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The Construction of Reduced Order Models for the HYBRID Repository

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INTRODUCTION

Power plants produce heat, which is typically used for electricity generation. However, this heat can also be used for non-electric applications such as hydrogen production or water desalination. When heat from a power plant is used for both electricity generation and heat applications, this is referred to as an integrated energy system (IES). Idaho National Laboratory, in the Integrated Energy Systems program, is developing a toolset for technoeconomic modeling and analyzing IES known as the Framework for Optimization of ResourCes and Economics (FORCE) [1]. FORCE will leverage IES program tools, currently used for separate technical and economic analysis, to create a single technoeconomic analysis tool for IES evaluation.

HYBRID, which is a part of FORCE, is a repository of physical transient process models, including a variety of methods for energy generation (light water reactor, advanced reactors), energy storage (batteries, thermal energy storage), and energy consumption (desalination, hydrogen production, etc.) [2]. These models can be combined to model and analyze different IES. For example, a water desalination model can be combined with a nuclear plant model to analyze the feasibility of a nuclear-powered desalination system. The HYBRID models, however, are complex and thus can be computationally expensive to run.

Reduced order models (ROMs) present an opportunity to reduce the computational burden of IES analysis using HYBRID models without significantly sacrificing data accuracy. Other applications of ROMs are digital twins, stochastic optimization studies, model exporting, and protection of proprietary information. In this paper the capability of creating ROMs of the models within the HYBRID repository will be demonstrated. Specifically, a linear regression ROM of a gas turbine and a dynamic mode decomposition with control (DMDc) ROM of a lithium-ion battery are constructed.

HYBRID MODELS

The HYBRID models are written in the Modelica language and compiled using Dymola [3]. Modelica is an acausal, object-oriented, equation-based language for modeling system components. Components or models can be combined using connectors to create even larger, more complex models. Two models used in this work are the gas turbine model, seen in Fig. 1 and the lithium-ion battery model seen in Fig. 2.

Gas Fired Turbine Model

The natural gas fired turbine is modeled to have a nominal generating capacity of 35MWe. It is constructed of a compressor, combustor, turbine, rotational moment of inertia, and power generator. The system is controlled by prescribing a desired power output that the system must match.

For this work a ROM that relates the fuel mass flow rate to the electrical power output is constructed. The gas fired turbine Dymola model is shown Figure 1 [2].

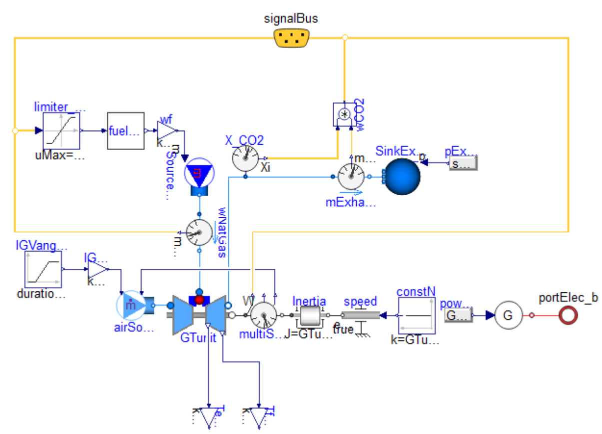

Fig. 1. The gas fired turbine Dymola model gives a power output based on a fuel mass flow rate [2].

Lithium Ion Battery Model

The lithium-ion battery model is a simple model of a battery that can be charged and discharged over time [4]. A charging and discharging signal are given and the battery state of charge over time is determined. The battery state of charge can range from zero to 20 Watts.

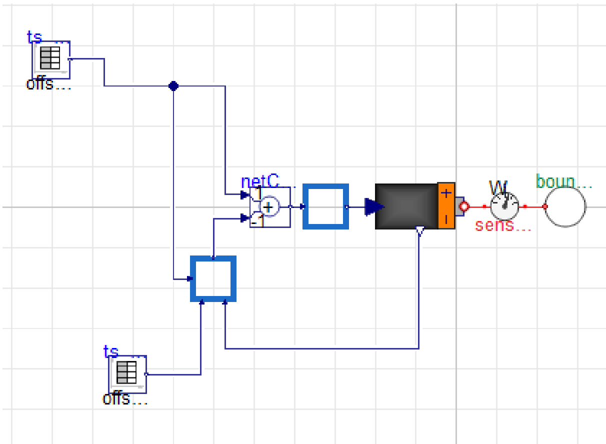

Fig. 2. Lithium-ion battery Dymola model calculates the battery state of charge over time based on a charging and discharging signal [4].

ROM CONSTRUCTION

In order to create the ROMs, the Risk Analysis Virtual ENviromnent (RAVEN) is used. RAVEN, upon which some of the FORCE toolset depends, is a "flexible and multi-purpose probabilistic risk analysis, validation and uncertainty quantification, parameter optimization, model reduction and data knowledge-discovering framework [5]." RAVEN is used to sample the Dymola model and then use this data to train a ROM. The general steps that are performed when using RAVEN to create a ROM are as follows:

1. RAVEN determines a set of input conditions for the Dymola models
2. RAVEN generates new Dymola input files containing the new input conditions
3. RAVEN instructs Dymola to run using the newly generated Dymola input files
4. Dymola results are output and accessible by RAVEN
5. The Dymola results can be used to train a ROM

ROM TYPES

RAVEN has the capability of creating over 70 different types of ROMs [5]. The purpose of these ROMs is to quickly predict the response of a system. Two of these ROMs will be demonstrated in this work: linear regression and dynamic mode decomposition with control (DMDc).

Linear Regression

The linear regression ROM in RAVEN is an ordinary least squares linear regression. In order to create a linear regression ROM, RAVEN needs to be supplied a list of features and targets. Feature variables will become the inputs to the ROM and target variables will become the outputs. The linear regression ROM is chosen for the gas turbine model, since this is a fairly simple model. The fuel mass flow rate to the turbine is directly related to the power output. If the fuel mass flow rate is constant over time, the turbine power output will also be constant over time. This relationship is well captured by the linear regression ROM.

Dynamic Mode Decomposition with Control

Dynamic mode decomposition (DMD) is a method of creating linear reduced order models of complex systems [6]. These ROMs are time-dependent, and data-driven, meaning that the ROM can be constructed without any information on the underlying physics of the system. Instead, a sample of inputs and outputs from the model are used to construct the ROM.

DMDc is an extension of DMD [6]. The difference is that with DMDc, the system is being acted upon by some external control. DMDc is able to separate the natural behavior of the system and the impact of the control acting upon the system. If DMD were used on a system that were being controlled, the entire behavior of the system would be mistaken as the natural behavior of the system. For example, DMD has traditionally been used to represent the time evolution of fluid flows [7], the dynamics of which are a natural response. An example of a past application of DMDc is to model the control of a nuclear power plant [8].

DMDc works by taking information about the system over time and breaking it up into snapshots of the system at distinct points in time and then determining how to maneuver from one snapshot to the next. A matrix of these snapshots is constructed and then a best fit linear operator is approximated for connecting the snapshots in time. This concept is shown in Equation 1:

$$x_{k+1} \approx \boldsymbol{A}x_k + \boldsymbol{B}u_k, \tag{1}$$

where x is a snapshot of the system at a given time k, u is a snapshot of the control input to the system at time k, and $\boldsymbol{A}$ and $\boldsymbol{B}$ are matrices that map x_k to x_{k+1}.

The capability of constructing DMDc ROMs of the HYBRID models using RAVEN is desired because of its time-dependent and data-driven nature. The HYBRID models simulate transient situations, so a time-dependent ROM is needed. Additionally, since DMDc is a data-driven model, these ROMs can be constructed without any input about the underlying physics, but rather just a sample of the input-output space. Another advantage of DMDc is that the ROM can be trained with a single simulation.

In this work a DMDc ROM of the lithium-ion battery is constructed. The features of this ROM are the charging and discharging signals and the battery initial charge. The targets are time and the battery state of charge. Referring to Equation

1, the variable x is the battery state of charge and u_k is a matrix of the charging and discharging signals.

RESULTS

Gas Fired Turbine ROM

A linear regression ROM of the gas turbine model was constructed using RAVEN. RAVEN is given a range of fuel mass flow rates (1-3 kg/s) and creates a set of Dymola inputs that are within this range. These inputs are used to run the Dymola model several times, collect the results, and generate the ROM. Just like the original model, the ROM can be used to calculate turbine power output given an input fuel mass flow rate. In order to verify that the ROM adequately represents the original mode, the results from the Dymola model are compared to the results from the ROM, as shown in Figure 3. For a given fuel mass flow rate the Dymola model and the ROM both give the same amount of power output, showing that the ROM is a good approximation of the original model.

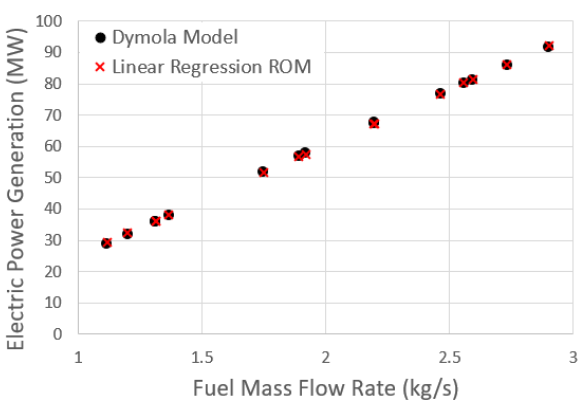

Fig. 3. The results from the original model match the results from the ROM.

Lithium-Ion Battery ROM

A DMDc ROM of the lithium-ion battery has been constructed using RAVEN. This model is time-dependent, so an initial state of charge is given as well as battery charging and discharging signals over time. The battery state of charge over time is then determined based on these values.

Two possible scenarios were tested: the first with a simple charging and discharging patterns, as shown in Figure 4, and the second with a random charging and discharging pattern, as shown in Figure 5. In both cases it is seen that the ROM somewhat captures the behavior of the original system, however it is not a perfect match.

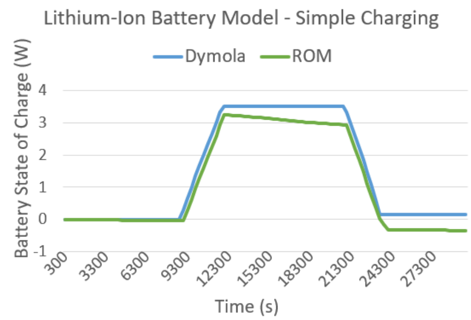

Fig. 4. The Dymola model and ROM outputs are compared for a simple charging and discharging signal

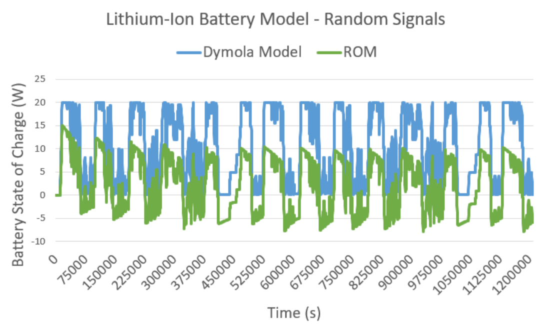

Fig. 5. The Dymola model and ROM outputs are compared for a random charging and discharging signal

In both cases, the ROM captures the general trend of the Dymola model, but the values are incorrect. The ROM outputs negative values for the battery state of charge, which is not physically possible. Further work is needed to determine how to better train the ROM. One possible approach would be to change the charging and discharging cycle. Cycling the system through a range of control inputs is needed to allow the A and B matrices of the DMDc ROM to accurately capture the system dynamics.

CONCLUSIONS

RAVEN was used to create reduced order models of two of the Modelica models within the HYBRID repository. The linear regression ROM of a gas fired turbine gives values which are similar to the original model. The DMDc ROM of the lithium-ion battery, however, does not show a good match to the original model. Further work is needed to determine why the DMDc ROM is not accurately capturing the model trends.

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