Model Learning with the CIET Facility Heater

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INTRODUCTION

The nuclear industry and research community traditionally uses best-estimate thermal-hydraulic system codes such as RELAP5-3D and TRACE to understand and predict nuclear reactor safety performance. While these codes are diligently tested and maintained standards for light water reactors, they have not yet been exhaustively validated for many advanced reactors using alternative coolants. The majority of advanced reactors are still in their pre-conceptual design phase yet use these standard codes for many studies that could be conducted without industry-specific, complex software. These codes are ideally-suited for licensing endeavors but can be cumbersome and unwieldy in exploratory projects. They are difficult to run in real-time due to computational constraints and can be subject to error and uncertainty in the implementation of system coefficients and discretization schemes.

There are modeling and simulation methods that can address these concerns, such as on-line model learning, but are difficult to implement in an industry that relies heavily on static verification and validation (V&V) basis for codes. Recognizing these limitations, the University of California, Berkeley (UCB) is using the Compact Integral Effects Test (CIET) facility to explore the development of simplified modeling algorithms that can be flexible and agile for application to the design phase of advanced nuclear reactors. Specifically, UCB is focusing on the potential benefits of diverse and redundant methods of system identification as well as new methods for on-line monitoring. Presented here is an early study exploring the applicability of model learning for parameter identification.

Description of the CIET Facility

CIET reproduces the primary and secondary flow paths of an early pre-conceptual design for a Fluoride-salt-cooled High-temperature Reactor (FHR) and was designed to provide experimental data for the V&V of best-estimate thermal-hydraulic system codes [1]. Pictured in Figure 1, CIET operates at reduced size, temperatures, and input powers while reproducing heat transfer, flow regime, and natural circulation in a prototypical FHR using the heat transfer oil Dowtherm A as a simulant fluid. The milder chemistry and temperature conditions afforded by CIET as compared to the fluoride-salt-cooled FHR enable the use of an electric resistance-heated section to replicate core heating.This heater section has exhibited interesting behavior related to conjugate heat transfer [2] and is our focus for this study.

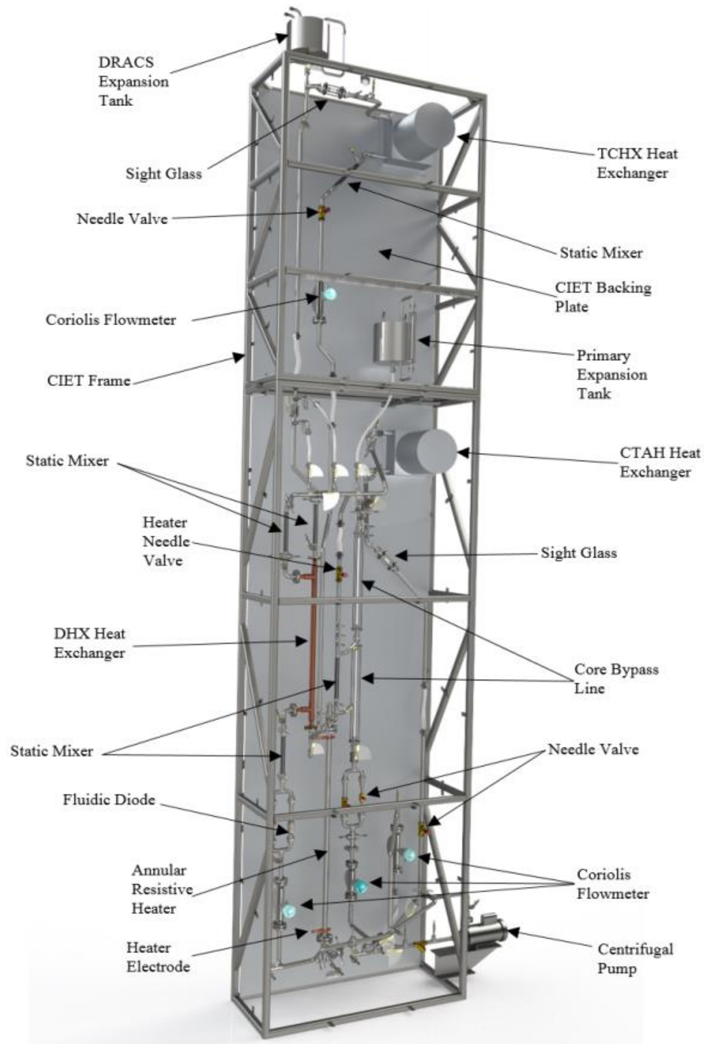

Fig. 1. Schematic of the CIET facility.

MODEL AND ALGORITHM

Making a number of simplifying assumptions, we develop a very concise model of the heater's time-dependent temperature behavior. For this study, UCB approximates the heater section as a cylindrical flow volume with heat transfer between the heated outer shell and the flowing inner fluid. This means we assume that the inner tube running through the center of the heater section, which has a complex flow geometry to ensure turbulent flow and promote fluid mixing, performs at the same temperature as the fluid with the two collectively considered as one lumped thermal mass. We also neglect variation of temperature across the length of the heater, collapsing it into one control volume. Finally, we assume that all parameters, including heat transfer coefficients and thermal inertias, are time-independent for the modeling conditions. Our reference schematic for the heater, shown in Figure 2, is very simple. This gives us the following differential equations for fluid temperature, T_F, and shell temperature, T_S:

$$\frac{dT_F}{dt} = \frac{(hA)_S}{(Mc_p)_F}(T_S - T_F) - \frac{1}{\tau}(T_F - T_{F,in}) \tag{1}$$

$$\frac{dT_S}{dt} = \frac{P}{(Mc_p)_S} - \frac{(hA)_S}{(Mc_p)_S}(T_S - T_F) \tag{2}$$

where τ is the fluid transit time in seconds, $T_{F,in}$ the fluid inlet temperature in degrees Celsius, $(hA)_S$ the mean thermal inertia of the shell in kilowatts per degree Celsius, $(Mc_p)_S$ and $(Mc_p)_F$ the heat capacities of the shell and fluid in kilojoules per degree Celsius, respectively, and *P* the power generation in the heater outer shell in kilowatts.

In order to employ our parameter identification algorithm, we must rewrite our model as a linear time-invariant system of the form

$$y(t) = \theta^T \phi(t) \tag{3}$$

where *y(t)* is our output, θ our parameter vector, and $\phi(t)$ our state vector. This formulation gives us the following two systems:

$$y_1(t) = \dot{T_F} \tag{4}$$

$$\theta_1 = \begin{bmatrix} \frac{1}{\tau} \\ \frac{(hA)_S}{(Mc_p)_F} \end{bmatrix} \quad \phi_1 = \begin{bmatrix} T_{F,in} - T_F \\ T_S - T_F \end{bmatrix} \tag{5}$$

$$y_2(t) = \dot{T_S} \tag{6}$$

$$\theta_2 = \begin{bmatrix} \frac{(hA)_S}{(Mc_p)_S} \\ \frac{1}{(Mc_p)_S} \end{bmatrix} \quad \phi_2 = \begin{bmatrix} T_F - T_S \\ P \end{bmatrix} \tag{7}$$

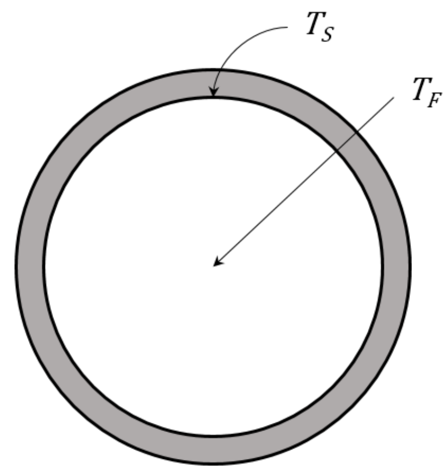

Fig. 2. Simplified schematic of the CIET heater cross-section

Algorithm Description

The essential principle of model learning algorithms is that they take an input dataset as “training” data and use the empirical relationships to identify a model. Our method for identifying the parameters in our θ vectors (following course material from UCB Prof. Scott Moura’s Civil Engineering 295: Energy Systems and Controls, Spring 2017) is to employ a gradient or steepest descent scheme in which each successive estimate of our parameters has a smaller error so that we can be sure our estimate converges. We therefore write an update law that takes the error from the current estimate, given a dataset that can be used to compute error, to determine feedback for our next estimate. This update law looks like:

$$\dot{\hat{\theta}}(t) = -\Gamma \frac{d}{d\hat{\theta}}\left[\frac{1}{2}(y - \hat{\theta}^T\phi)^2\right] = \Gamma(y - \hat{\theta}^T\phi)\phi \tag{8}$$

where Γ is a symmetric, positive definite matrix, chosen by the user to influence convergence time without compromising accuracy. By selecting an initial guess for the parameter vectors, the gradient algorithm can take the “training” dataset and converge to an estimate. UCB has implemented this algorithm in MATLAB for the above systems.

TEST CASE

UCB has been exploring frequency response testing as a methodology for better understanding conjugate heat transfer in the CIET heater and in scaled integral effects tests in general [3]. In past experiments, the outer shell and fluid of the heater have proven to oscillate in temperature at different amplitude and phase under periodic power forcing. We have been motivated to capitalize on this separation to characterize thermal inertia, heat capacity, and thermal response time constants for ours and other molten salt systems. UCB is consequentially investigating time-domain parameter identification methods as a complementary strategy to further inform and develop a frequency response testing methodology. Therefore, we base our test case for this study on oscillation data for ease of comparison. The chosen example "training" dataset comes from a frequency response test run in October 2017 and shown graphically in Figure 3.

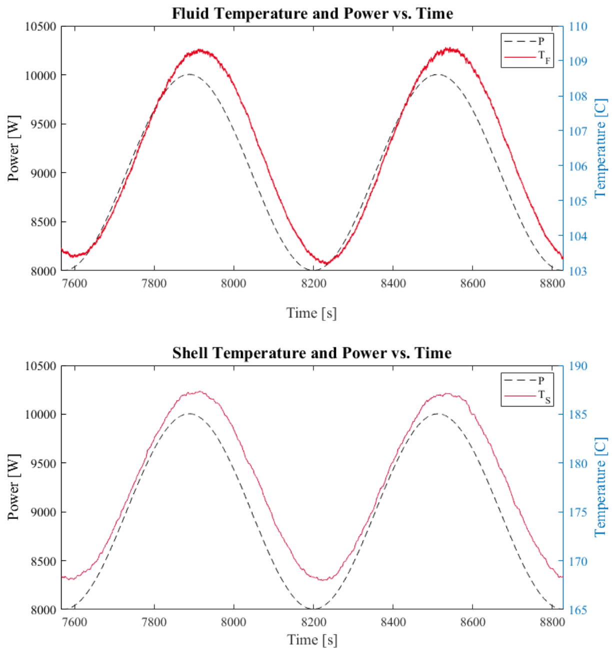

Fig. 3. Example "training" dataset from October 2017

The important characteristics of this dataset are that the fluid and shell temperatures each lag the power oscillation in their response while also being slightly out of phase with one another. Additionally, each has a distinct amplitude of oscillation. With this study, we intend to assess whether our very simple model is capable of representing the complex physical relationships in our system and reveal any gaps or errors in our modeling that may assist our work in frequency response testing.

It is important to note that this was one of many sub-tests from a battery of frequencies in October 2017, many of which we used to test our parameter identification algorithm. We focus here on a single sub-test as an example.

RESULTS

Using an initial guess for all parameters at unity (as they are ratios that might represent scaling criteria), the "training" dataset (and all others tested) resulted in the same parameter estimates. These parameter estimates can then be used to construct a state-space model, which can easily simulate any other dataset in MATLAB. The resulting parameter estimates used to build our simple state-space model are given in Equations 9 and 10:

$$\hat{\theta}_1 = \begin{bmatrix} \frac{1}{\tau} \\ \frac{(hA)_S}{(Mc_p)_F} \end{bmatrix} = \begin{bmatrix} 1.2039 \\ 0.4613 \end{bmatrix} \tag{9}$$

$$\hat{\theta}_2 = \begin{bmatrix} \frac{(hA)_S}{(Mc_p)_S} \\ \frac{1}{(Mc_p)_S} \end{bmatrix} = \begin{bmatrix} 1.0080 \\ 0.0082 \end{bmatrix} \tag{10}$$

We then used the parameter estimates and loaded a new dataset to use as input (power and inlet fluid temperature) to investigate if the trained model could accurately predict the fluid and shell temperature response. The prediction and experimental results from this validation data are presented in Figure 4.

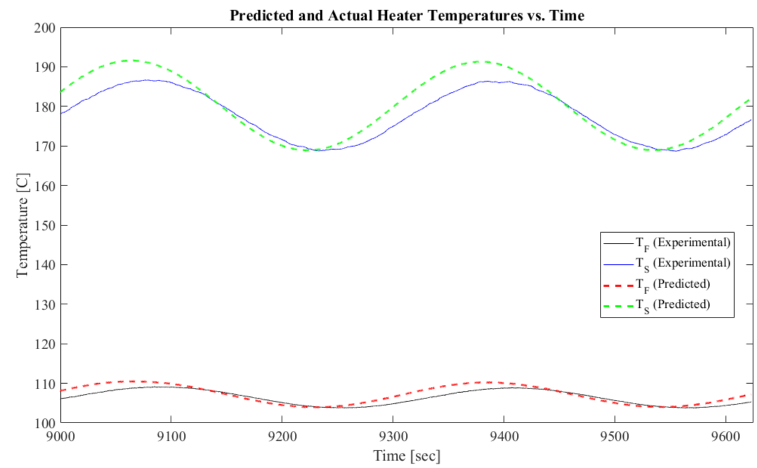

Fig. 4. Model results vs. validation dataset

The average percent difference between the experimental data and the model-generated data for this sub-test is 0.98 % for T_F and 1.66% for T_S.

Analysis and Discussion

The key takeaways from this study are qualitative rather than quantitative. From a single dataset and a physics-based model, we have obtained a "trained" model via identification of the parameters and have predicted state evolution with reasonable accuracy. However, it would be premature to draw conclusions from the numerical values of the identified parameters or the specific percentage error.

What we can say is that our very simple model, which rests on many simplifying assumptions, is able to predict oscillatory behavior of T_F and T_S quite well in terms of overall behavior. This provides a basis for believing we've captured most first-order effects and dependencies in our simplified model.

On the other hand, our model is unable to predict the specific amplitude and phase lag exhibited by the physical system. In particular, it appears that the model keeps the two temperatures in phase while the lag between the two is the most interesting aspect of frequency response experiments. The trained model also overpredicts the amplitude and steady-state values of each temperature. The effect is greater with T_S, which may indicate that the effect grows as the temperature magnitude grows.

The amplitude and phase lag discrepancies lead us to believe that there is some second-order effect missing from our model that may better define frequency response behavior. One possible candidate is to include a third term and equation for the heater inner tube temperature evolution. There may also be an issue in our chosen averaging methods for T_F and T_S.

CONCLUSIONS AND FUTURE WORK

Using first-principles physics-based modeling with many simplifying assumptions and a single training dataset, we have obtained a trained model that is able to predict overall qualitative behavior of the CIET heater under oscillatory power forcing conditions. Rather than using this model to draw conclusions about our system or predict its behavior, its combined simplicity and accuracy provide evidence that our model captures most first-order effects of the system.

This study has also proven useful in hinting at what might be missing from our model to truly capture frequency response behavior. Small discrepancies in amplitude and phase lag show that some second-order effects may still need to be incorporated. Possible candidates include modeling the heater inner tube and reassessing our temperature averaging methods.

We will run more tests using this trained model to better understand its strengths and limitations so that we can focus our efforts to improve our physics-based description. We will then incorporate those changes into the model so that we can more confidently apply frequency response methods. This will lead to a standardized methodology for parameter identification and formulation of sophisticated but simple system models that can run in real-time for online system monitoring and further exploratory studies of advanced reactor development.

NOMENCLATURE

$(hA)_S$ = mean thermal inertia of shell [kW/°C]
$(Mc_p)_F$ = heat capacity of the fluid [kJ/°C]
$(Mc_p)_S$ = heat capacity of the shell [kJ/°C]
P = power generation in shell [kW]
τ = fluid transit time [sec]
T_F = fluid temperature
$\dot{T}_F$ = time derivative of fluid temperature [°C/s]
$T_{F,in}$ = fluid inlet temperature [°C]
T_S = shell temperature
$\dot{T}_S$ = time derivative of shell temperature [°C/s]
$y(t)$ = output temperature in parametric model [°C]
θ = parameter vector
$\dot{\hat{\theta}}$ = estimated parameter vector
$\phi(t)$ = state vector
Γ = user-defined "gain" matrix

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