Methodology for Constructing Reduced-Order Power Block Performance Models for CSP Applications

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METHODOLOGY FOR CONSTRUCTING REDUCED-ORDER POWER BLOCK PERFORMANCE MODELS FOR CSP APPLICATIONS

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1   Introduction

Superheated steam Rankine cycle technology is widely used in utility-scale power generation and is well understood for fossil-fuel, nuclear, and biomass applications. These fuel-consuming power plants typically operate in a narrow range of conditions near their design point, but concentrating solar power (CSP) plant operating conditions can vary much more widely depending on solar resource availability, storage capacity, or ambient conditions. Consequently, CSP technology performance models must maintain a high level of accuracy in off-design simulation to avoid significant error in annual electricity yield totals.

Yield analysis studies evaluating power plant economic feasibility have not traditionally required detailed performance models of off-design heat absorption rates or varying heat source inlet temperatures. This is the case since traditional plants spend most of their life operating at a fixed thermal load and resource temperature; only variation in ambient temperature is of notable concern. Models that do accommodate off-design thermal loads and temperatures tend to fall into two categories: they either are robust models with detailed fundamental calculations like [1], [2], and [3], or they are simplified empirical models that only capture top-level performance like [4].

The inherent variability of the solar resource presents a unique challenge for CSP systems. Incident solar irradiation can fluctuate widely over a short time scale, but plant performance must be assessed for long time periods. As a result, annual simulations with hourly (or sub-hourly) timesteps are the norm in CSP analysis. A highly detailed power cycle model provides accuracy but tends to suffer from prohibitively long run-times; alternatively, simplified empirical models can run quickly but don't always provide enough information, accuracy, or flexibility for the modeler.

The ideal model for feasibility-level analysis incorporates both the detail and accuracy of a first-principle model with the low computational load of a regression model. The work presented in this paper proposes a methodology for organizing and extracting information from the performance output of a detailed model, then using it to develop a flexible reduced-order regression model in a systematic and structured way. A similar but less generalized approach for characterizing power cycle performance has been presented in [5], and a reduced-order modeling methodology for CFD analysis of heat transfer from electronic devices is discussed in [6]. This paper builds on these publications and the non-dimensional approach originally described in [7].[1]

2   Proposed modeling approach

Instead of relying on part-load polynomial curves or lookup tables to predict plant performance in off-design conditions, this methodology uses a structured design-of-experiments approach [8] to characterize plant behavior using detailed process modeling software, then extracts output dependence from that information within the framework of statistical effects and interactions.

To illustrate this idea, consider the input and output of interest in a Rankine power cycle model. For CSP plants, the modeler is primarily interested in the total power output, thermal absorption from the heat transfer fluid (HTF), HTF return temperature, and cooling system load. These in turn depend on inputs like HTF inlet temperature, turbine back-pressure, HTF mass flow rate, and others. If the HTF flow rate varies exclusively, a simple part-load curve might adequately capture the performance impact. However, accurate results are unlikely if the inlet HTF temperature and mass flow rate both vary simultaneously and the two independent effect functions are overlaid. The proposed approach not only captures the impact of varying a single input, but also captures competing interaction effects introduced by concurrent off-design variation.

3 Off-design response framework

The ultimate goal of this method is to convert a complex and detailed power block model into a descriptive simplified model. To accomplish this task, a thorough information set is required that describes the cycle's off-design performance as a function of operating conditions, and a detailed process simulation software tool like IPSEpro$^{\text{TM}}$, GateCycle$^{\text{TM}}$, or ThermoFlow$^{\text{TM}}$ provides this information. One purpose of this methodology is to minimize the modeling effort that is required to develop a thorough system performance map, and this is achieved through strategic selection of the simulation parameters. The response framework provides a design for the analytical experiment that meets these criteria.

The first step in constructing the response framework is establishing which quantities impact cycle performance (model inputs) and which are required to fully describe the observed performance (model outputs). Cycle performance is fundamentally expressed in terms of power output ($\dot{W}$) and heat absorption ($\dot{Q}$); the relationship between the independent variables and these two values allows the calculation of secondary information including cycle efficiency, heat rejection load, and HTF temperature drop. For any given cycle design, performance is a function of three independent variables[2]: HTF inlet temperature (T_{in}), condenser steam pressure (P_c), and HTF mass flow rate ($\dot{m}$). Deviation among these three variables from their design-point values adversely impacts the heat-to-power conversion efficiency of the cycle.

3.1 Parameter normalization

The input and output variables are readily expressed in normalized terms, and the regression methodology presented below requires this generalized state. The power output, heat input, and HTF mass flow rate are simply divided by their design-point values such that they are equal to 1.0 when they match the design rate. The two exceptions to this approach are the condenser pressure and the inlet HTF temperature. Condenser pressure does not generally scale up or down as the size of the power block varies, so it is left in dimensional form.

Inlet HTF temperature is normalized with respect to the superheater temperature rise. For cycles with superheat, most of the heat transfer from the HTF to the steam working fluid occurs in boiling and superheat. Steam evaporates at a constant temperature for a given boiler pressure, and this temperature represents the effective minimum temperature at which the HTF could enter the power block and still provide heat flow into the steam. Therefore, the boiler steam temperature (not the HTF outlet temperature) is considered to be the zero-value for normalized HTF inlet temperature.

$$\hat{T_{in}} = \frac{T_{in} - T_{boil}}{T_{in,des} - T_{boil}} \tag{1}$$

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[2]This statement assumes that the turbine inlet pressure is either fixed or varies systematically with HTF inlet temperature.

3.2 Experimental design

The three independent variables are varied parametrically within the response framework to obtain the required performance information. Each independent variable has a direct impact on performance, but simultaneous variation of the independent variables can also induce secondary impacts that adversely affect accuracy. To measure these "interaction" effects, the analysis includes parametric runs where the inputs are evaluated concurrently at design and off-design conditions.

Table 1 provides the experimental design framework for this methodology. Each run in the table represents a parametric set of simulations where the variable indicated with "⌣" is varied stepwise from the lower to upper bounds. The other two variables are held fixed at either their lower bound (-), upper bound (+), or design-point value (0). Runs 2, 5, and 8 measure the primary effects of one of the three independent variables while the other two are held at their design-point value. The remainder of runs 1-9 aid in measuring the impact of two-variable interaction (denoted A⟩B), and runs 10-13 measure the impact of the three-variable interaction (which is often negligible and has been neglected in this paper). The upper and lower bounds are selected based on practical operation limits of the power cycle. For example, if the minimum turn-down state for the modeled cycle is 30% of design (i.e. a 70% reduction in operation), the lower bound on $\dot{m}$ should be $0.3 \times \dot{m}_{des}$.

Run	T_{in}	P_c	$\dot{m}$	Measures
1	⌣	0	-	$f(\dot{m}\rangle T_{in})$
2	⌣	0	0	$f(T_{in})$
3	⌣	0	+	$f(\dot{m}\rangle T_{in})$
4	-	⌣	0	$f(T_{in}\rangle P_c)$
5	0	⌣	0	$f(P_c)$
6	+	⌣	0	$f(T_{in}\rangle P_c)$
7	0	-	⌣	$f(P_c\rangle \dot{m})$
8	0	0	⌣	$f(\dot{m})$
9	0	+	⌣	$f(P_c\rangle \dot{m})$
10	-	-	⌣	$f(T_{in}\rangle P_c\rangle \dot{m})$
11	-	+	⌣	$f(T_{in}\rangle P_c\rangle \dot{m})$
12	+	-	⌣	$f(T_{in}\rangle P_c\rangle \dot{m})$
13	+	+	⌣	$f(T_{in}\rangle P_c\rangle \dot{m})$

Table 1: The experimental design for characterizing power block performance. The experiment is adapted from a three-level full-factorial design.

4 Formulating a model

The output of the runs in Table 1 is used to generate a model that can express both heat absorption and power output as functions of the three independent variables and their interactions. The intermediate result of each run is a table that relates heat absorption or power output to a particular arrangement of T_{in}, P_c, and $\dot{m}$. For example, Run #1 will produce a pair of functions that vary with HTF inlet temperature at a fixed lower-bound value for HTF mass flow rate. Substituting the general output variable Y for $\dot{Q}$ and $\dot{W}$:

$$Y_{Run1} = f\left(T_{in}, \dot{m}^{(-)}\right) \tag{2}$$

Figure 1 corresponds to runs 4-6 in Table 1 and shows how power (left) and heat (right) output vary as a function of parameterizing P_c at three distinct levels of T_{in}. The central lines in Figure 1 represent the situation where only P_c is varied and both T_{in} and $\dot{m}$ are left at their design-point values (run #5).

This methodology asserts that the upper and lower curves observed in Figure 1 can be approximated by multiplying the main effects of $Y_{ME}(T_{in})$ and $Y_{ME}(P_c)$, where the two-variable interaction effect $Y_{INT}(T_{in}\rangle P_c)$ scales the impact of the second main effect. Since the purpose of the interaction effect is
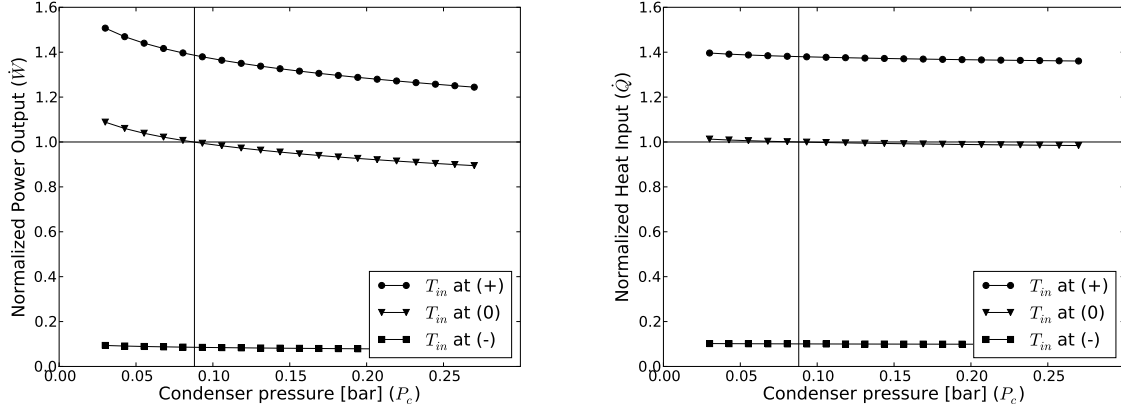
Figure 1: Data showing how the power and heat output varies with condenser pressure [bar] at three distinct levels of HTF inlet temperature.

to adjust the magnitude of main effect's impact on the output, the interaction effect is applied only to the difference between the calculated main effect and the basis normalized value (i.e. $Y_{ME} - 1$). Since all effect functions in the set Y are normalized about 1, the main effect must first be shifted from 1 to 0 before being multiplied by the interaction effect. The product is then readjusted to 1.0 as shown in Eq.[3]. In general terms, the calculated output variable Y^* is determined for any set of inputs X_i with the relationship:

$$Y^* = \prod_{i=1}^{nX} \left[(Y_{ME}(X_i) - 1) \cdot Y_{INT}(X_j \rangle X_i) + 1 \right] \tag{3}$$

In Eq.[3], X_j represents the input variable that interacts with X_i. For example, in Table 1, $\dot{m}$ interacts with T_{in}, and this effect is measured in runs #1-3. In this example, $X_j \equiv \dot{m}$ and $X_i \equiv T_{in}$.

Interaction effects measure the relative difference between the calculated value that is predicted by multiplying only main effects and the actual value observed from the detailed modeling simulation. Mathematically speaking, the interaction is the ratio of values (Observed - Main Effect)/(Predicted - Main Effect), as shown in Eq.[4] (the $\hat{Y}$ notation indicates a data point obtained from the detailed model). The interaction equation can be formulated for either the lower or upper bound runs ($\pm$), assuming either the lower or upper bound of $\hat{X}_j$ is used.

$$Y_{INT}^{(\pm)}\left(\hat{X}_j^{(\pm)} \rangle \hat{X}_i\right) = \frac{\hat{Y}^{(\pm)}(\hat{X}_i) - Y_{ME}(\hat{X}_i)}{Y_{ME}(\hat{X}_i)\left(Y_{ME}(\hat{X}_j^{(\pm)}) - 1\right)} \tag{4}$$

The interaction calculations provide a function that indicates how variation in one independent variable influences the effect of another varying independent variable. The relative impact of an interaction effect applies consistently to the main effect that it's adjusting. In other words, if two independent variables X_i and X_j simultaneously deviate from their design, the magnitude of the interaction effect that is applied to the main effect is only a function of the value of the first independent variable X_i. Consequently, interaction effects that are calculated for the lower and upper limit values for a particular effect (i.e. runs #1 and #3 for run #2) both represent the same interaction effect and can be averaged to estimate a better interaction curve as shown in Eq.[5].

$$Y_{INT}(X_j \rangle X_i) = \frac{Y_{INT}^{(+)}\left(X_j^{(+)} \rangle X_i\right) + Y_{INT}^{(-)}\left(X_j^{(-)} \rangle X_i\right)}{2} \tag{5}$$

4

Note that the resulting expression for $Y_{INT}(X_j\rangle X_i)$ contains arguments for X_j and X_i; however, the function is only truly dependent on X_i, retaining X_j in the nomenclature merely as a reference to the two interacting variables. Figure 2 shows the heat absorption and power output as a function of HTF temperature for three mass flow rates and the associated interaction effect curves. This shows that even for cases where the output appears to be linearly related to the independent variables, interaction effects can have a significant relative impact.
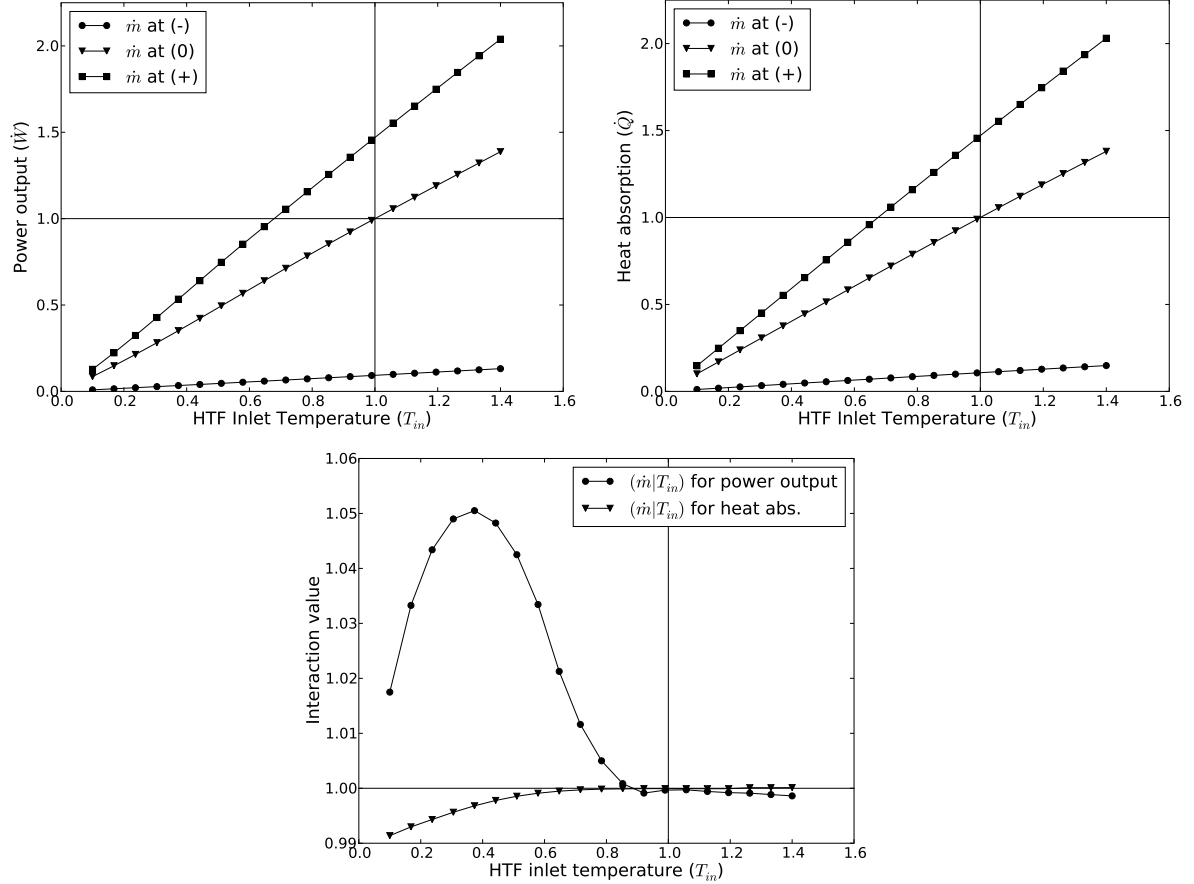

Figure 2: Data showing how the power and heat output varies with HTF temperature at three distinct levels of HTF mass flow rate (top), and the associated interaction effects (bottom).

4.1 Other calculated output

Since the power block model regresses only power output and heat input as functions of HTF temperature, condenser pressure, and mass flow rate, other performance values need to be calculated. The calculation of power cycle efficiency is straightforward. Thermodynamic power cycle efficiency is determined by simply dividing the work output by the required heat input.

$$\eta_{cycle} = \frac{\dot{W}}{\dot{Q}} \tag{6}$$

The outlet HTF temperature from the power cycle is calculated by considering the HTF mass flow rate, the heat input, the inlet temperature, and the specific heat of the HTF. The specific heat is assumed to vary linearly over the range of the inlet and outlet temperatures. Thus, an average specific heat value is

used and is recalculated throughout the simulation.

$$T_{out} = T_{in} - \frac{\dot{Q}}{\dot{m}\,c_{p,ave}} \tag{7}$$

Since the power block does not directly include heat rejection equipment, it must supply information to an external cooling model on how much heat should be rejected. This value is equal to the difference between work output and heat absorption, or alternatively:

$$\dot{q}_{rej} = (1 - \eta_{cycle})\,\dot{Q} \tag{8}$$

5 Model validation

To test how well the regression model fits data from the detailed model, 1000 random combinations of the three input variables T_{in}, P_c, and $\dot{m}$ spanning the full range of operation of the power cycle were generated and modeled using both a detailed modeling software tool and the corresponding regression model. The difference between the value predicted by the regression model and the actual value from the modeling software represents the methodology error. Table 2 quantifies the error for the two outputs $\dot{W}$ and $\dot{Q}$.

	$\dot{W}$	$\dot{Q}$
Upper max. error (%)	0.69	0.15
Lower max. error (%)	-2.01	-0.16
Average error(%)	-0.24	-7.4×10^{-5}
Error standard deviation (%)	0.49	0.04

Table 2: Quantification of the error from 1000 runs of the regression model as compared to the detailed modeling software. Errors are shown for both heat absorption and power output.

The analysis shows good regression model agreement, with standard deviation in error between the two models of less than half of one percent for both power output and heat absorption. A histogram plot of the error shown in Figure 3 indicates that the majority of the simulation points produce errors very near to zero.
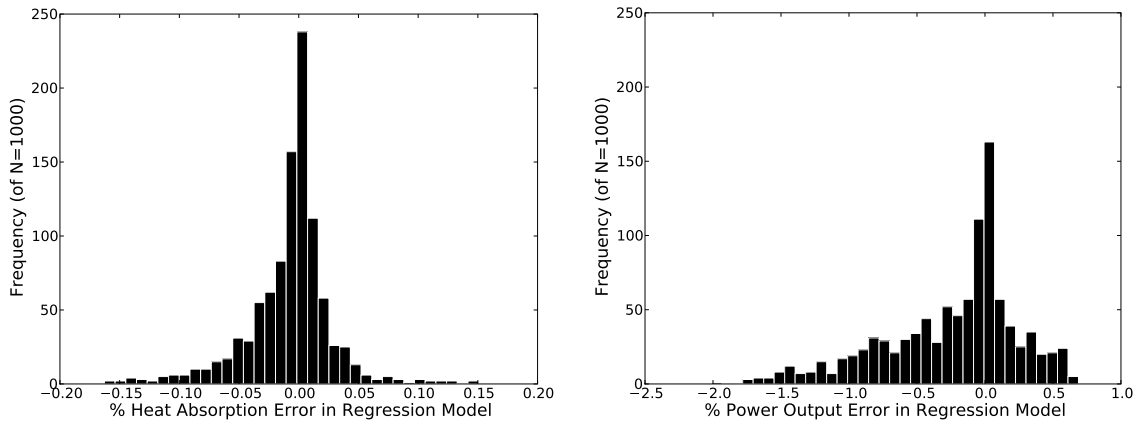

Figure 3: Histogram plots of the % error in the regression model for Heat Absorption and Power Output.

Figure 4 presents plots of the error for each of the three independent variable combinations, where the size of the marker is proportional to the magnitude of the modeling error. The inputs for each simulation were selected randomly within the range handled by the model, and each simulation is plotted as a single

point with the unweighted points provided in the leftmost plot as a location reference. The size of the largest markers are equal to the maximum error values in Table 2. The error for each simulation is plotted three times - once for each unique two-variable combination of the input variables P_c, T_{in}, and $\dot{m}$. The plots in Figure 4 and the values in Table 2 indicate that the heat absorption regression fares somewhat better than the power output, though both exhibit reasonable modeling errors in light of the information in Table 2.
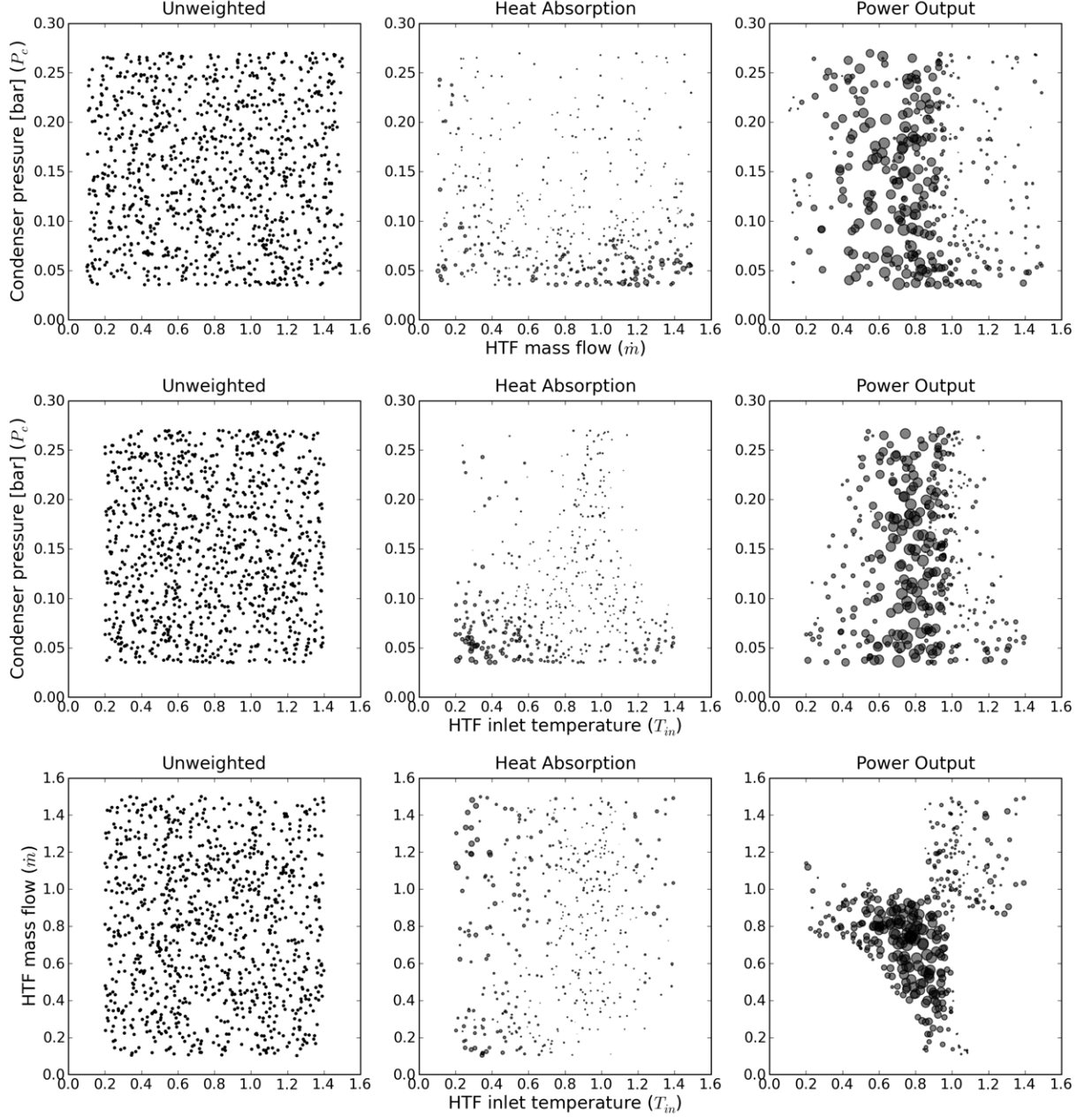

Figure 4: Plots mapping the relative error in the regression model for each of the three unique independent variable combinations. The leftmost plot shows the unweighted points, and the right two plots in each group show error in heat absorption and power output predictions.

6 Conclusions

This paper presents a regression methodology that is useful in characterizing detailed systems like the Rankine power cycle. Since regression models are less computationally demanding than detailed iterative models, they are most useful in preliminary feasibility analyses. To this end, the regression model presented in this paper has been incorporated into NREL's Solar Advisor Model (SAM) tool [9] for both the Power Tower and Physical Trough model.

Though the regression model reproduces the detailed model performance map with relatively low error, space for improvement still exists. In particular, the accuracy of the power output regression is worst near the design-point value for each independent variable. Improvement in estimating the interaction effects could mitigate this problem, and future work will focus on this aspect of the model.

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