INL/RPT-23-74181

Summer Internship Report

Parametric and Sensitivity Analysis of a Physics-based Steam Generator Model

July 2023

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INL/RPT-23-74181
Revision 0

Parametric and Sensitivity Analysis of a Steam Generator Model Using Python and Machine-Learning Tools

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Month 2023

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Prepared for the
U.S. Department of Energy
Office of Nuclear Energy
Under DOE Idaho Operations Office
Contract DE-AC07-05ID14517

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ABSTRACT

For this study, we used Python and machine-learning tools to perform a comprehensive parametric and sensitivity analysis on a steam generator (SG) model. (The Python model was based on a previously completed MATLAB framework for the Holtec SMR-160 SG.) We investigated the influence of various input parameters (e.g., heat transfer coefficient [HTC], Nusselt number, and heat exchanger effectiveness) on the system's output. With machine-learning tools such as the Risk Analysis Virtual Environment (RAVEN), which was developed at Idaho National Laboratory, we were then able to perform an automated analysis of the SG inputs' effect on the HTC. The analysis results give valuable insights into the performance and optimization of SG systems.

We found the inlet mass flow rate (MFR) to have the greatest impact on the HTC, followed closely by the inlet temperature, and then pressure. Shifting of the input parameters causes the location of the maximum HTC along the SG length to change incrementally. The cold leg (CL) MFR was also found to impact the HTC magnitude as well as the location of the maximum HTC. At between 0.4–0.9 of the total SG length, the input parameters experience maximum impact on the HTC, leading us to suggest that sensors be efficiently placed on the SG so as to closely and effectively monitor thermal-hydraulic properties during reactor operation. We also found that the sensitivity data calculated manually agrees with the RAVEN – based data, confirming the same range of maximum sensitivity. However, the RAVEN-based analysis showed that cold leg pressure and hot leg temperature have a greater impact on the heat transfer coefficient than the mass flow rate, implying that a manual sensitivity study taking only two samples is not accurate.

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ACKNOWLEDGEMENTS

1. Piyush Sabharwall, PhD – Manager, Irradiation Experiments and Thermal Hydraulics Analysis, Idaho National Laboratory
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ACRONYMS

CL	cold leg
HL	hot leg
HTC	heat transfer coefficient
MFR	mass flow rate
RAVEN	Risk Analysis Virtual Environment
SG	steam generator
SMR	small modular reactor

Parametric and Sensitivity Analysis of a Steam Generator Model Using Python and Machine-Learning Tools

1. INTRODUCTION

1.1 Background and Motivation

Recent modern innovations have led to the advancement of novel reactor technologies, many of which carry the potential to greatly reduce carbon emissions while still maintaining safety and efficiency. Small modular reactors (SMRs) are one such technology, thanks to their modular capabilities. Recently, they have received increased attention due to their economic and safety advantages.

Steam generators (SGs) are used in power generation industries to produce steam via methods of heat transfer. They transmit heat from a heat source to a secondary fluid in which heat is dumped. The steam spins the turbines and converts the heat output from the power plant into usable electrical energy. The vertical, once-through SG that is the subject of this study comes from a SMR reactor design with passive safety features. Reactor heat is fed into a hot fluid that enters the hot leg (HL) through the riser section and is then carried through the many small SG tubes. This is referred to as the primary side. The secondary side consists of the shell that encases the SG tubes and provides a path along which the secondary fluid can flow, enabling heat transfer between the primary and secondary fluids to occur. As this secondary fluid travels up the SG, it gains heat and eventually turns into dry superheated steam.

In Figure 1, the SG tubes are supported by baffles positioned within the shell where the secondary fluid flows. The middle column, or riser, experiences a change in cross-sectional area, becoming wider at the top. It is at this point that the hot fluid is all gathered up before being sent directly back down into the SG tubes. It is in this manner that heat transfer is initiated between it and the secondary fluid in the shell. Modeling the thermal-hydraulic performance of this system is important, as it is crucial to both reactor safety and normal operations that the SG's capability to remove heat from the reactor primary coolant. It allows for a conceptual addition to computational fluid mechanics (CFD) modeling, as known correlations can be used so that the results can be cross-checked according to the laws of physics.

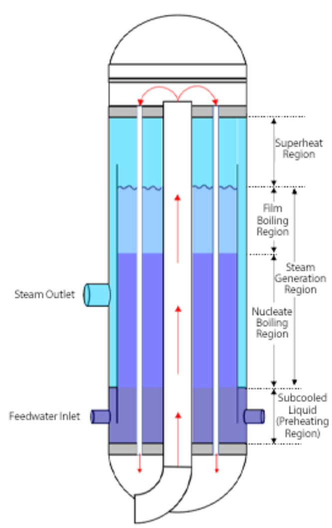

Figure 1. SMR once-through SG (Taken from: https://holtecinternational.com/products-and-services/smr/, Accessed date: August 10, 2023).

The steam generator Python code is based on iterative calculations. The SG's entire length is split into over a thousand small sections, with the fluid properties assumed constant in each. The initial outlet temperature is estimated, then input parameters are used to find the boundary conditions for each consecutive interval. This enables spatial analysis of thermodynamic data. The calculation loop is repeated across the SG's entire length until the error between the estimated and the calculated value becomes low enough for the code to be considered complete. The code also accounts for the phase changes in the secondary side of the SG, which transitions from subcooled boiling, to nucleate boiling, to film boiling, and eventually to superheated steam.

The original code upon which ours was based was created in the MATLAB language as part of a scaling analysis conducted by Dr. Xiaodong Sun of the University of Michigan. As Idaho National Laboratory recently ended its lab-wide MATLAB subscription, Python, which offers similar capabilities, was chosen as a viable alternative. Apart from syntax differences, MATLAB and Python are very similar, though the latter requires add-ons in order to complete the same tasks as MATLAB. Python is free and open source, and I therefore used the MATLAB code framework to develop a Python-based counterpart. Python also presents advantages from a data analysis perspective, and the fact that it is open-source allows for integration with machine-learning platforms such as the Risk Analysis Virtual Environment (RAVEN), which was developed by Idaho National Laboratory. This allows for an artificial intelligence (AI)-based approach to conducting a sensitivity analysis of the SG data.

1.2 Objectives of the Study

The goals of this study are (1) to translate the MATLAB code into the Python language, (2) to produce similar results when inputting the same data into both the MATLAB and Python codes, and (3) to perform a parametric and sensitivity analysis of the SG code in order to investigate the extent to which the correlations work under each type of input. The parametric study will shed light on how tweaking each input parameter by a set amount changes the overall output in terms of the heat transfer coefficient (HTC) or the temperature and pressure profile. A sensitivity analysis will reveal how each individual input parameter affects the overall HTC output. Tracking this sensitivity spatially will give us a model that describes the SG's local sensitivities to different parameters. This is important, as knowing where certain properties are sensitive to change can foster effective placement of sensors and related equipment. We will track sensitivity by manually changing the input parameters, then we will implement RAVEN to run the code over and over again to obtain sensitivity data.

1.3 Scope of the Study

This sensitivity and parametric study can help identify regions in the SG length where certain parameters are more sensitive to change. This can aid in strategically placing sensors where they can effectively monitor the thermodynamic conditions in the SG. It also helps with stress testing the SG. Running the code over and over again helps determine the range over which the correlations used in the code remain viable. The RAVEN – based analysis also leaves room for more implementation in the future. With the source code and the RAVEN input file, one can obtain more than just sensitivity data for the steam generator. RAVEN capabilities include anomaly detection and optimization to show the ideal input conditions for steam generator operation. Further down the road, we can build off the RAVEN sensitivity analysis to obtain a more in-depth understanding of the thermodynamic SG model.

2. STEAM GENERATOR MODEL

2.1 System Description

As mentioned earlier, the code operates by splitting the SG length into over a thousand intervals and then evaluating consecutive boundary conditions to determine the thermal-hydraulic properties.

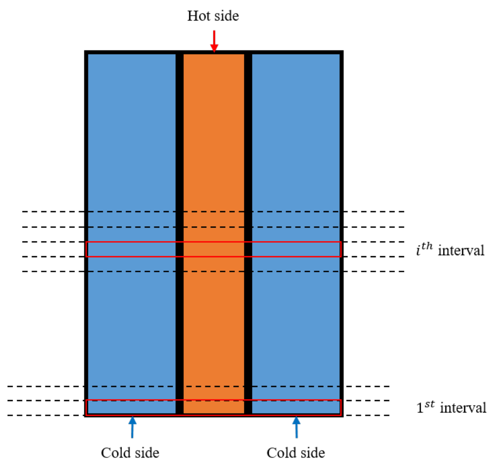

Figure 2. Schematic of the Python code computational grid.

The code considers both subcooled water and superheated steam. In scaled-down models, such as in our case with the SMR-160 half-height design, the flow may transition from turbulent to laminar. Thus, the code accounts for laminar, transitional, and turbulent flow regimes, using Reynolds numbers 2,300 and 3,000 as the boundaries. To ensure smooth transitions, the frictional factor and HTC in the transitional flow region are interpolated based on laminar and turbulent flow conditions.

The Python code considers frictional, gravitational, and accelerational pressure drops in the hydrodynamic calculation. It uses specific correlations for computing frictional factors in both single- and two-phase flows. In addition to calculations for the tube and shell side, the code also includes the thermal-hydraulic behavior of the riser section, which requires an additional loop in order to achieve consistent calculations.

2.2 Governing Equations and Correlations

Table 1. Some governing equations and correlations.

Parameter	Model/correlation	Applicable Range	Reference
Single-phase frictional factor	$f = \frac{64}{Re}$	$0 < Re < 2300$	White [1]
	$f = (0.79 \ln Re - 1.64)^{-2}$	$3000 < Re \leq 5 \times 10^6$	Petukhov et al. [2]
Two-phase fictional pressure drop	$\Delta p_f = (\Delta p_f)_l \Phi_l^2$ $\Phi_l^2 = (1-\alpha)^{\frac{n-5}{2}}$	$0 < x < 1$	Lockhart and Martinelli [3]
Two-phase acceleration drop	$\Delta p_a = G^2 \left[\frac{x^2}{\alpha \rho_v} + \frac{(1-x)^2}{(1-\alpha)\rho_l} \right]$	$0 < \alpha < 1$	Todreas and Kazimi [4]
Two-phase gravitational pressure drop	$\Delta p_g = [\alpha \rho_v + (1-\alpha)\rho_l] gL$	$0 < \alpha < 1$	Todreas and Kazimi [4]

Parameter	Model/correlation	Applicable Range	Reference
Single-phase Nusselt Number	$Nu = 4.36$	$0 < Re < 2300$	Incropera et al. [5]
	$Nu = \frac{(f/8)(\mathrm{Re} - 1000)\mathrm{Pr}}{1 + 12.7(f/8)^{1/2}(\mathrm{Pr}^{2/3} - 1)}$	$3000 < Re \leq 5 \times 10^6$	Gnielinski [6]
Subcooled boiling heat transfer rate	$\dot{q}'' = h_{NB}(T_{\mathrm{wall}} - T_{\mathrm{sat}}) + h_{\mathrm{COV}}(T_{\mathrm{wall}} - T_{\mathrm{bulk}})$ $h_{\mathrm{COV}} = F\left(0.023Re_l^{0.8}\mathrm{Pr}_l^{0.4}\frac{k_l}{D_h}\right)$ $h_{NB} = S\left[0.00122\left(\frac{k_l^{0.79}c_{p,l}^{0.45}\rho_l^{0.49}}{\sigma^{0.5}\mu_l^{0.29}h_{lv}^{0.24}\rho_v^{0.24}}\right)\Delta T_{sat}^{0.24}\Delta p^{0.75}\right]$	$x < 0$ $T_{\mathrm{wall}} > T_{\mathrm{sat}}$	Chen [7
Nucleate boiling heat transfer rate	$\dot{q}'' = h_{NB}(T_{\mathrm{wall}} - T_{\mathrm{sat}}) + h_C(T_{\mathrm{wall}} - T_{\mathrm{sat}})$ $h_{\mathrm{COV}} = F\left(0.023\mathrm{Re}_l^{0.8}\ \mathrm{Pr}_l^{0.4}\frac{k_l}{D_h}\right)$ $h_{NB} = S\left[0.00122\left(\frac{k_l^{0.79}c_{p,l}^{0.45}\rho_l^{0.49}}{\sigma^{0.5}\mu_l^{0.29}h_{lv}^{0.24}\rho_v^{0.24}}\right)\Delta T_{sat}^{0.24}\Delta p^{0.75}\right]$	$x > 0$ $\alpha < 0.99$	Chen [7]

2.3 MATLAB-based Reference Heat Exchanger Model

Dr. Xiaodong Sun's scaling analysis generated results pertaining to the thermodynamic properties of the half height 2 MW SMR-160. To validate the performance of the new Python-based code, we must compare the results generated when applying the same inputs to both codes (i.e., the provided MATLAB code and the new Python code). Figure 3 shows the SG pressure, thermodynamic quality, and temperature, as calculated via both the provided MATLAB code and the newly developed Python code. Both codes generated similar outputs, and the data exhibited similar trends.

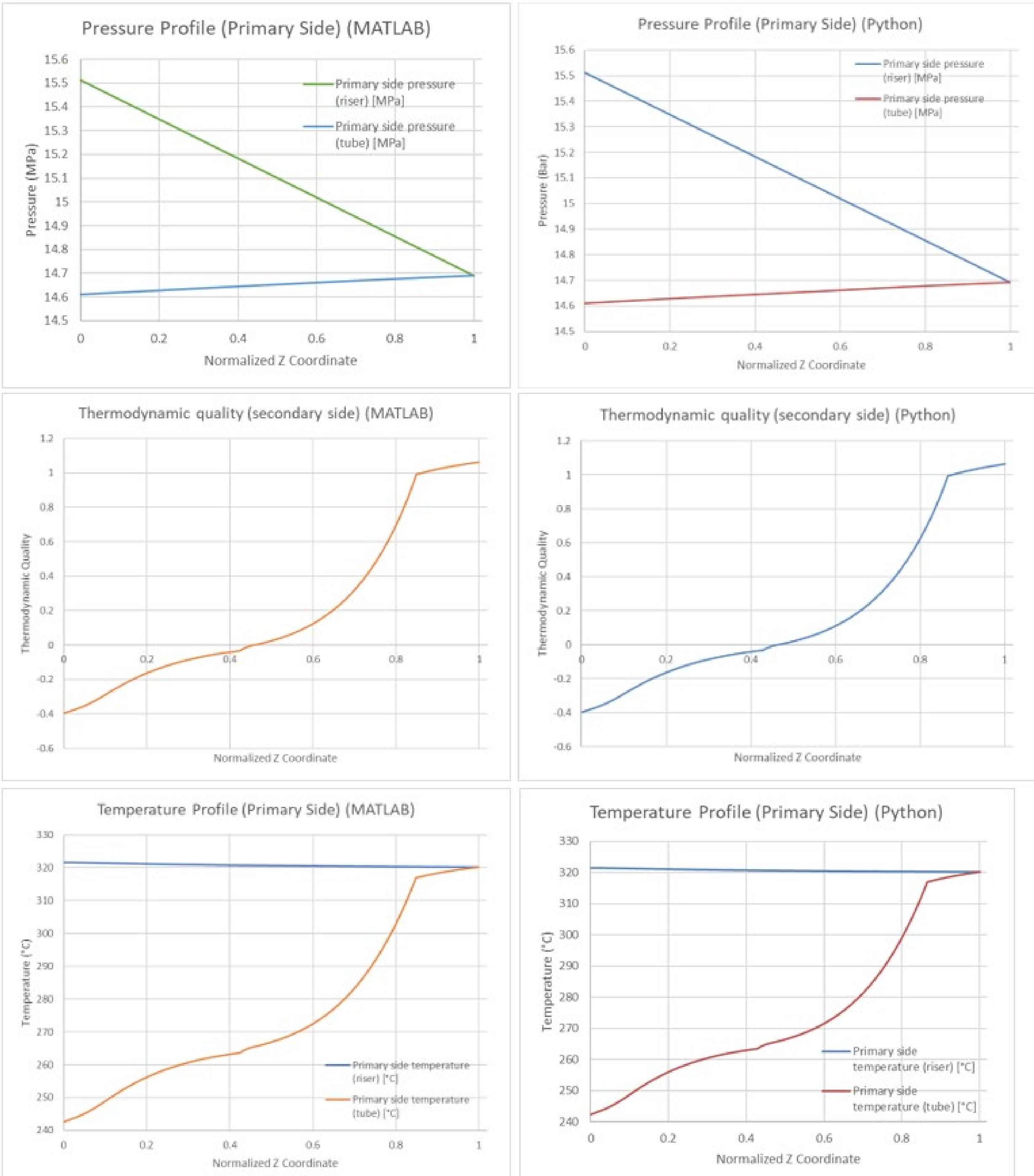

Figure 3. Plots comparing the output of the MATLAB-based code to that of the Python-based code.

3. PARAMETRIC STUDY

3.1 Methodology

The parametric study assessed how the code output was impacted after changing all the input parameters by either increasing or decreasing percentages. This was done by running the Python SG code and changing the inputs in each run's input file. Each run then provided us with SG data we could compare against each other to view, in graphical terms, the impact of the changes (with each output parameter being compared spatially against the SG length so as to also allow for a localized analysis).

3.2 Input Parameters and Their Ranges

The input parameters were as follows:

- HL/cold-leg (CL) inlet pressure
- HL/CL inlet temperature
- HL/CL inlet mass flow rate (MFR)

The baseline inputs were the 2-MW half-height SG model parameters provided by Dr. Xaiodong Sun:

Table 2. Baseline inputs for the parametric study (values are removed as it prosperity information).

Primary-side pressure (MPa)
Primary-side inlet temperature (K)
Primary-side MFR (kg/s)
Secondary-side pressure (Mpa)
Secondary-side inlet temperature (K)
Secondary-side MFR (kg/s)

After many test runs of the Python code, I observed a specific range of accepted input values over which the correlations used in the code were viable:

- HL pressure input: 5% below to 5% above the baseline
- HL temperature input: 0.2% below to 1% above the baseline
- HL MFR input: 2% below to 5% above the baseline
- CL pressure input: 1% below to 1% above the baseline
- CL temperature input: 5% below to 1% above the baseline
- CL MFR input: 3% below to 2% above the baseline.

3.3 Output Parameters

The output parameters used are as follows:

- Tube/riser HTC
- Primary-side pressure profile (riser and tube)
- Secondary-side pressure profile
- Primary-side temperature profile (riser and tube)
- Secondary-side temperature profile.

3.4 One-at-a-time Approach

The one-at-a-time approach bases the parametric analysis on a series of distinct steps one must follow. Once the input and desired output parameters are identified, this method helps define a baseline set of input values that we can vary and that can be compared against. We also define the range over which the input parameters will vary, allowing the data output to slightly differ based on these changes. In our case, we varied all six inputs by increasing them in increments of 0.1% to 0.5%. This process can be repeated to see how the outputs change in accordance with the altered input, and should give us an in-depth review of the different outputs and how they were impacted by the various magnitudes of changes applied to the inputs.

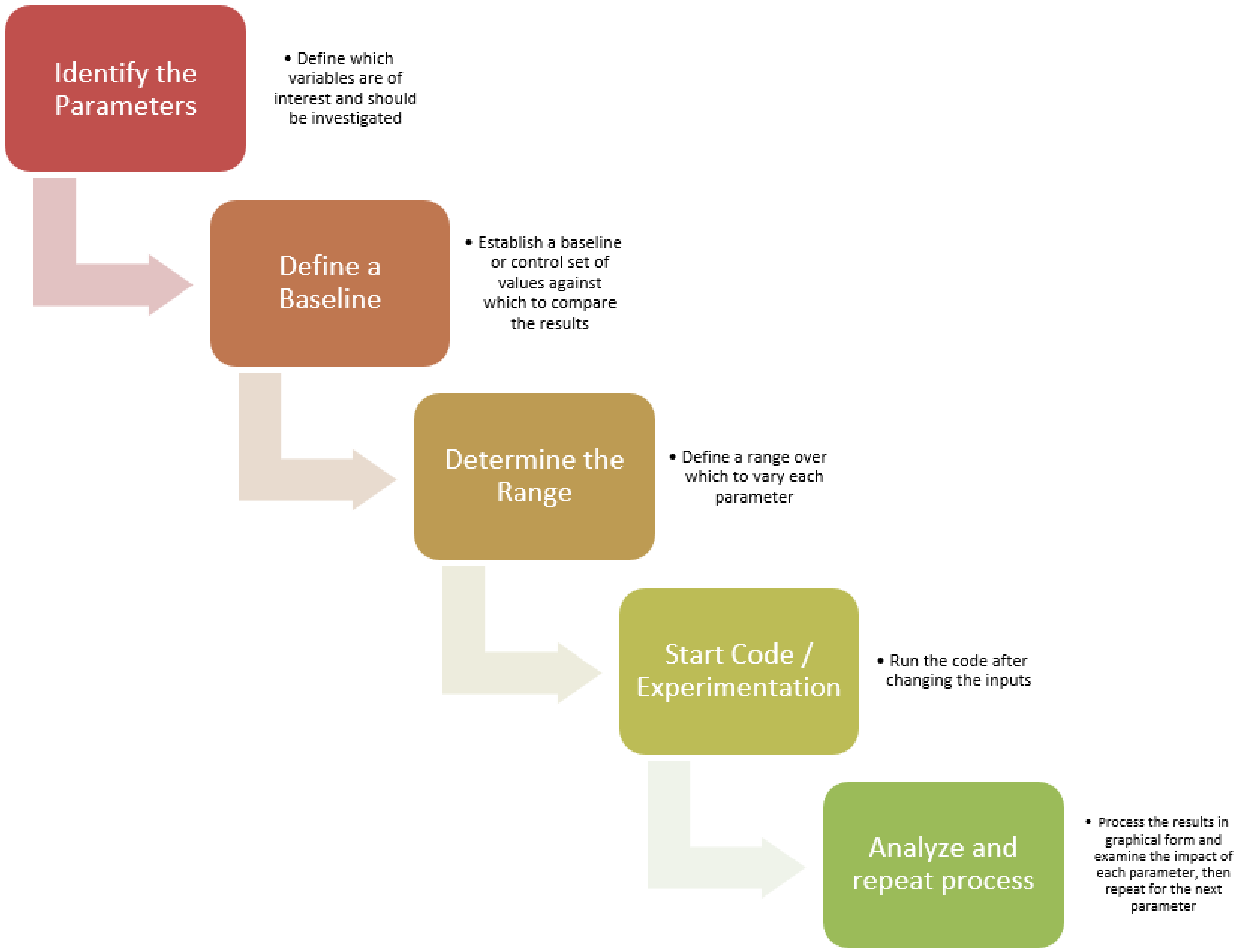

Figure 4. One-at-a-time approach.

3.5 Results and Discussion

3.5.1 Influence of Input Changes on the HTC

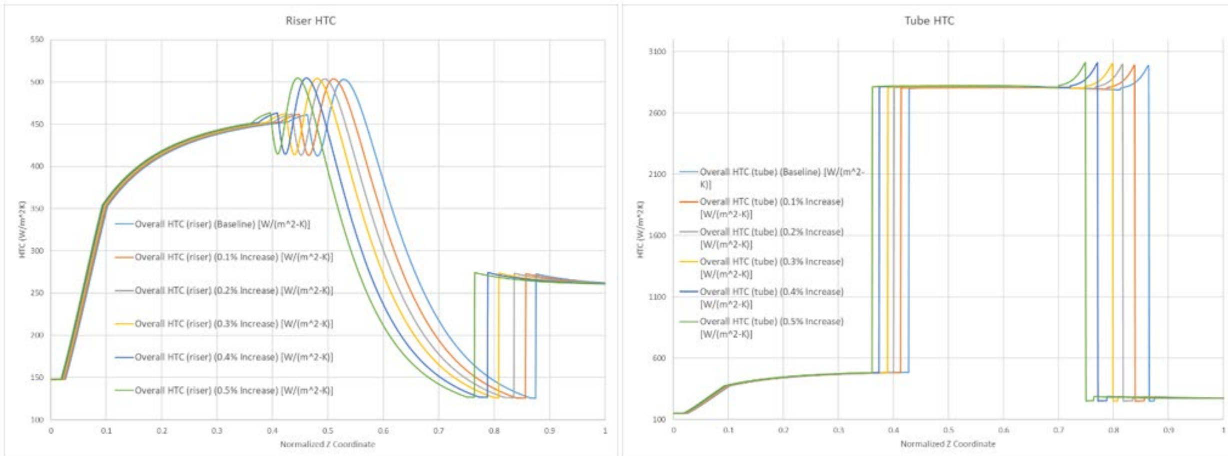

Figure 5. SG HTC under varied inputs.

The riser and tube HTCs vary as the input parameter values are increased from the baseline values in increments of 0.1%. On the riser side, there is little variation in the values until reaching around 0.4 of the SG length, at which point the HTC starts to fluctuate. For the baseline inputs, this fluctuation peaks at a normalized z-coordinate of around 0.52. At a 0.5% increase, it occurs prior to that at a normalized z-coordinate of around 0.44. This shows that when all the parameters are increased, the HTC starts fluctuating at different locations along the SG. A similar phenomenon was observed for the tube HTC, the fluctuation of which reached its peak value at a normalized z-coordinate of 0.87 when using the baseline inputs. After a 0.5% increase, the peak HTC occurs at a normalized z-coordinate of 0.75, while also showing a slight increase in the peak HTC value as the input parameters increased. This information is useful, as it indicates where properties of interest (e.g., the HTC) reach their maximum. It also shows how the HTC reacts to changed inputs. We clearly see that most HTC value changes that occur with respect to increases in the input parameters take place in a specific region of the SG. On both the riser and tube sides, this region is located somewhere between normalized z-coordinates of around 0.3–0.9. This means that, along this section of the SG, the HTC is most responsive to incremental changes made to the input parameters. Overall, the riser and tube HTCs are heavily impacted by input changes, as the peak HTCs take place at different locations. Furthermore, the tube HTC slightly increases as the input values increase.

3.5.2 Influence of Input Changes on the SG Pressure Profile

The primary- and secondary-side pressures are also significantly affected by changes to the inputs, as seen in Figure 6. The primary-side riser pressure decreases as the normalized z-coordinate increases. As the inputs are increased incrementally, the initial and final riser pressures slightly increase, such that the slope is the same as before, but with different intercepts. The primary-side tube pressure seems to follow a similar trend, except that, in this case, the pressure increases as the normalized z-coordinate increases. With each small change in the inputs, it is again observed that only the intercepts of the pressure profile increase, whereas the slope remains constant. The secondary-side shell pressure decreases as the normalized z-coordinate increases. Each run of the code generated the pressure values become farther apart at a normalized z-coordinate of 0.4.

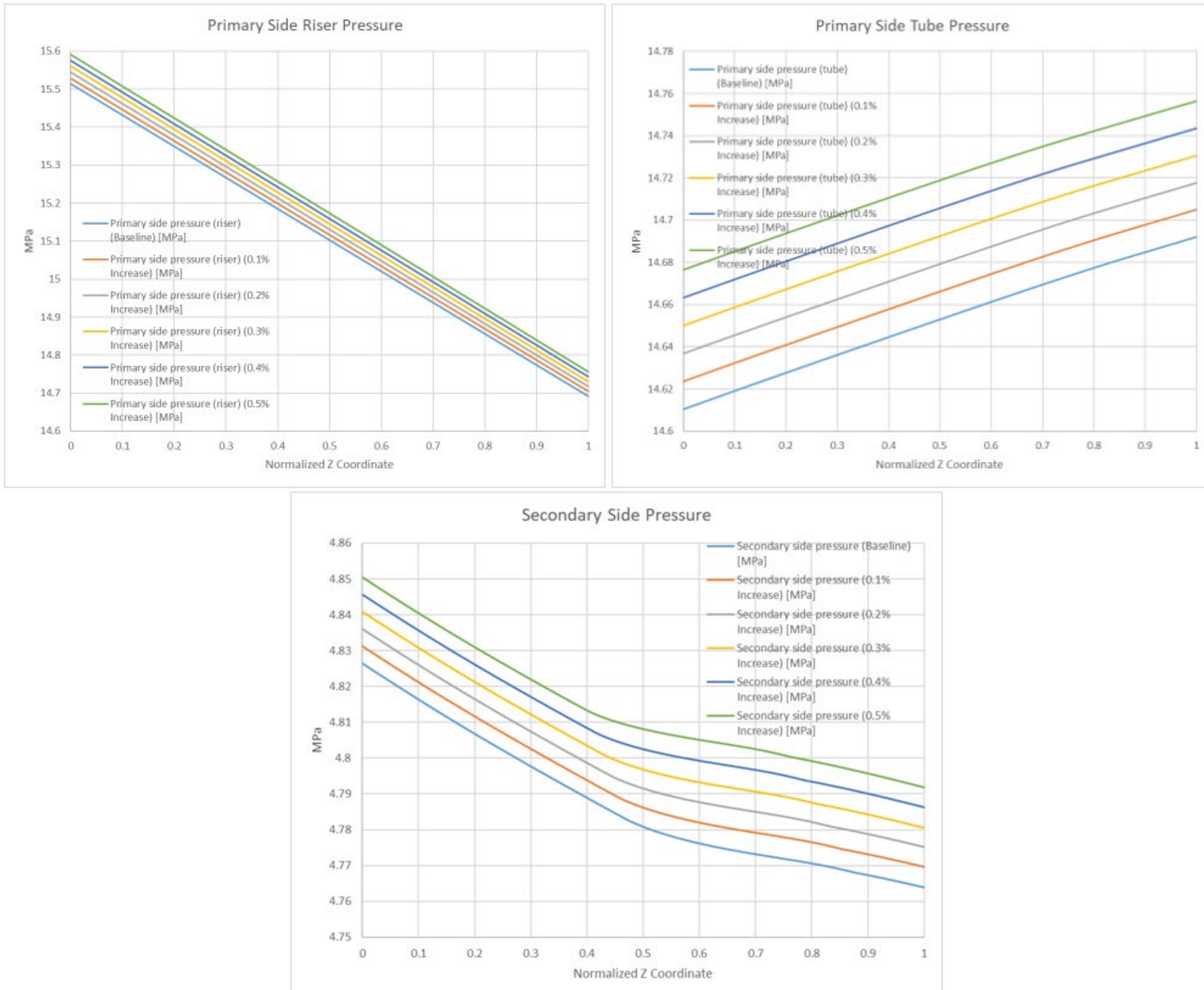

Figure 6. SG pressure profile under various inputs.

Overall, the pressure-based parametric study reveals that the pressure increases as the inputs are increased. This increased pressure can be observed in the SG riser, tube, and shell. A 0.5% increase led to an increase of around 0.1 MPa in the initial primary-side riser pressure, a 0.07 MPa increase in the initial primary-side tube pressure, and a 0.025 MPa increase in the initial secondary-side shell pressure.

3.5.3 Influence of Input Changes on the SG Temperature Profile

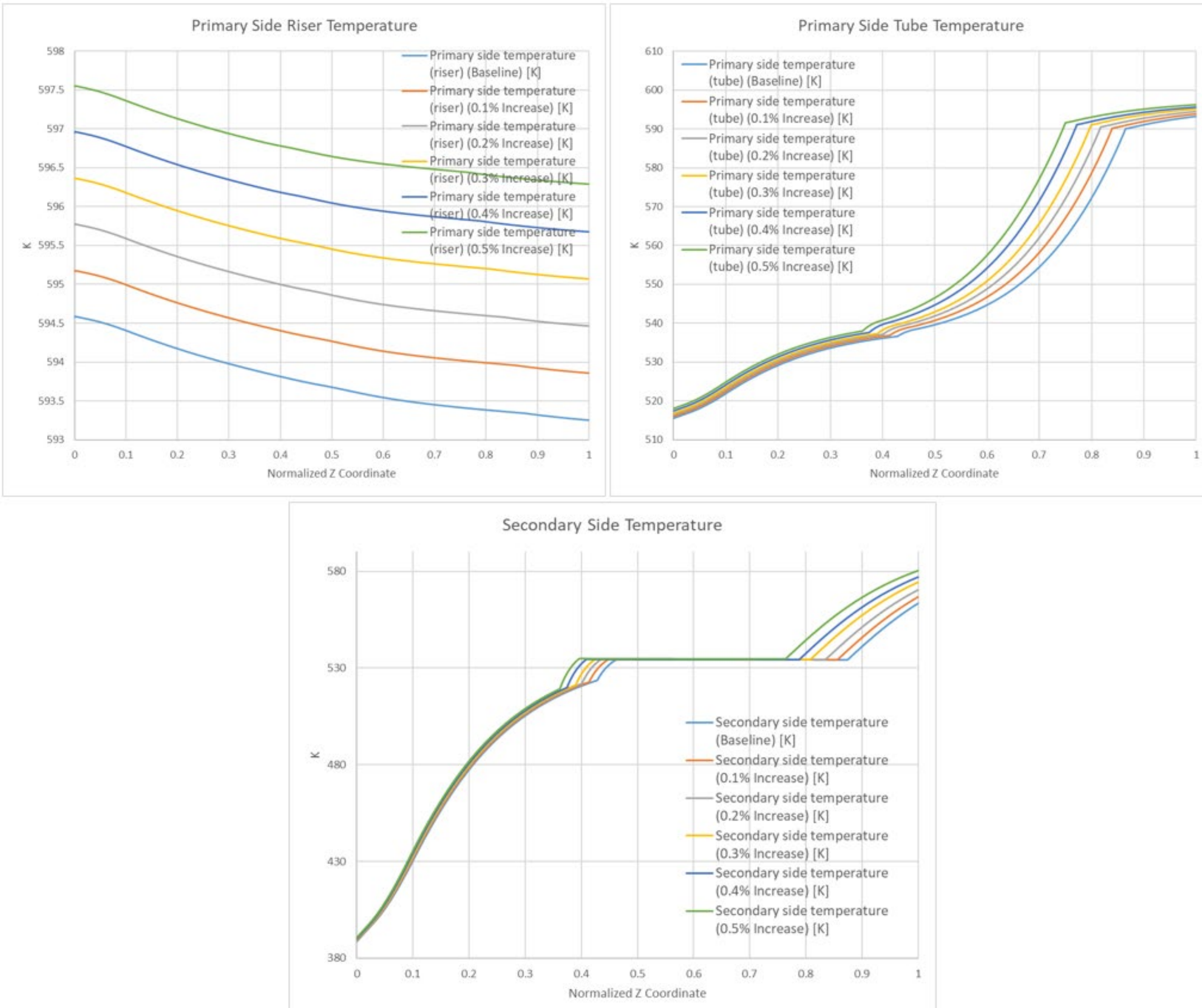

Figure 7. SG temperature profile under various inputs.

3.6 Identifying Critical Parameters

4. SENSITIVITY STUDY

4.1 Methodology

4.1.1 Manual Sensitivity Analysis

A sensitivity analysis is performed on the SG code. Sensitivity analyses differ from parametric analyses in that they focus on how one specific input parameter affects the output as a whole, and each input is not varied a certain amount for each run. We will perform this analysis in two ways. Initially, we will manually vary the input parameters to obtain sensitivity data, with each input being assigned two different values within the given range in order to obtain the effect on the resulting output. We will then use RAVEN and its built-in techniques—paired with the Python code—to obtain AI-generated sensitivity data based on additional input perturbations, thus making the data more reliable.

To perform a manual sensitivity analysis, we must define the sensitivity coefficient, which is a value that gives information on how significantly the input affects the output. A positive coefficient indicates that increasing the input should increase the output, and the magnitude of the coefficient tells us whether the input parameter has a great or a minimal effect on the output.

The sensitivity coefficient can be calculated mathematically via many methods, the simplest being to divide the change in output by the change in input:

$$Sensitivity\ Coefficient\ (S) = \frac{\Delta y}{\Delta x}$$

To find the sensitivity coefficient of our inputs, we can use the following formula:

$$S = \frac{\Delta\ output}{\Delta\ input}$$

For example, to determine the SG HTC's sensitivity to HL temperature, we can use the following formula:

$$S = \frac{New\ HTC - Initial\ HTC}{New\ Temperature - Initial\ Temperature}$$

For each interval along the vertical axis of the SG, the code calculates the pressure and temperature at that node. This means that each node has a specific spatial-based HTC value. For each node, this value will change when the inputs are changed, giving us new and initial HTC values usable for determining the sensitivity at each node. This enables us to conduct, for different input parameters, a localized analysis of sensitivity along the length of the SG.

Within the range of accepted values listed in Section 3: Parametric Study, I chose two different values for each input to see the resulting effect on the HTC output:

- HL pressure input: 5% below and 5% above the baseline
- HL temperature input: 0.2% below and 0.2% above the baseline
- HL MFR input: 2% below and 2% above the baseline
- CL pressure input: 1% below and 1% above the baseline
- CL temperature input: 1% below and 1% above the baseline
- CL MFR input: 2% below and 2% above the baseline.

4.1.2 RAVEN-based Sensitivity Analysis

RAVEN is a machine learning platform developed by the INL (Idaho National Laboratory) to process large amounts of data. It runs a code multiple times, as decided by the user, and samples the data according to certain principles. In our case, we use RAVEN to run our SG code 28 times, each time perturbing the inputs according to the Monte Carlo model. This allows us to have a large data set of heat transfer coefficients for each perturbed input. We can then utilize the analytic power of RAVEN to find the sensitivity coefficients for each input on the heat transfer coefficient. It is important to note that the more perturbations that RAVEN makes, the more accurate the sensitivity data is. When doing the analysis manually, it took a long time just to tweak the inputs twice, as the Python code itself is computationally intensive and it takes time to complete each run. Sensitivity data after running the code through RAVEN 28 times is much more accurate than the manual method, as sampling is done randomly, and sensitivity coefficients can be averaged for overall accuracy. This RAVEN implementation is a proof of concept. With more time and more powerful computing, this RAVEN implementation can be done with 100 Monte Carlo samples or more – further increasing the accuracy of the sensitivity result. In the following RAVEN – based sensitivity results, the range of perturbations for the Monte Carlo samples are within 0.2% above and 0.2% below the original baseline inputs, to ensure that the correlations in the code will not break down while running in RAVEN.

4.2 Results and Discussion

4.2.1 Sensitivity Study of Hot Leg Inputs

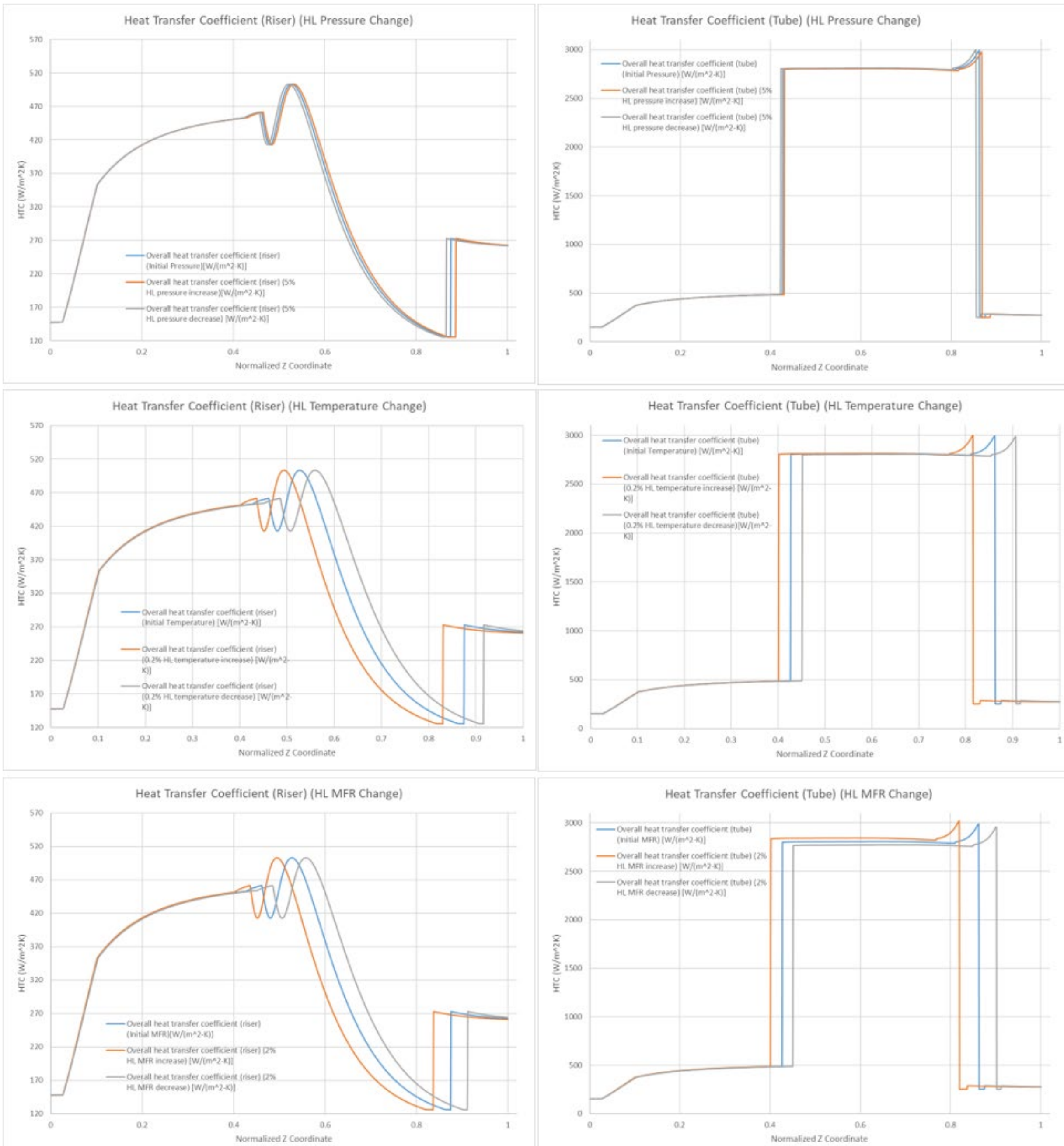

Figure 8. HL HTC based on pressure, temperature, and MFR input changes.

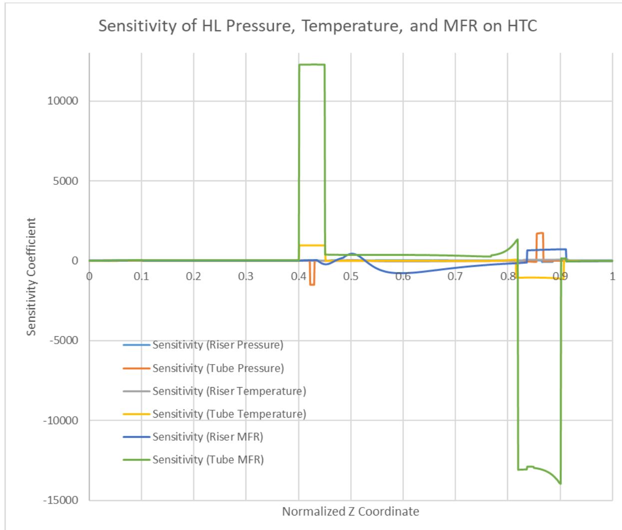

Figure 9. (Left) Effects of various HL inputs on the HTC along the SG length.

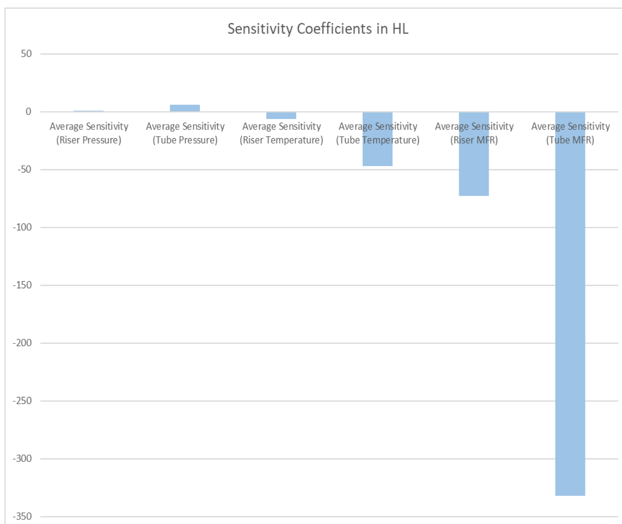

Figure 10. (Right) Average HL sensitivity coefficients for each input parameter.

The HTC for the primary side of the SG is significantly affected by the pressure, temperature, and MFR at the inlet. Temperature and MFR seemingly have a greater impact on the location of the maximum HTC. When these two parameters are increased, the maximum HTC moves closer toward the SG inlet, while a decrease brings the peak HTC closer to the outlet. The HTC reaction to pressure shows the opposite effect. As the pressure input is increased, the maximum HTC moves toward the outlet instead.

We can also gain a better understanding of the approximate sensitivity results obtained along the SG length. Under all parameters, sensitivity greatly increases within the 0.4–0.9 region of the SG length. Within this range, the tube MFR most impacts the HTC, with the riser MFR following closely behind. One observation is that the inlet MFR has the greatest impact on the HTC in general, while inlet pressure has the least. This is seen clearly in Figure 10, which shows the average sensitivity results for each parameter.

4.2.2 Sensitivity Study of Cold Leg Inputs

Below, we see how the CL inlet conditions affect the SG HTC profile. Compared to the HL input, CL pressure has a greater impact on the location of the maximum HTC. In this case, MFR and temperature affect the HTC across the entire SG length, not just within the 0.4–0.9 normalized z-coordinate bounds. The HTC magnitudes, along with the location of the maximum HTC, are both affected by these input changes. Another observation is that CL temperature has less impact on the HTC than does HL temperature, and increasing the CL MFR produces a bigger HTC increase than increasing the HL MFR.

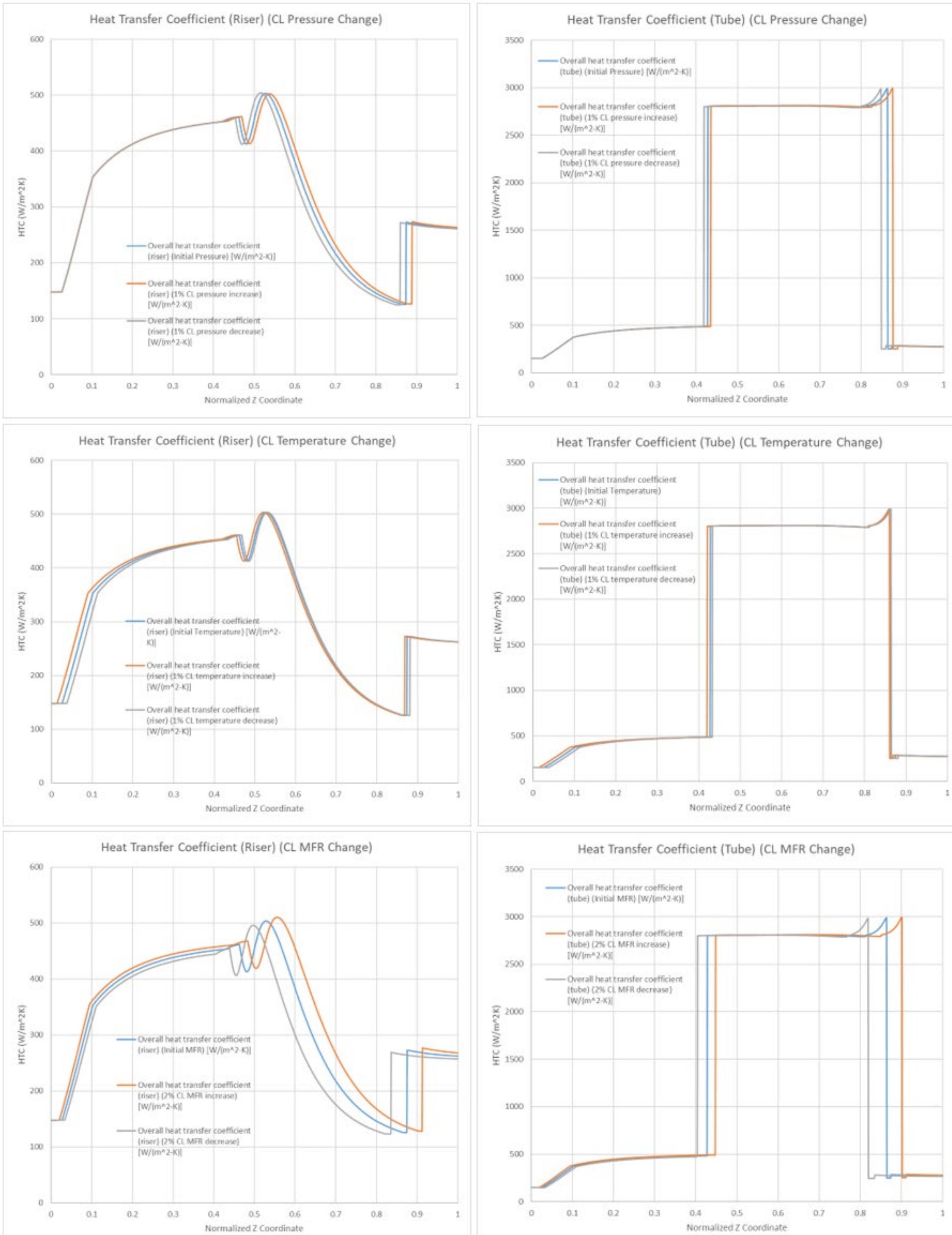

Figure 11. CL HTC based on pressure, temperature, and MFR input changes.

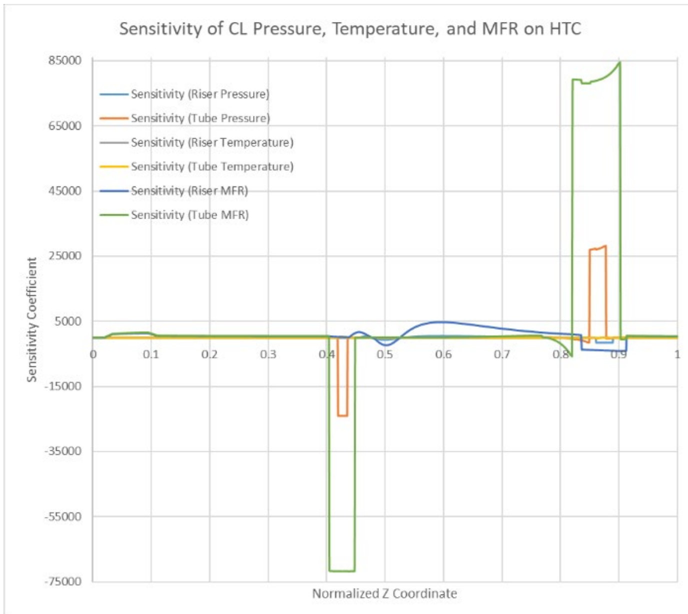

Figure 12. (Left) Effects of various CL inputs on the HTC along the SG length

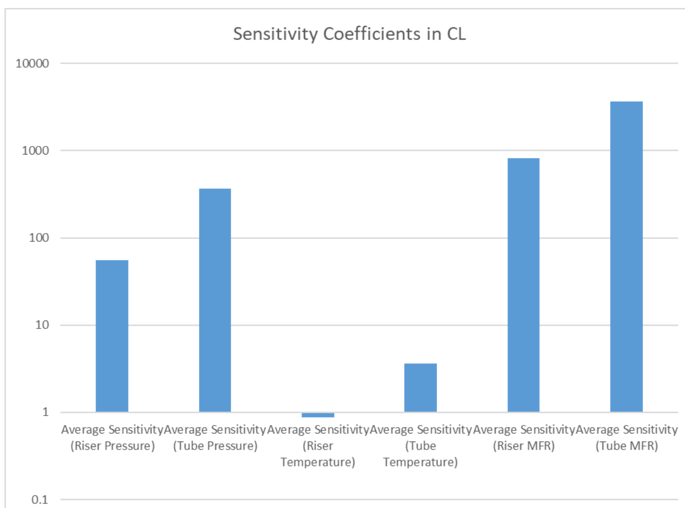

Figure 13. (Right) Average CL sensitivity coefficients for each input parameter.

The sensitivity across the SG length slightly increases for the tube MFR and tube temperature close to the SG inlet. The inlet parameters seemingly display a greater impact on tube conditions—as opposed to riser conditions—and thus impact occur globally across the SG. CL temperature has the least impact on both the riser and tube, with its average sensitivity on the riser HTC being negligible with respect to the other parameters.

4.2.3 RAVEN-based Sensitivity Results

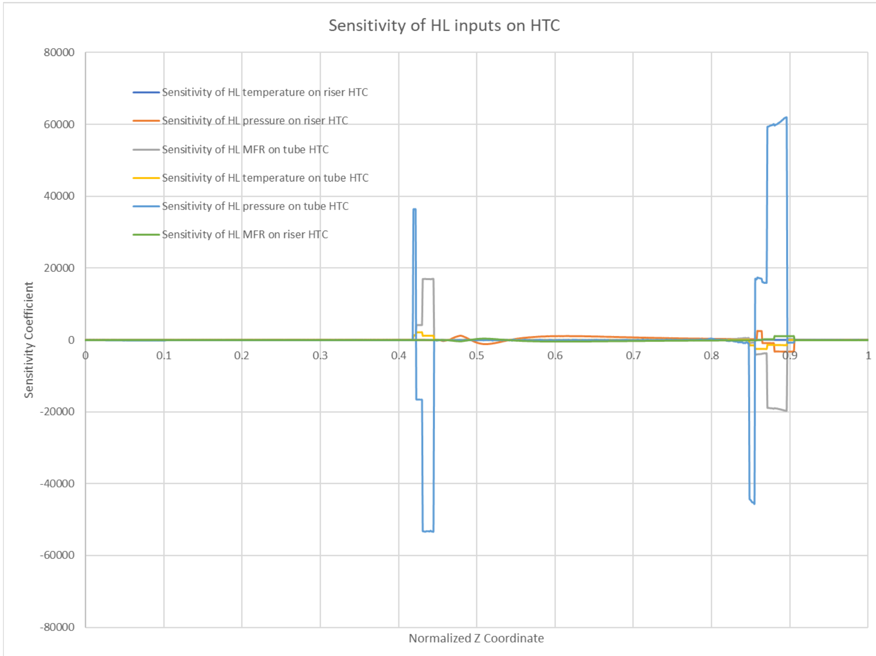

Figure 14. RAVEN-based sensitivity results for the HL inputs

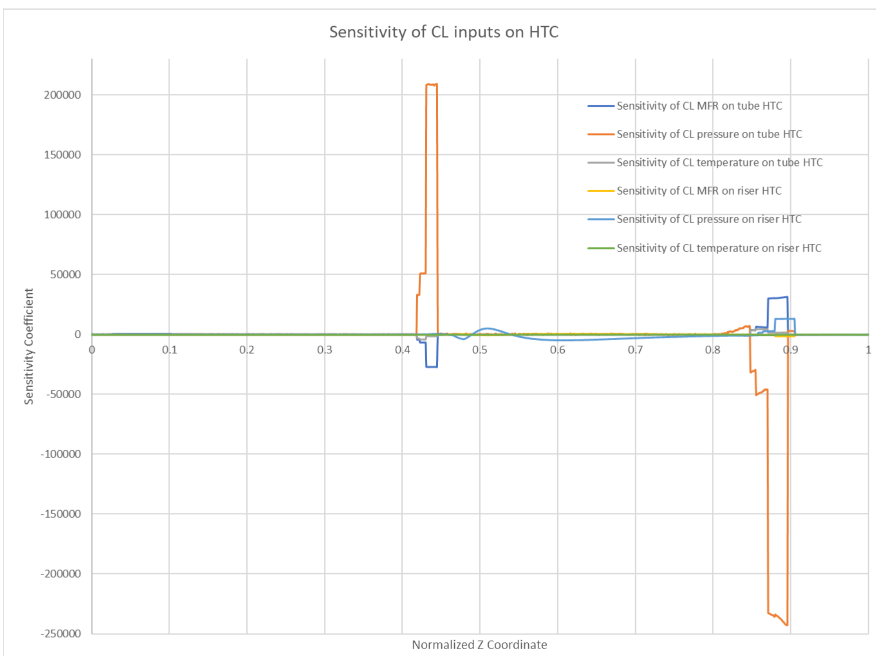

Figure 15. RAVEN-based sensitivity results for the CL inputs

The results from the RAVEN analysis agree with the manual sensitivity study. The range of peak sensitivity is between 0.4 and 0.9 normalized z-coordinate. The values of the RAVEN-based sensitivity indicate that the CL pressure has a significant impact on the tube HTC, and the HL temperature on the riser HTC. This differs from the manual results that show that the mass flow rate is the key influencing factor on the HTC. The RAVEN based study takes 28 samples, while the manual study only takes two samples. This gives more redundancy in calculations to obtain a better result – hence implying that the pressure and temperature have more of an impact on HTC than previously calculated.

4.3 Implications for SG Model Optimization

5. CONCLUSIONS

5.1 Summary of Key Findings

HL/CL temperature, pressure, and MFR have varied effects on the SG HTC. The MFR's impact on the HTC is greatest, followed by temperature and then pressure. However, the RAVEN-based results show that pressure and temperature also have a significant impact on the HTC, more than that of the MFR. Due to the increased accuracy of the RAVEN results, as it runs the code 28 times versus 2, it implies that original manual sensitivity analysis of the effect of temperature and pressure on the HTC is slightly skewed or inaccurate. In the sensitivity analysis, the location of the maximum HTC was affected by increasing or decreasing certain parameters. When HL and CL pressures increase, the maximum HTC location moves closer to the inlet, and vice versa. However, temperature and MFR increase, the location of the maximum SG HTC moves closer to the inlet. Overall, the maximum sensitivity for all parameters falls within the 0.4–0.9 normalized z-coordinate bounds, with certain parameters (e.g., CL temperature and MFR) having a more global impact on HTC. The RAVEN based study ran the code 28 times, versus 2 times for the manual analysis. The machine learning algorithm produced a result that agreed with the manual analysis, and also confirmed the range of 0.4 to 0.9.

The parametric study showed that incrementally increasing all parameters causes the maximum HTC to move closer to the inlet. It also affects the SG pressure profile. As the input values increase, the pressure profile rises, such that its intercepts increase while maintaining a similar slope. The same observation can be made for temperature; however, for the secondary-side temperature, the input parameters have little to no impact within the 0.45–0.76 region.

5.2 Implications for SG Design and Operation

The SG sensitivity profile shows that, within a certain range, the HTC is significantly affected by each input parameter. Thus, it may be deemed necessary to place more sensors in that area so sudden changes in HTC can be monitored closely. The maximum HTC also occurs within this range. Monitoring the HTC to make sure it remains within acceptable bounds is important for SG operation. The same can be said for temperature and pressure both of which are directly measurable. Pressure transducers and thermocouples can be placed in locations showing spikes in sensitivity, such as the 0.4–0.9 normalized z-coordinate bounds. At these locations, the inlet pressure and temperature have the greatest impact on the HTC.

5.3 Future Research Directions

Going further, we can utilize RAVEN on HPC (High Power Computing). With more time, we can run the code hundreds of times such that our sensitivity data is much more accurate. We can use the RAVEN input file and source code to obtain more statistical information about the steam generator properties so that more detailed information on the behavior of the important parameters like the HTC can be obtained.

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