Model Predictive Control for a Synchronous Turbine Generator of Full and Reduced Order

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***Abstract*—In this paper we perform model predictive control (MPC) for a synchronous turbine generator of full and reduced order. The model reduction aims at facilitation of controller design and reduction of computational complexity in investigating the considered system. The suggested method for model reduction is a two stage method where balanced realization and Legendre polynomials approximation is presented. Then model predictive control design for the considered system also is performed. A numerical experiment is discussed showing that the computed responses for the turbine generator of full and reduced order are practically the same. This fact reveals the good approximation capabilities of the proposed approach.**

Keywords—model order reduction, synchronous generator, model predictive control

I. INTRODUCTION

The physical model that we consider in this paper represents a synchronous generator connected to the electrical power network. In order to study the process of delivering power to the network, it is necessary to develop sufficiently accurate model of the synchronous generator machine.

System modeling is an important part of the controller design procedure. The higher the degree of accuracy by adding more detail in model description, the higher the level of complication in model treatment by handling its different features and properties. One possible way to resolve this tradeoff is by using model reduction techniques. A good reference, describing different methods and techniques for model reduction, is the book [1]. This book considers the main approaches for order reduction and gives the details in their implementation. An important approach in this area is the procedure of balancing and then, applying the method of balanced truncation, which is initially developed in [2]. The balanced truncation method uses preliminary balancing, where the system gramians are transformed into equal diagonal matrices. The diagonal elements of these gramians show the contribution of system states to the system energy. The balanced truncation procedure is further extended to balanced residualization [3], [4], and [5]. The balanced residualization procedure utilizes singular perturbation approximation, where system states are divided into slow and fast modes. The derivatives of the fastest modes are allowed to approach zero and then, substituted in the state equation. The advantage of using balanced residualization is preservation of system gain and good approximation properties at low frequencies, while balanced truncation is characterized by good approximation properties at high frequencies. Another extension of balanced model reduction is where, system gramians are presented in terms of certain system trajectories, which are approximated by using Legendre orthogonal polynomials [6].

MPC is a regulation strategy based on numerical optimization [7]. Future plant responses and control inputs are predicted with a system model and an optimization procedure is then applied at given time intervals for a specified cost function. MPC with inputs and states constraints is considered in [8]. MPC is an approach applied to improve control specifications in many industrial applications and emerges as the most applied advanced control method used in industry nowadays [9].

There exist several papers devoted to MPC of turbine generators. In [10] model predictive control technique is used to improve the power system stability. A data-driven MPC approach for oscillation damping for power system via excitation is applied in [11]. A predictive optimized adaptive technique in turbine generators is incorporated in [12].

The remaining part of the note is structured in the following way. A Legendre polynomials approximation method is presented in Chapter 2. In Chapter 3 the mathematical description of the synchronous turbine generator is considered. Chapter 4 is devoted to illustration of the applied MPC design technique. Chapter 5 reveals a numerical example where the MPC design is performed to the generator of full and reduced order. Finally we finish our paper with some concluding remarks.

II. BALANCED RESIDUALIZATION BY USING LEGENDRE ORTHOGONAL POLYNOMIALS APPROXIMATION

We consider the linear state space model as follows:

$$\dot{x}(t) = Ax(t) + Bu(t), \quad x(0) = x_0, \tag{1}$$

$$y(t) = Cx(t) + Du(t), \quad t \geq 0, \tag{2}$$

where $x(t) \in \mathbb{R}^n$, $u(t) \in \mathbb{R}^m$, $y(t) \in \mathbb{R}^p$. System balancing and balanced model reduction are basic methods related with reducing the size of the system describing equations. A central role for these methods implementation play the system gramians. The controllability gramian of the system is determined by the expression:

$$W_c(0,T) = \int_0^T e^{At} BB^T e^{A^T t}\, dt, \tag{3}$$

where $[0, T]$ is the time interval, where the gramian is computed. The observability gramian on the same time interval is determined from the expression:

$$W_o(0, T) = \int_0^T e^{A^T t} C^T C e^{At}\, dt \tag{4}$$

For asymptotically stable systems and $T \to \infty$, the gramians can be computed by solving the Lyapunov matrix equations:

$$AW_c + W_c A^T + BB^T = 0, \tag{5}$$

$$A^T W_o + W_o A + C^T C = 0 \tag{6}$$

Based on the computed gramians, one can derive similarity transformation, which transforms the system into a balanced form:

$$\widetilde{W}_c(0, T) = \widetilde{W}_o(0, T) = diag\{\sigma_1, \sigma_2, \cdots, \sigma_n\} \tag{7}$$

A specific feature of this form is that the gramians are presented by equal, diagonal matrices, with Hankel singular values as diagonal elements. The states, corresponding to small Hankel singular values are simultaneously difficult to control and observe. Truncating these system states will have a small impact on the system input/output relation. This approach for model reduction by truncating the states corresponding to small Hankel singular values is called balanced truncation. The similarity transformation matrices for balancing the system are computed as follows: $P = \Xi^{-1/2} V^T L^T$ and $P^{-1} = UW\Xi^{-1/2}$, where matrix L is the Cholesky factor of the observability gramian $W_o = LL^T$, U is the Cholesky factor of the controllability gramian $W_c = UU^T$, W and V are derived from the singular value decomposition of the Cholesky factors product $U^T L = W \Xi V^T$.

Another approach for model reduction by using balancing is based on the singular perturbation approximation of system equations. Using the information from the set of Hankel singular values, the already balanced system can be partitioned in two parts. The first part $\Sigma_1 = \{A_{11}, B_1, C_1, D\}$ corresponds to the large Hankel singular values and the second part $\Sigma_2 = \{A_{22}, B_2, C_2, D\}$ corresponds to small ones. We assume that matrix A_{22} is Hurwitz and therefore, invertible. By solving the already balanced system with respect to the state vector of Σ_2, we obtain the reduced order system as follows:

$$\dot{x}_1 = (A_{11} - A_{12} A_{22}^{-1} A_{21}) x_1 + (B_1 - A_{12} A_{22}^{-1} B_2), \tag{8}$$

$$y = (C_1 - C_2 A_{22}^{-1} A_{21}) x_1 + (D - C_2 A_{22}^{-1} B_2) u \tag{9}$$

The system, described by state equations (8) and output equation (9) is called a balanced residualization realization. Balanced residualization represents a singular perturbation approximation of the balanced system. Since the balanced residualization system comprise the second part of the balancing process, the error of model reduction at very high frequencies tends to zero [4]. The balanced residualization system preserves the DC gain [5] and therefore, the model reduction procedure has small error at low and high frequencies.

From the presentation so far, it is clear that the key feature of the balancing procedure is to derive the system gramians. The standard approach is by solving the equations of Lyapunov, and thus obtaining the steady-state gramians. The problem with this approach is when the relative stability of the linear system is small. The low level of relative stability is a source of numerical errors. This is the reason to propose a method for computing the gramians, which avoids solving the equations of Lyapunov.

Our method relies on the information obtained from the system trajectories and is based on Legendre series approximation of these trajectories to compute the gramians. The Legendre polynomials are easy to compute due to the existing recurrence procedure and do not require a weighting function for deriving the series expansion coefficients. The proposed method is practical since the system trajectories can be obtained either by measurement or by computer simulations. The proposed method is derived in detail in [6] and here we present its short description.

Let us consider the state solution of equation (1):

$$x(t) = e^{At} x_0 + \int_0^t e^{A(t-\tau)} Bu(\tau) d\tau \tag{10}$$

We first consider the zero-input part, where the external input $u(t) = 0$. In order to obtain the observability gramian, we consider expression (10) and compute the output, i.e. $y(t) = Ce^{At} x_0$. From the definition of the observability gramian (4), it is clear that the expression under interest is $(t) = (Ce^{At})^T$, which is obtained by sequentially assuming x_0 to be the columns of the identity matrix I_n. We consider first the SISO case. The observability gramian can be presented in the form:

$$W_o(0, T) = \int_0^T q(t) q^T(t) dt \tag{11}$$

Therefore, the observability gramian can be obtained by implementing Legendre orthogonal polynomials series approximation of the signal $q(t)$.

Legendre orthogonal polynomials form a complete set of orthogonal polynomials in the Hilbert space $L_2[-1,1]$. From the theorem of Weierstrass follows that any continuous function on the interval $[-1,1]$ can be approximated arbitrarily close by a series of orthogonal polynomials. The Legendre orthogonal polynomials are derived by a recurrence relation:

$$L_{n+1}(t) = \frac{1}{n+1}[(2n+1) t L_n(t) - n L_{n-1}(t)], \tag{12}$$

where $L_0(t) = 1$, $L_1(t) = t$, $n = 1, 2, \cdots$. The Legendre polynomials are additionally normalized for obtaining the Legendre orthonormal functions $\phi_n(t) = \sqrt{\frac{2n+1}{2}} L_n(t)$. When the time interval is different than $[-1,1]$, the Legendre orthonormal functions can be shifted. For example, the Legendre orthonormal functions in the vector space $L_2[0, T]$ are obtained by introducing a change of variables as follows:

$$\phi_n(t) = \sqrt{\frac{2n+1}{2}} L_n\left(\frac{2}{T} t - 1\right), \text{ for } t \in [0, T] \tag{13}$$

The Legendre orthogonal series representation of the vector function $q(t)$ takes the form:

$$q(t) = \sum_{n=0}^{\infty} g_n \sqrt{\frac{2n+1}{2}} L_n\left(\frac{2}{T} t - 1\right) =$$

$$= \sum_{n=0}^{\infty} g_n \phi_n(t), \qquad t \in [0, T] \tag{14}$$

where the series vector coefficients are computed as follows:

$$g_n = \sqrt{\frac{2n+1}{2}} \int_0^T q(t) L_n\left(\frac{2}{T} t - 1\right) dt \tag{15}$$

Therefore, the observability gramian (4) is computed as follows [6]:

$$W_o(0,T) = \int_0^T e^{A^T t} C^T C e^{At}\, dt = \int_0^T q(t) q^T(t) dt =$$
$$= \frac{T}{2} \int_0^T \sum_{n=0}^{M} g_n \phi_n(t) \sum_{n=0}^{M} g_n^T \phi_n(t)\, dt = \frac{T}{2} \sum_{n=0}^{M} g_n\, g_n^T, \tag{16}$$

where M is the series truncation order and the orthogonal series are truncated, thus introducing certain error of approximation.

In order to obtain the controllability gramian, we consider the linear system impulse response, when $u(t) = \delta(t)$ is a delta impulse, and then we have $x(t) = e^{At} B$. The controllability gramian can be written in the form:

$$W_c(0,T) = \int_0^T e^{At} B B^T e^{A^T t}\, dt = \int_0^T x(t) x^T(t) dt$$

Then using similar arguments as for the observability gramian, we obtain the controllability gramian as [6]:

$$W_c(0,T) \approx \frac{T}{2} \sum_{n=0}^{M} f_n\, f_n^T, \tag{17}$$

where, $f_n,\ n = 0,1,2,\cdots$ are the Legendre series coefficients for the system impulse response, i.e. $x(t) = \sum_{n=0}^{\infty} f_n \phi_n(t)$ and M is the truncation order.

In the MIMO case, we use the dyadic expansion of the product of two matrices. If there exist three matrices $B \in \mathbb{R}^{m \times n}$, $C \in \mathbb{R}^{n \times p}$ and $D \in \mathbb{R}^{m \times p}$, such that $D = BC$, then matrix D can be presented in the form $D = \sum_{i=1}^{n} b_i c_i^T$, where b_i is the i^{th} column of B and c_i^T is the i^{th} row of C, $i = 1,2,\cdots,n$. Applying this property of the dyadic expansion, we can compute the system gramians in the MIMO case as:

$$W_o(0,T) \approx \frac{T}{2} \sum_{n=0}^{M} \sum_{j=1}^{p} g_n^j \left(g_n^j\right)^T, \tag{18}$$

$$W_c(0,T) \approx \frac{T}{2} \sum_{n=0}^{M} \sum_{i=1}^{m} f_n^i (f_n^i)^T, \tag{19}$$

where g_n^j are the Legendre orthogonal series vector coefficients with respect to the j^{th} row of matrix C, $j = 1,2,\cdots,p$ and f_n^i are the Legendre orthogonal series vector coefficients with respect to the i^{th} column of matrix B, $i = 1,2,\cdots,m$, see [6].

III. Mathematical Description of the Synhronuous Turbine Generator

The small signal behavior of synchronous turbine generator is initially described by the classical linearized model developed in [13] and finds its detailed characterization in [14]. A short description of the linearized model is provided in [15], where it is shown that it has $m = 2$ input signals, $p = 2$ output signals and $n = 10$ state variables. The first input signal is the voltage reference signal to the generator $u_1 = V_{ref}$ and the second input signal is the mechanical torque $u_2 = T_m$. The first output signal is the base rotor angle $y_1 = \delta$ and the second output signal is the generator terminal voltage $y_2 = V_t$. The state variables are presented as follows: the field flux linkage voltage $x_1 = E_q$, the per unit speed deviation $x_2 = \omega_r$, the base rotor angle $x_3 = \delta$, the output voltage of the transducer $x_4 = V_1$, the output voltage of the rate feedback $x_5 = V_2$, the output voltage of the phase lead circuit first stage $x_6 = V_3$, the output voltage of the phase lead circuit second stage $x_7 = V_4$, the output voltage of the washout circuit $x_8 = V_5$, the lag circuit output voltage $x_9 = V_R$ and the field voltage $x_{10} = E_{FD}$. The system matrices are presented as follows:

$$A = \begin{bmatrix} -0.55 & 0 & -0.31 & 0 & 0 & 0 & 0 & 0 & 0 & 0.17 \\ -0.04 & 0 & -0.04 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 314.16 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 9.55 & 0 & -0.87 & -20 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0.04 & -0.03 \\ -0.2 & 10.87 & -0.17 & 0 & 0 & -10.87 & 0 & 0 & 0 & 0 \\ -0.94 & 51.98 & -0.8 & 0 & 0 & -41.12 & -10.87 & 0 & 0 & 0 \\ -0.94 & 51.98 & -0.8 & 0 & 0 & -41.11 & -10.87 & -0.1 & 0 & 0 \\ 0 & 0 & 0 & -1000 & -1000 & 0 & 0 & 1000 & -20 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1.05 & -0.82 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1000 & 0 \\ 0 & 0.09 & 0 & 0 & 0 & 0.44 & 2.12 & 2.12 & 0 & 0 \end{bmatrix}^T$$

$$C = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.48 & 0 & -0.04 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

It is clear that the system model is of order ten. We apply the balanced residualization model reduction procedure from the previous section and obtain the reduced fifth order model as follows:

$$A = \begin{bmatrix} -0.21 & -3.2 & -0.42 & -0.17 & 0.09 \\ 3.17 & -0.24 & -0.46 & -0.23 & 0.11 \\ 0.27 & 0.16 & -0.84 & -1.6 & 0.53 \\ -0.17 & 0.13 & 1.59 & -0.71 & 0.79 \\ 0.04 & 0.13 & -0.66 & 0.63 & -2.3 \end{bmatrix},$$

$$B = \begin{bmatrix} 0.86 & 0.32 & -2.04 & 1.03 & -0.77 \\ 2.12 & -2.22 & -0.23 & 0.61 & 0.1 \end{bmatrix}^T,$$

$$C = \begin{bmatrix} 2.29 & 2.23 & 1.95 & 0.93 & -0.42 \\ -0.11 & -0.22 & -0.59 & -0.76 & 0.65 \end{bmatrix},$$

$$D = \begin{bmatrix} 0.0015 & -0.0006 \\ 0.0078 & -0.0036 \end{bmatrix}.$$

Further we will discretize the presented model using zero-order hold on the inputs.

IV. Model Predictive Control Design

The main advantage of the MPC in general is based on the fact that it is the main robust design technique suitable to control industrial plants and processes. The advantage of the considered MPC method considered in this chapter is connected with the possibility to formulate a control law that ensures very good reference tracking of the output signal.

Let the discretized system is depicted by the set of equations:

$$x(k+1) = Fx(k) + Gu(k),$$
$$y(k) = Cx(k) \tag{20}$$

The predicted elements formed by the expression (20) with input elements ***u(k)*** can be written

$$x(k|k) = x(k)$$
$$x(k+1|k) = Fx(k) + Gu(k|k)$$
$$x(k+2|k) = F^2 x(k) + FGu(k|k) + Gu(k+1|k)$$
$$\vdots$$

In vector-matrix represemtation:

$$x(k+i|k) = F^i x(k) + \mathbb{C}_i\, \boldsymbol{u}(k), \quad i = 0,\ldots,N$$

$$x(k) = \mathbb{M}x(k) + \mathbb{C}\,u(k), \text{ where } \mathbb{M} = \begin{bmatrix} F \\ F^2 \\ \vdots \\ F^N \end{bmatrix}. \qquad (21)$$

Here $\mathbb{C}$ is the (convolution) matrix with rows $\mathbb{C}_i$, that is defined by the expression:

$$\mathbb{C} = \begin{bmatrix} G & 0 & \cdots & 0 \\ FG & G & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ F^{N-1}G & F^{N-2}G & \cdots & G \end{bmatrix}, \qquad (22)$$

where $\mathbb{C}_0 = 0$, and $\mathbb{C}_i = i$ th block row of $\mathbb{C}$.

If we create the vector of the predicted values of the output N samples ahead (prediction horizon) and the vector of the predicted control actions in the separate samples

$$\boldsymbol{y} = \begin{bmatrix} y(k+1) \\ y(k+2) \\ \vdots \\ y(k+N) \end{bmatrix}, \ \boldsymbol{u} = \begin{bmatrix} u(k) \\ u(k+1) \\ \vdots \\ u(k+N-1) \end{bmatrix} \qquad (23)$$

then for the predicted values of the output we derive the equation

$$\boldsymbol{y} = C_F x(k) + C_G \boldsymbol{u}. \qquad (24)$$

The matrices C_F and C_G are derived when applying the terms (21) and (22) after multiplying each of the corresponding elements with the matrix C from (20). Finally the matrices C_F and C_G are of the following type

$$C_F = \begin{bmatrix} CF \\ CF^2 \\ \vdots \\ CF^N \end{bmatrix}, \ C_G = \begin{bmatrix} CG & 0 & \cdots & 0 \\ CFG & CG & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CF^{N-1}G & CF^{N-2}G & \cdots & CG \end{bmatrix} \qquad (25)$$

Let's the vector of the reference elements is specified as:

$$\boldsymbol{r} = [r(k+1) \quad r(k+2) \quad \cdots \quad r(k+N)]^T. \qquad (26)$$

The following cost function is formulated as:

$$J = (\boldsymbol{y} - \boldsymbol{r})^T Q (\boldsymbol{y} - \boldsymbol{r}) + \boldsymbol{u}^T R \boldsymbol{u}. \qquad (27)$$

Here Q and R are performance weighting functions and $\boldsymbol{y}$ and $\boldsymbol{r}$ are the vectors defined in (23) and (26). After applying expression (24) for $\boldsymbol{y}$ for the cost function we are able to obtain

$$J = (C_F \boldsymbol{x(k)} + C_G \boldsymbol{u} - \boldsymbol{r})^T Q (C_F \boldsymbol{x(k)} + C_G \boldsymbol{u} - \boldsymbol{r}) + \boldsymbol{u}^T R \boldsymbol{u}. \qquad (28)$$

The first derivative of the relation (28) towards to the control vector $\boldsymbol{u}$ is calculated as shown:

$$\frac{\partial J}{\partial \boldsymbol{u}} = 2{C_G}^T Q (C_G \boldsymbol{u} + C_F x(k) - \boldsymbol{r}) + 2R\boldsymbol{u} =$$
$$= 2({C_G}^T Q C_G + R)\boldsymbol{u} + 2{C_G}^T Q (C_F x(k) - \boldsymbol{r}) \qquad (29)$$

The minimum value of the expression (28) is a solution of the equation $\frac{\partial J}{\partial \boldsymbol{u}} = 0$ i.e.

$$({C_G}^T Q C_G + R)\boldsymbol{u} + {C_G}^T Q (C_F x(k) - \boldsymbol{r}) = 0$$

So, the control vector can be computed as follows:

$$\boldsymbol{u} = -\left(({C_G}^T Q C_G + R)^{-1} {C_G}^T Q (C_F x(k) - \boldsymbol{r}) \right). \qquad (30)$$

We introduce the following notation

$$P = ({C_G}^T Q C_G + R)^{-1} {C_G}^T Q \qquad (31)$$

in order to obtain the control vector as follows:

$$\boldsymbol{u} = -P(C_F x(k) - \boldsymbol{r}). \qquad (32)$$

V. Simulation Results

In this part of the note we perform MPC applying the technique presented in Chapter 4 for the turbine generator of full and reduced-fifth order. We consider the continuous-time system presented in the Section 3, which is discretized with sampling time $T_s = 0.1 sec$. The performance weighting matrices are chosen as $Q = C^T C$ and $R = 0.01$. The numerical experiments are conducted with prediction horizon N, which has the value of 30 samples ahead.

In Figure 1 the transient responses of the closed-loop system with respect to the input signal $u_1 = V_{ref}$ [V] and the output signal $y_1 = \delta$ [rad] for the generator full and reduced fifth order models are presented.

In Figure 2 the transient responses of the corresponding system with respect to the input signal $u_2 = T_m$ [Nm] and the output signal $y_1 = \delta$ [rad] for the generator full and reduced fifth order models are shown.

In Figure 3 the transient responses of the closed-loop system with respect to the input signal $u_1 = V_{ref}$ [V] and the output signal $y_2 = V_t$ [V] for the generator full and reduced fifth order models are given.

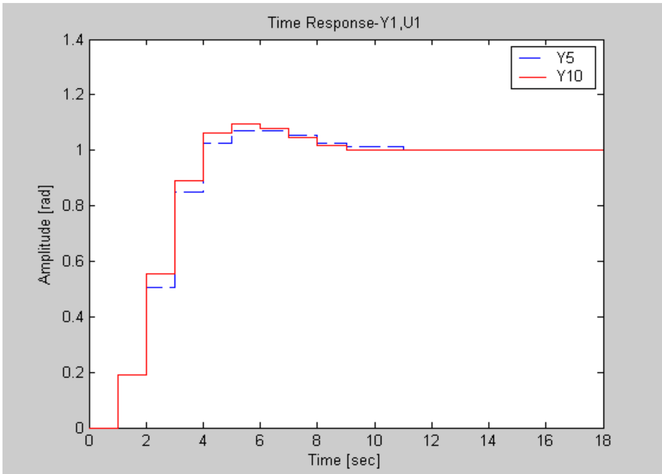

Fig.1. Transient closed-loop system response $u_1 = V_{ref}$ v.s. $y_1 = \delta$, full order – red and reduced order - blue.

In Figure 4 the transient responses of the corresponding system with respect to the input signal $u_2 = T_m$ [Nm] and the output signal $y_2 = V_t$ [V] for the generator full order model and the corresponding reduced fifth order model are illustrated.

It is obvious that all transient responses of the closed-loop system for the generator full order and reduced – fifth order models are almost the same i.e. the difference between them is very small and can be neglected. This fact confirms the good approximation capabilities of the presented balanced residualization technique, when applied for reducing the generator model in MPC.

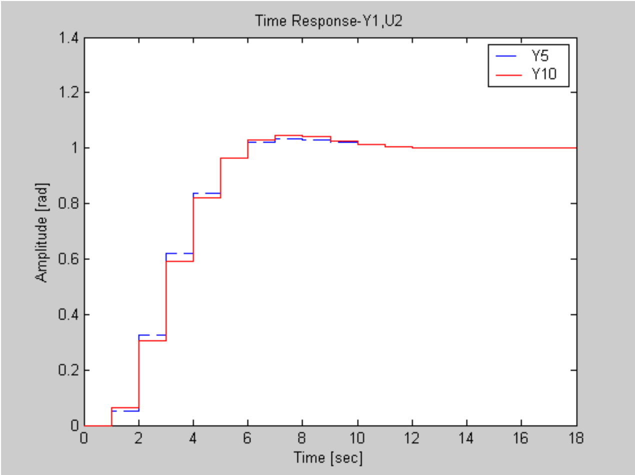

Fig.2. Transient closed-loop system response $u_2 = T_m$ v.s. $y_1 = \delta$, full order – red and reduced order - blue.

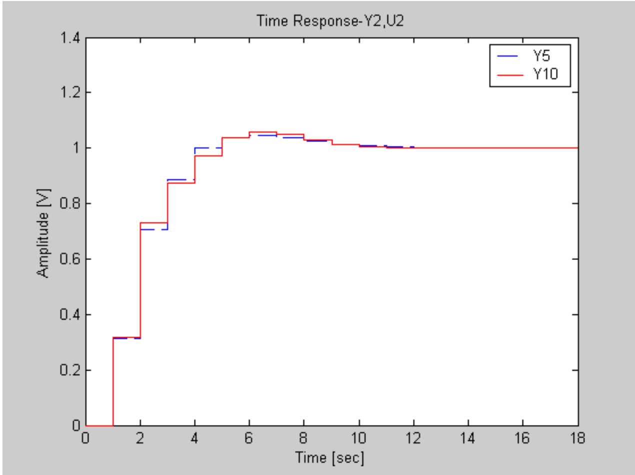

Fig.4. Transient closed-loop system response $u_2 = T_m$ v.s. $y_2 = V_t$, full order – red and reduced order - blue.

CONCLUSIONS

In this paper we perform MPC for a synchronous turbine generator of full and reduced order. The presented method utilizes model reduction technique based on balanced residualization and Legendre polynomials approximation. Several experiments are conducted comparing the transient responses of the full and reduced-fifth order models of the considered closed-loop system with the designed model predictive controller. The simulation results show almost complete coincidence of the simulated characteristics in time domain. This fact confirms the good approximation capabilities of the method and its ability to reduce the complexity of the control system problem.

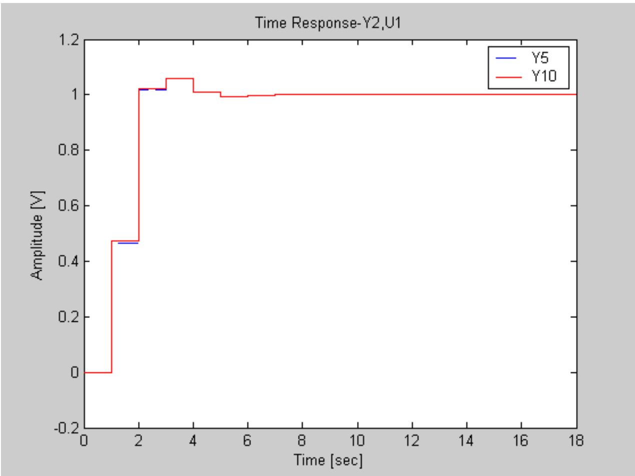

Fig.3. Transient closed-loop system response $u_1 = V_{ref}$ v.s. $y_2 = V_t$, full order – red and reduced order - blue.

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