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Linear regression and sensitivity analysis in nuclear reactor design

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ABSTRACT

The paper presents a general strategy applicable for sensitivity analysis (SA), and uncertainity quantification analysis (UA) of parameters related to a nuclear reactor design. This work also validates the use of linear regression (LR) for predictive analysis in a nuclear reactor design. The analysis helps to determine the parameters on which a LR model can be fit for predictive analysis. For those parameters, a regression surface is created based on trial data and predictions are made using this surface. A general strategy of SA to determine and identify the influential parameters those affect the operation of the reactor is mentioned. Identification of design parameters and validation of linearity assumption for the application of LR of reactor design based on a set of tests is performed. The testing methods used to determine the behavior of the parameters can be used as a general strategy for UA, and SA of nuclear reactor models, and thermal hydraulics calculations. A design of a gas cooled fast breeder reactor (GCFBR), with thermal–hydraulics, and energy transfer has been used for the demonstration of this method. MCNP6 is used to simulate the GCFBR design, and perform the necessary criticality calculations. Java is used to build and run input samples, and to extract data from the output files of MCNP6, and R is used to perform regression analysis and other multivariate variance, and analysis of the collinearity of data.

1. Introduction

In this section the background, motivation, and literature review of this work has been presented. This section also presents a brief introduction to the current work.

1.1. Background and motivation

Nuclear reactors are complex systems having numerous parameters those affect the system independently, as well as in an interactive fashion. In addition, the system has an inherent uncertainty in the model structure. The interaction between the parameters are usually of a higher order, hence modeling those uncertainties, is a difficult problem to solve. These parameters also have a non-linear effect on the system behavior. Software codes have been developed based on stochastic as well as deterministic methods to model these systems, however with an increase in complexity due to a need for heterogeneity, and accuracy, the codes are expensive to use. Therefore, it is important to understand the behavior of these uncertainties in the model to perform an acceptable predictive analysis. Uncertainty quantification analysis (UA), and sensitivity analysis (SA) provide a very accurate understanding of the uncertainties in the system, which is imperative for predictive analysis. UA may be used to assess the variability i.e. imprecision in the predictions in the output parameter that is due to the uncertainty in estimating the values of the input parameters. This is due to the propagation of uncertainties in the system. However, SA deals with identifying the input parameters those are important in contributing to the imprecisions in the prediction of the output parameter. In simple words, SA is a means to quantify how sensitive a parameter is to the behavior of the system. UA and SA of complex models are usually conducted by executing the model many times with a set of random samples while varying the parameter inputs (Saltelli et al., 2000). Varying all the input parameters simultaneously allows analysis of the model response to individual input parameters and their interaction. In addition, this analysis helps in understanding the robustness of the system, and behavior of parameter relationship such as, non-linearity, independence, and association.

Linear regression (LR) analysis (LRA) is the art of fitting straight lines to a pattern of data. In a LR model, the output parameter is predicted from the set of input parameters using a linear equation. The output parameter can be inherently and non-linear function of the input parameters, however, a transformation to this non-linear relationship to achieve linearity is called LR. Assume that $\hat{Y} = \alpha X^2$, is a non-linear relationship. If $Q = X^2, \hat{Y}$ can be transformed and

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written as $\hat{Y} = \alpha Q$, which is actually a linear representation of the non-linear equation $\hat{Y} = \alpha X^2$. This transformation has underlying assumptions, and a detailed analysis of the validity of LR in the system needs to be addressed. Nuclear reactor designs are non-linear systems, but with extensive transformations, a linear model can be fit to certain relationships between the parameters. In LR, a regression surface or a linear fit is built based on a set of trial data. The trial data is obtained from experiments or from simulations. The regression surface is used to predict the output parameters for a set of test input parameters (test data). In addition, a neutron transport and depletion code like MCNP (X-5 Monte Carlo Team, 2008), SERPENT take a significantly long execution time if higher accuracy of results is desired. And, in a global optimization technique like GA (Kumar and Tsvetkov (2015)), simulated annealing, particle swarm optimization the code needs to be run for a significant number of input samples before a desired solution is obtained. Hence, regression methods could be useful to emulate the physics solver in the code, and preform a predictive analysis for test data. However, this is possible only if there is a detailed analysis of the accuracy of the predictions given by the regression method. Therefore, the validity of LR in terms of linearity, normality, association, independence, and other methods needs to be done.

1.2. Current work

SA is performed on a specific set of explanatory parameters, and the behavior of the predictors is analyzed. Trial input set is built using samples obtained from the Latin Hypercube Sampling (LHS) method. Analysis has been done to determine the sensitivity of input parameters on the output parameters. It is to be noted that the output parameters defined in this work are the quantities of interest (QOI). An LR fit is used to perform predictive analysis. The regression fit is obtained from a set of trial data. Trial output parameters are obtained when MCNP6 is run on a predetermined sample of input set obtained from LHS method. The combination of the trial input set, and trial output parameters form the trial data. The trial data is used to build the regression fit for the parameters. The regression fit is applied on the test data to perform predictive analysis in a satisfactory confidence level. The accuracy of the predictions depend on the size of samples used as trial data. In addition, analysis has been done to determine the measure of importance, measure of association, test of normality, test of linearity, distribution statistics, and homoscedasticity of the parameters on the regression surface to determine the validity of LR.

The model of a gas cooled fast breeder reactor (GCFBR) design (Kumar et al., 2014) is used to perform the SA, and LR analysis. The system consists of a, heterogeneous neutronics model for criticality, and flux calculations, basic thermal hydraulics calculation for transfer of heat from the fuel pin to the coolant, and energy transfer using the Brayton's cycle. Following physics based modules have been determined to perform the analysis. The first module, is the fuel pin cell module that determines the infinite neutron multiplication factor, K_∞ (KINF), fraction of fission due to intermediate energy neutrons, $T_{i,f}$ (INTERFF), and fraction of fission due to fast energy neutrons, $T_{f,f}$ (FASTFF) based on a specific radius of the fuel element, r_F (RADIUS), and enrichment of U-233 in $(U - Th)O_2$ fuel (ENRICH). Therefore, the input parameters defined in this module are RADIUS, and ENRICH, and the output parameters are KINF, INTERFF, and FASTFF. The second module, is the design of the whole core of the GCFBR reactor. The output parameters in this module are the radial power peaking factor, $F_{PF,rad}$ (RADPF), axial power peaking factor, $F_{PF,ax}$ (AXPF), and effective neutron multiplication factor, K_{eff} (KEFF). This module has the same input parameters as defined in the first module. The third module, is a basic thermal–hydraulics and heat transfer module, where a hot channel analysis is performed to analyze the heat transfer across the fuel pin cell i.e. the flow of heat from fuel pin to the coolant wherein, the input parameters are the core inlet temperature, T_{in} (TIN), and, flow rate of the coolant, W (W) to determine the core outlet temperature, T_{out} (TOUT), and pressure drop, ΔP (DELTAP) across the flow channel. In this module the input parameters are, TIN, W, and ENRICH, and the output parameters are TOUT, and DELTAP. The fourth module is the energy transfer module that performs a basic Brayton's cycle calculation to determine the thermal efficiency (EFF). The input parameters defined in this module are TOUT, TIN, and the out parameter is EFF. A detailed description of the parameters of the mentioned modules is presented in a future section.

It is very important to understand the validity of LR in a non-linear system like the reactor power system. Particularly, when it is a steady state calculation with no depletion, based on

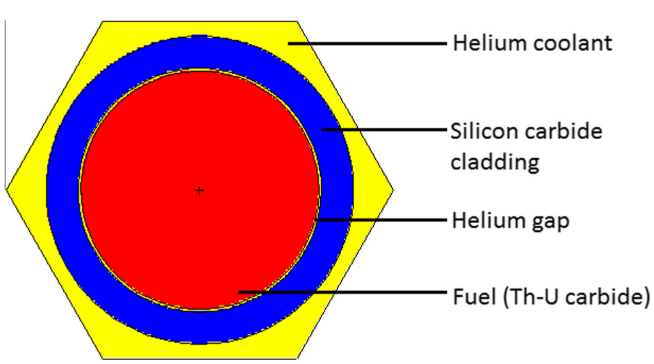

Fig. 1. Single fuel pin cell with reflective boundary conditions.

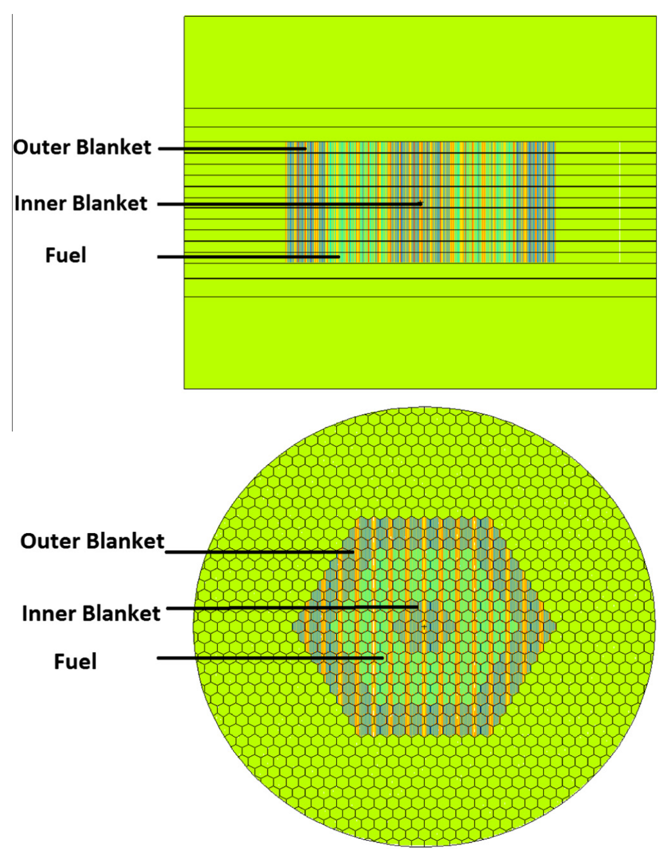

Fig. 2. Axial and radial view of the whole core.

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