. And it was necessary to provide a condition for switching from one surrogate model to another. For this purpose, in contrast to previous work [30], it is proposed to use a special switching scheme, and the concept of a multi-model scheme itself is put forward. This switching moment is clearly visible in Figure 3, near the 0.5th second of the simulation. Normalized root mean square error of current $\varepsilon_I \approx 3{,}310\%$. If we include not two, but four surrogate models in the interaction scheme, the result is significantly better (Figure 4), the normalized root-mean-square error in current $\varepsilon_I \approx 1{,}217\%$, which largely corresponds to the previously obtained results in [30]. This error ε_I, as well as voltage error ε_U depends significantly on the step at which the identification was carried out.

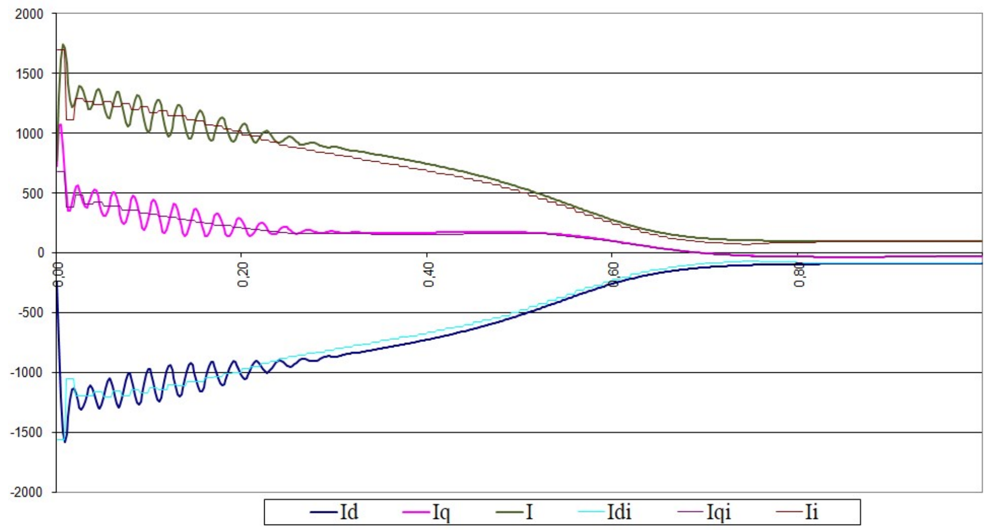

Fig. 4. Currents during starting of an asynchronous motor (diagram of interaction of four surrogate models)

Let us try to change the structure of the surrogate model (7), and introduce the slip S into the vector of variables obtained from the complex model: $\mathbf{X} = \begin{pmatrix} U_d & U_q & I_d & I_q & S \end{pmatrix}^T$, where $S = (\omega - \omega_{AD}) / \omega$ – the slip. In this case, even with one surrogate model, the following transition process is obtained (Figure 5), $\varepsilon_I \approx 2{,}031\%$, with two surrogate models the error achieved is equal to $\varepsilon_I \approx 0{,}670\%$.

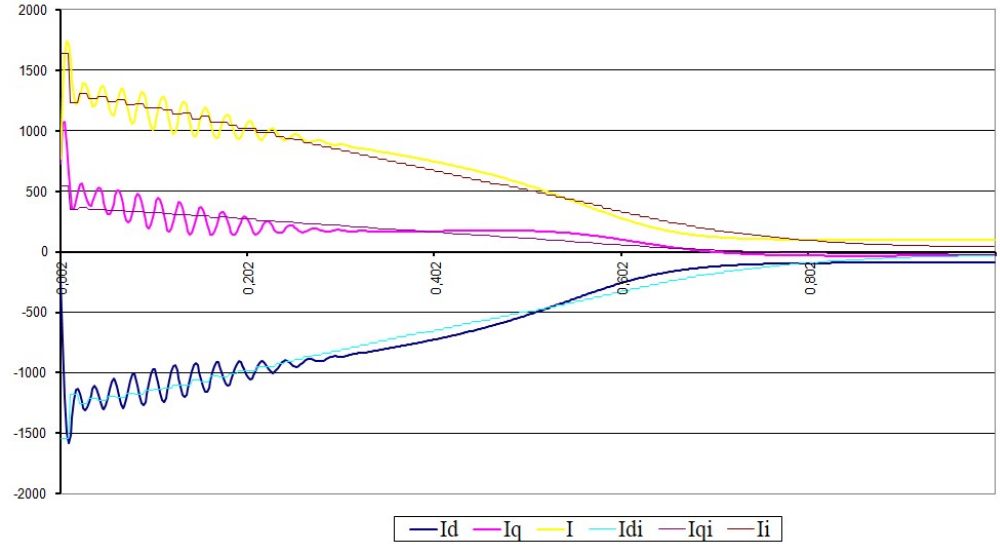

Fig. 5. Currents at starting of an asynchronous motor taking into account slip

Let us change the structure of the surrogate model (7) again and introduce into the vector **X** one more variable: $\mathbf{X} = \left(U_d \quad U_q \quad I_d \quad I_q \quad S \quad I_f\right)^T$, where I_f – excitation current of a synchronous generator. We will use a multi-model scheme of two surrogate models (Figure 6), $\varepsilon_I \approx 0{,}527\%$.

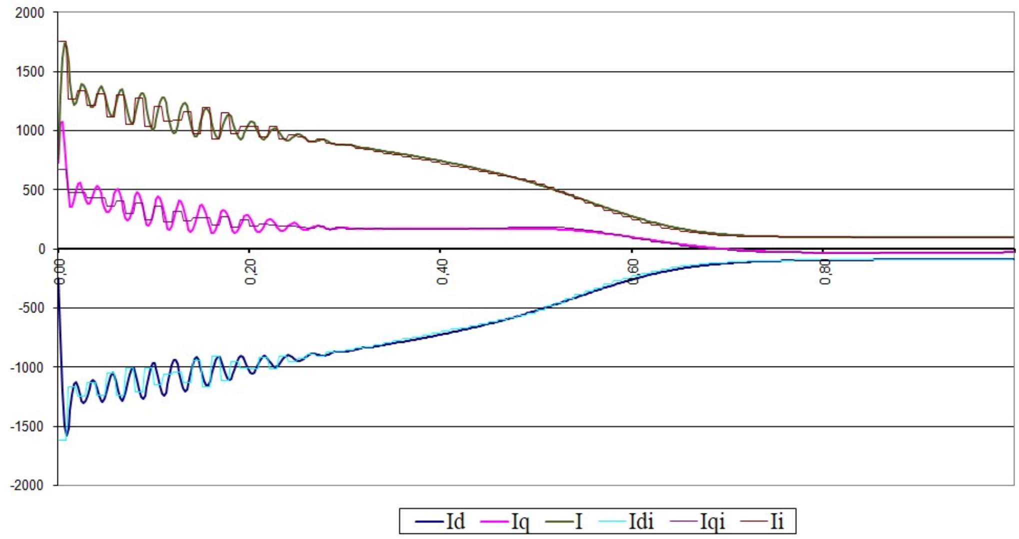

Fig. 6. Currents during starting of an asynchronous motor taking into account slip and excitation current (diagram of interaction of two surrogate models)

Other surrogate model structures were tested, including: $\mathbf{X} = \left(U_d \quad U_q \quad I_d \quad I_q \quad I_D \quad I_Q\right)^T$, $\mathbf{X} = \left(U_d \quad U_q \quad I_d \quad I_q \quad S \quad U_f\right)^T$, $\mathbf{X} = \left(U_d \quad U_q \quad I_d \quad I_q \quad I_f \quad U_f\right)^T$, $\mathbf{X} = \left(U_d \quad U_q \quad I_d \quad I_q \quad \omega_{AD}\right)^T$, but they failed to achieve a significant improvement in the quality of the simulation. These models, as well as the model in Figure 6, were not previously considered in [30].

5. CONCLUSION

It is assumed that in the future the considered multi-model approach will allow obtaining surrogate models suitable for solving various optimization problems.

The following main results were obtained.

1. It is shown that well-known simplified high-speed models presented in the form of systems of differential equations with constant parameters, written in vector-matrix form, can be used as surrogate models.

2. It is shown how such models can be obtained using least squares identification from experimental data on a complex model of the power system.

3. It is proposed to use simplified models previously obtained in another mathematical description in [30] as surrogate models of electrical load. New models not previously considered were also obtained.

4. A multi-model scheme is proposed that combines several surrogate models, and, in contrast to work [30], the concept of a multi-model surrogate model itself is proposed.

The immediate goals for further research are as follows.

1. Explore the possibilities of the proposed multi-model approach. Find such methods of switching from one surrogate model to another, which achieve a good area of adequacy of simulation, which is important when solving optimization problems.

2. Continue searching for such a structure of the surrogate model that will enable reliable use of a single surrogate model in the entire area of the process under study. That is, continue the search structural identification. Moreover, develop appropriate recommendations.

3. To develop a methodology for using various classes of surrogate models of electrical loads when simulating electrical systems and power plants in various applied problems.

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