Teaching Modern Control Theory to Undergraduates Using a State Space Model of a Synchronous Generator

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***Abstract*—Modern control system analysis and design uses state space methods to develop models of both physical systems and their respective controllers. However, teaching state space to undergraduate students is often difficult due to the mathematical complexity and lack of visual validation when compared to classical control system design. The authors in this paper have employed state space analysis to design controllers for a reduced-order model of a synchronous generator to demonstrate the advantages of state space techniques over classical control design. The information in this paper was presented to both Electrical Engineering (EE) as well as Electrical and Computer Engineering Technology (ECET) students as an out-of-class assignment to implement the various controller designs and reflect on the results. A survey was administered to these students after completion of the assignment to assess their active and reflective learning. This survey included both Likert scale as well as open-ended questions to gauge their ability to both build and simulate the control system as well as reflect on the importance of state space. Based on the survey results provided, students were generally able to implement the various controllers but the ECET students had difficulty relating their results to a more general understanding of the importance of state space.**

***Index Terms*—Control Design, Optimal Control, State Space, Synchronous Generator, Education.**

I. Introduction

Modern control theory has had a profound impact on the ability to provide control to previously intractable systems. Whereas classical control theory is applicable almost exclusively to linear, time-invariant, single-input/single-output systems, modern control theory has no such restrictions, enabling its use in such wide-ranging applications as aircraft [1], robotics [2], and vehicle systems [3]. Unfortunately, modern control theory is more difficult to present to undergraduate electrical engineering students than classical control theory. First, it is less intuitive than classical control theory. Second, because of the complexity required in solving state equations by hand, students are either required to solve trivial systems that could be easily solved using classical control theory, or are provided with systems that are too complex for thorough analysis within a reasonable amount of class time. Third, modern control theory is often allotted only a small amount of time in a required undergraduate control systems course. Efforts have been made to address some of the challenges of teaching modern control techniques. For instance, an interactive methodology is proposed by Guzman in [4]. Astrom explains the challenges in teaching control system in [5]. Niemann *et. al* describe a new concept for teaching an introductory course in control engineering in [6].

In this paper, a reduced order, linearized model of a synchronous generator with prime mover and electrical excitation is presented as a developmental tool in a control systems course without requiring instructors or students to have an intimate knowledge of the material beforehand. The model development and controller design approaches can therefore be a valuable teaching tool for an undergraduate control systems course. The objectives of this paper are for undergraduate engineering and engineering technology students to (1) understand the model and dynamic behavior of a MIMO synchronous generator, (2) develop and simulate controllers for a reduced order synchronous generator using state space techniques, and (3) use the developed models to identify the advantages of state space-based controllers as compared to classical control system design.

The synchronous generator dynamic model is presented in Section II. In Section III, controller design methods for MIMO state space models are presented. Numerical results are demonstrated in Section IV. Results from student implementation of the MIMO system and self-assessment are provided in Section V. Section VI concludes the paper.

II. Synchronous Generator Dynamic Model

A. Model Description

A dynamic model of the synchronous generator is necessary when looking at the transient response of the generator, such as in the design of Power System Stabilizers (PSS) [7]–[9]. The IEEE standard 1110 [10] discusses the synchronous generator dynamic models. Krause *et al.* analyze the detailed 8^{th} order nonlinear model of a synchronous machine in [11]. However, if the generator is in steady state, and perturbations around the operating point are less than 10% of the nominal values, then a linearized 3^{rd} order model may be employed. A simple 3^{rd} order model that is commonly used in power system stability studies is the Heffron-Phillips model [9], [12].

To linearize the model, the variables from the original nonlinear system must initially be in steady state. Once the model has been linearized, as shown in Figure 1, the variables become the *changes* of the original nonlinear model variables. The Heffron-Phillips model in Figure 1 has two main loops, a

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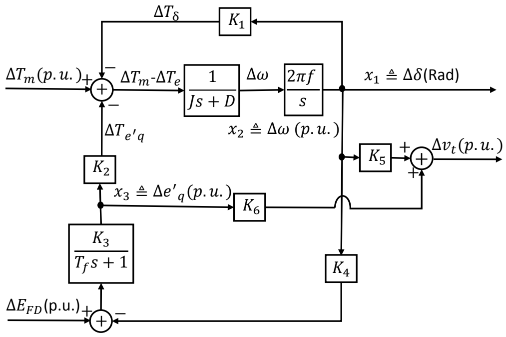

Fig. 1: Heffron-Phillips model of a single synchronous generator supplying power to a large grid (infinite bus).

mechanical loop on top and an electrical loop at the bottom. Six constants are also included in Figure 1. The derivation of constants K_1 through K_6 can be found in [7], [8], [13]. The Heffron-Phillips model is derived based on the linearized state space equations of a 3^{rd} order synchronous generator, i.e.,

$$\frac{d\Delta\delta}{dt} = (2\pi f)\Delta\omega \tag{1a}$$
$$\frac{d\Delta\omega}{dt} = \frac{1}{J}(\Delta T_m - K_1\Delta\delta - K_2\Delta e_q' - D\Delta\omega) \tag{1b}$$
$$\frac{d\Delta e_q'}{dt} = \frac{K_3}{T_f}(\Delta E_{FD} - K_4\Delta\delta) - \frac{1}{T_f}\Delta e_q' \tag{1c}$$

The Laplace transform of the above equations, around an operating point, becomes

$$\Delta\delta = \frac{(2\pi f)\Delta\omega}{s} \tag{2a}$$
$$\Delta\omega = \frac{1}{Js+D}(\Delta T_m - K_1\Delta\delta - K_2\Delta e_q') \tag{2b}$$
$$\Delta e_q' = \frac{K_3}{T_f s+1}(\Delta E_{FD} - K_4\Delta\delta) \tag{2c}$$

Variables in (2) are in the Laplace domain. The block diagram of Figure 1 can directly be built from (2a) through (2c).

B. State Space representation of the Linearized Model

To obtain the state space form of the model shown in Figure 1 and described by (1), the state variables, inputs and outputs are defined as

$$\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta e_q' \end{bmatrix}, \boldsymbol{u} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} \Delta T_m \\ \Delta E_{FD} \end{bmatrix}, \boldsymbol{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \Delta\delta \\ \Delta v_t \end{bmatrix} \tag{3}$$

Remark 2.1: Bold lower and uppercase letters will denote vectors and matrices.

Outputs are the changes in the rotor angle, $\Delta\delta$, and terminal voltage, Δv_t [14], [15]. The state space matrices for Figure 1 are derived from equation (1) and the definitions in (3) as

$$\dot{\boldsymbol{x}} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} \tag{4a}$$
$$\boldsymbol{y} = \boldsymbol{C}\boldsymbol{x} \tag{4b}$$

where

$$\boldsymbol{A} = \begin{bmatrix} 0 & 2\pi f & 0 \\ -\frac{K_1}{J} & -\frac{D}{J} & -\frac{K_2}{J} \\ -\frac{K_3K_4}{T_f} & 0 & -\frac{1}{T_f} \end{bmatrix} \tag{5a}$$

$$\boldsymbol{B} = \begin{bmatrix} 0 & 0 \\ \frac{1}{J} & 0 \\ 0 & \frac{K_3}{T_f} \end{bmatrix}, \boldsymbol{C} = \begin{bmatrix} 1 & 0 & 0 \\ K_5 & 0 & K_6 \end{bmatrix} \tag{5b}$$

III. Controller Design in the State Space for MIMO Systems and its Application to a Synchronous Generator

When the state space representation of the system is available, several approaches such as pole-placement, robust control, and the quadratic optimal regulator can be used to design a controller [16]–[20]. In the pole-placement method, a state feedback gain matrix is designed to place all the closed-loop poles at desired locations. However, in a MIMO system, the state-feedback gain matrix is not unique [16], [21], [22]. Furthermore, the desirable pole locations may not always be known. If the model obtained for a system is subject to significant uncertainties and disturbances, a robust control method is more desirable to provide stability and performance robustness. However, these methods require advanced level mathematical background and can be pursued in a graduate level course. In an optimal control system, a performance index of the system, which is often a function of the state variables and the control signals, is optimized. This method gives a systematic approach to compute the state feedback control gain. Stability is inherently included in the design based on the quadratic performance index [19], [20].

A. Linear Quadratic Regulator (LQR)

In classical control system design such as the root locus and phase lead/lag compensation methods, a trade-off is often necessary to achieve a suitable performance, such as between the allowable deviation of the output from the desired trajectory, and optimization of the control signal, which correlates to the energy applied to the system. Unfortunately, when expanding into MIMO systems, the various effects between different inputs and outputs make the process of controller design difficult because satisfying one set of constraints often negatively impacts the rest of the system [16], [17]. The numerous iterations required to meet all of the system specifications necessitates an alternative approach. A better approach is to start with the two competing objectives discussed above (minimizing energy required, which is reflected in the control effort, and minimizing deviations from the desired outputs) and develop an optimal control solution that works with any number of inputs and outputs. Weights can be applied that target which inputs should provide less energy, and which outputs shall follow the desired response more strictly.

Consider the state space representation in (4). The goal is to find a state feedback gain matrix $\boldsymbol{K}$ in a feedback loop as

$$\boldsymbol{u}(t) = -\boldsymbol{K}\boldsymbol{x}(t) \tag{6}$$

such that the performance index is minimized. For a generator, the input mechanical torque and the generator field voltage are

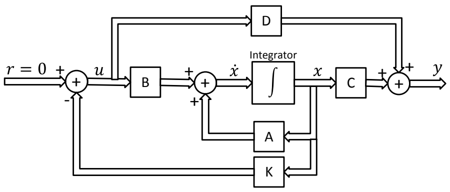

Fig. 2: Regulator state feedback block diagram.

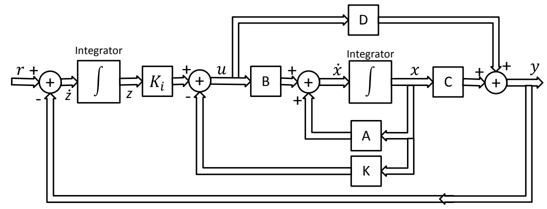

Fig. 3: A tracking feedback control system with internal model design (integral action).

the sources of energy that need to be minimized. Also, the rotor oscillations, which originate from the rotor speed (and angle) need to be minimized. First, for simplicity, consider a case that any deviation from an equilibrium point is an error. Thus, the desired trajectory $\boldsymbol{x}_d = 0$, and hence the sum of squared error for each state variable is computed by integrating x_i^2. Therefore, a performance index that includes all variables with different weighting factors is defined for the Heffron-Phillips model.

$$\Gamma = \int_0^T \left[q_1 x_1^2(t) + q_2 x_2^2(t) + q_3 x_3^2(t) + r_1 u_1^2(t) + r_2 u_2^2(t)\right] dt \quad (7)$$

where $q_i,\ i = 1, 2, 3$, and $r_j,\ j = 1, 2$, are the weights associated with each state and control input variable, respectively. Equation (7) is the basis for the Linear Quadratic Regulator (LQR), which is one of the commonly used optimal control methods [18]. Note that the desired state deviations are considered to be zero for a regulator [21], [22]. In the LQR problem, let the final time of interest be $T = \infty$. Also, a compact representation can be achieved by using (usually diagonal) weighting matrices $\boldsymbol{Q}$, and $\boldsymbol{R}$. Thus,

$$\Gamma = \int_0^\infty (\boldsymbol{x}^T \boldsymbol{Q} \boldsymbol{x} + \boldsymbol{u}^T \boldsymbol{R} \boldsymbol{u}) dt \quad (8)$$

In general, $\boldsymbol{Q}$ is a user-defined symmetric matrix with non-negative eigenvalues, and $\boldsymbol{R}$ is also a predefined symmetric matrix with positive eigenvalues. The control system is illustrated in Figure 2. The solution that minimizes the performance index (8) transfers the initial states of the system, $\boldsymbol{x}(0)$, to the desired values of the states if the system is *controllable*. Also, the control law in (6) requires that all state variables be available for feedback [16], [17]. A state observer may be necessary to estimate some of the states that are not readily available. Thus, another condition to build an LQR controller is availability or *observability* of the states. Note that the eigenvalues of the controlled system will change from the roots of the characteristic equation of the uncontrolled system $|s\boldsymbol{I} - \boldsymbol{A}|$ to those of $|s\boldsymbol{I} - \boldsymbol{A} + \boldsymbol{B}\boldsymbol{K}|$. If the solution to (8) exists, the optimal feedback gain matrix $\boldsymbol{K}$ is obtained as

$$\boldsymbol{K} = \boldsymbol{R}^{-1} \boldsymbol{B}^T \boldsymbol{P} \quad (9)$$

where the unique positive definite matrix $\boldsymbol{P}$ is the solution to the *algebraic Riccati equation* [22]:

$$\boldsymbol{P}\boldsymbol{A} + \boldsymbol{A}^T \boldsymbol{P} - \boldsymbol{P}\boldsymbol{B}\boldsymbol{R}^{-1}\boldsymbol{B}^T\boldsymbol{P} + \boldsymbol{Q} = \boldsymbol{0} \quad (10)$$

The above equation can be solved in MATLAB using the *lqr* command. In servo control systems, the performance index in (8) is given in terms of the system outputs, that is,

$$\Gamma = \int_0^\infty (\boldsymbol{y}^T \boldsymbol{Q} \boldsymbol{y} + \boldsymbol{u}^T \boldsymbol{R} \boldsymbol{u}) dt \quad (11)$$

From $\boldsymbol{y} = \boldsymbol{C}\boldsymbol{x}$, Equation (11) can be written as

$$\Gamma = \int_0^\infty (\boldsymbol{x}^T \boldsymbol{C}^T \boldsymbol{Q} \boldsymbol{C} \boldsymbol{x} + \boldsymbol{u}^T \boldsymbol{R} \boldsymbol{u}) dt \quad (12)$$

Hence, by a change of variable $\boldsymbol{Q}_n = \boldsymbol{C}^T \boldsymbol{Q} \boldsymbol{C}$, the same design procedure can be used to obtain the gain matrix $\boldsymbol{K}$.

B. Linear Quadratic Integral (LQI)

One approach to guarantee a zero steady state error for a step input in the presence of uncertainty and disturbance is *internal model* design [17], or *integral action* [18] where an integrator is utilized in the feedback loop. In this method, a new set of variables is defined to represent the tracking error, i.e., $\dot{\boldsymbol{z}} = \boldsymbol{r} - \boldsymbol{y}$, and is augmented with the system equations.

$$\begin{bmatrix} \dot{\boldsymbol{x}} \\ \dot{\boldsymbol{z}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} \\ \boldsymbol{r} - \boldsymbol{y} \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} \\ \boldsymbol{r} - \boldsymbol{C}\boldsymbol{x} \end{bmatrix} \quad (13)$$

The control law is similar to that of the LQR case with the addition of the augmented variables, i.e.,

$$\boldsymbol{u} = [-\boldsymbol{K} \quad \boldsymbol{K}_i] \begin{bmatrix} \boldsymbol{x} \\ \int_0^t \boldsymbol{z}(\tau) d\tau \end{bmatrix} \quad (14)$$

where $\boldsymbol{K}_i$ is the integral term due to the error signal. Figure 3 shows the block diagram of this case. The overall state-space matrices of the LQI case can be written as

$$\underbrace{\begin{bmatrix} \dot{\boldsymbol{x}} \\ \dot{\boldsymbol{z}} \end{bmatrix}}_{\dot{\boldsymbol{x}}_n} = \underbrace{\begin{bmatrix} \boldsymbol{A} - \boldsymbol{B}\boldsymbol{K} & \boldsymbol{B}\boldsymbol{K}_i \\ -\boldsymbol{C} & \boldsymbol{0} \end{bmatrix}}_{\boldsymbol{A}_n} \underbrace{\begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{z} \end{bmatrix}}_{\boldsymbol{x}_n} + \underbrace{\begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{1} \end{bmatrix}}_{\boldsymbol{B}_n} \boldsymbol{r} \quad (15)$$

$$\boldsymbol{y} = \underbrace{[\boldsymbol{C} \quad \boldsymbol{0}]}_{\boldsymbol{C}_n} \underbrace{\begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{z} \end{bmatrix}}_{\boldsymbol{x}_n} + \boldsymbol{D}\boldsymbol{u} \quad (16)$$

The *lqi* command in MATLAB provides the feedback gain. Note that MATLAB produces $-[\boldsymbol{K} \quad \boldsymbol{K}_i]$.

1) Weighting matrices selection: One key question in the LQR method is how to choose the weighting matrices. The matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$ determine the relative weight of state variables and inputs respectively in the performance index. Hence, a knowledge of the system variables and their physical importance need to be used. Each diagonal entry corresponds to the relative significance of each state or input in the cost function. In matrix $\boldsymbol{Q}$, the speed deviation can be weighted several times that of the angle deviation as acceleration is the cause of speed deviations, which in turn is the reason for angle deviations. Another reason is that the unit chosen for $\Delta\omega$ is per unit whereas $\Delta\delta$ is measured in radians. The selection of the weighting matrix $\boldsymbol{Q}$ based on left-shift of the dominant eigenvalues of the system is discussed in [8].

IV. Numerical Results

In this section, the behavior of the Heffron-Phillips model is simulated to demonstrate the theory presented in the previous sections, and to evaluate the performance of different types of controllers. A 10% increase in the applied mechanical torque from $t = 0.5$ to $t = 1$ s is considered to compare the system responses for the following types of controllers: Controller designed based on (1) the optimal LQR method, (2) the optimal LQI method, and (3) a conventional PSS [7].

A. System Parameters

The parameters used in the simulation are listed in Table I [7]. The weighting matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$ for the LQR method are

TABLE I: System parameters.

$K_1 = 0.7643$ $K_5 = -0.1463$ $K_A = 200$ $T_1 = 0.154\ s$	$K_2 = 0.8649$ $K_6 = 0.4168$ $K_s = 9.5$ $T_2 = 0.033\ s$	$K_3 = 0.3230$ $J = 6$ $f = 60\ Hz$ $T_w = 1.4\ s$	$K_4 = 1.4187$ $D = 2$ $T_f = 2.365\ s$

diagonal matrices. Speed deviation is weighted more heavily as it is the root cause of electromechanical oscillations, and it is measured in per unit. The armature transient voltage is a less significant variable compared to $\Delta\delta$ and $\Delta\omega$, and is weighted less. Thus, $\boldsymbol{Q} = diag([1 \quad 1000 \quad 0.1])$. Also, the mechanical input is weighted twice the field voltage as it affects the mechanical components. Hence, $\boldsymbol{R} = diag([2 \quad 1])$. In the LQI method two additional weights are needed for the error signal, $\boldsymbol{y} - \boldsymbol{r}$. These weights are assumed to be unity.

B. Test Results

1) System Response with and without Controllers: The state space system represented by (4) and (5) is simulated using the parameters given in Table I. In order to test the performance of the controllers designed for the linearized Heffron-Phillips model, a 10% change in the applied mechanical torque ΔT_m, which can excite the electromechanical modes, is considered. The results are shown in Figure 4. It is observed that the system without the controller experiences severe oscillations. Among the controllers, the LQI method outperforms the other types of controllers. However, the LQR method is also superior to the conventional PSS. Compared to a single-input/single-output controller, the LQR/LQI utilizes all state variables and covers a wider frequency range. The LQI controller also guarantees zero steady state error even when external disturbances are present.

V. Survey Results

Three EE and five ECET students, in a 3-credit control systems course, attempted an assignment to recreate the results shown in Figure 4, as both sets of students were already familiar with classical control system design. The assignment included a step-by-step procedure to simulate the synchronous machine, design and implement modern and conventional controllers and compare the results. They then completed surveys after the assignment was submitted. Since the assignment includes both active (develop the simulations)

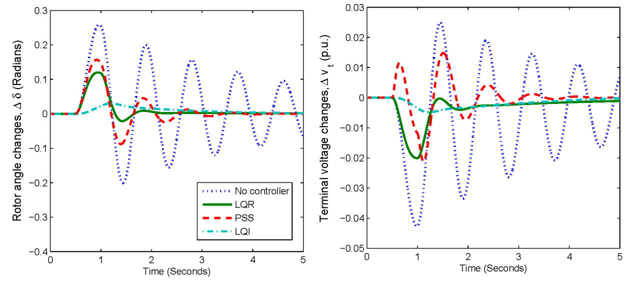

Fig. 4: Response of the synchronous generator to 10% increase in the mechanical torque from $t = 0.5$ to $t = 1$ s with no control, LQR, PSS, and LQI controllers.

and reflective (consider the value of state space relative to classical control) learning styles according to Felder *et al*, the survey was designed to measure both elements [23]. In addition, the assignment includes a strong sequential learning style for the simulation development, with a less intensive global style in the evaluation of the overall assignment. All of the students agreed that they were able to build a Simulink model to recreate the system without a controller and with the PSS. Six students agreed to being able to build and simulate the MIMO systems response with an LQR controller, while half agreed regarding the LQI controller. All of the EE students strongly agreed the assignment was worthwhile, while three of the ECET students were neutral and the other two disagreed. Comments from the EE students were more positive than the ones from ECET students. One EE student stated, "This really helped strive the point that state space is a lot better than Laplace for most systems." On the other hand, one ECET student wrote, "Mostly the assignment was more so plug and chug than understanding what was actually happening. More background would be needed in the classroom and more practice to understand it." This indicates that the ECET students were less able to provide a global learning perspective to their results, although admittedly the sample size is small. Including additional classroom lectures may help students better prepare for this assignment.

VI. Conclusion

A linearized state space model of a synchronous generator can be an effective tool for demonstrating the value of state space control systems. In addition to having multiple inputs and outputs, it can be readily simulated by students to show the improved system dynamics using modern controllers over classical control approaches. An assignment to simulate the generator with various classical and modern controls was presented to EE and ECET students. Overall student survey results were mixed. The ability to simulate the system was generally accomplished by all of the students, but the ECET students were not able to process their simulation results and see its significance. It is hoped that refinement of the lecture materials as well as the assignment will improve student perspectives and perceived learning of state space analysis. Future work will include giving the revised lectures and assignment to a larger class of students learning control systems and evaluating their comprehension.

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