



Machine learning based system performance prediction model for reactor control

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ARTICLE INFO

Article history:

Received 7 March 2017

Received in revised form 27 August 2017

Accepted 6 November 2017

Keywords:

Machine learning
Performance predicting
Particle filtering
Autonomous control
TFHR

ABSTRACT

A machine learning based system performance prediction model is currently created to support the development of autonomous control for small reactors, such as the Transportable Fluoride-salt-cooled High-temperature Reactor (TFHR), which is a 20 MWth compact core proposed by MIT for remote site applications. The prediction model consists of a reactor physics model and a thermal-hydraulic model. It is presently constructed using support vector regression (SVR) with training data generated by multiple cases of a one-dimensional reactor system model. A particle filtering framework is utilized to estimate and update model parameters with noisy instrument measurements. Verifications of the prediction and filtering models have been carried out using the TFHR reactivity insertion events. Satisfactory performance in predicting the core behavior and in recognizing transient parameters such as reactivity insertion timing and rate is concluded.

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1. Introduction

Particular interest is recently drawn on the design of small reactors which are promising solutions for the problem of energy supply for off-grid applications such as Antarctic bases, remote mining sites, container ships, military bases, etc. Since the transportation costs of electricity and heat from conventional sources to these remote areas are usually quite high, a compact design nuclear reactor which can be transported by a truck, a train or an airplane becomes an attractive option, in spite of its higher average capital cost compared with conventional nuclear reactors. To meet this market, a conceptual design of 20 MWth, 18-month once-through fuel cycle Transportable Fluoride-salt-cooled High-temperature Reactor (TFHR) is proposed by MIT in the framework of a second-term Integrated Research Project (IRP) to facilitate the development of a commercially attractive FHR (Macdonald, 2014). The detailed neutronic and thermal-hydraulic design of the TFHR are presented in References Sun et al. (2016) and Wang (2015), respectively. Since the nuclear plant is expected to be deployed at isolated areas, autonomous control system that is capable to maintain the operation of reactor system with minimum operator intervention under most circumstances becomes compelling. It

could help in managing the operation crews under reasonable size, as well as achieve more efficient operation and higher level safety performance.

A “prediction and decision” framework for the TFHR autonomous control is created based on the concept of anticipatory control (Uhrig and Tsoukalas, 2003), as shown in Fig. 1. The proposed system mainly consists of two modules: 1) a prediction module that gathers and analyzes information and data from instrumentation system to estimate the current performance of the reactor system and predict its future evolution; and 2) a decision module that make decisions for control system motion based on performance assessments from the prediction module. Therefore, in this anticipatory framework, the control system action lies on the foundation of insights into the current and anticipated state of the reactor system in the near future.

A well-established prediction module is essential. Specifically, to meet the requirement of autonomous control, the prediction module should be sufficiently accurate, while in the meantime computationally efficient, to provide appropriate evaluation of the reactor system condition in current and the near future on real time. Additionally, the prediction algorithm is also expected to have self-adjustment capability according to instrument measurements. In particular, one should address uncertainties associated with differences among various plants, epistemic uncertainties of certain parameters, unanticipated factors and events in actual operation, as well as the deterioration of reactor system and

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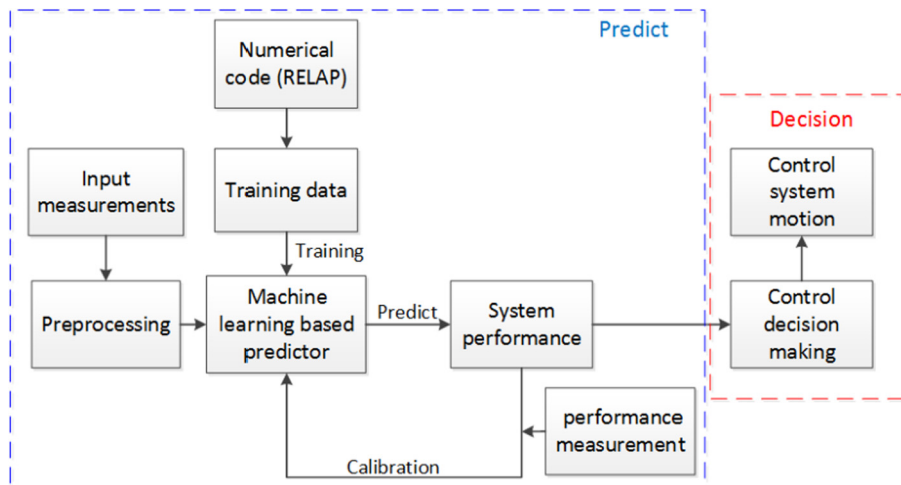


Fig. 1. "Prediction and decision" framework towards autonomous control for the TFHR.

components over time. It could improve the robustness and adaptability of the proposed system for different applications.

Even though the high performance computational capability nowadays allows insightful simulations with credible fidelity, it is still not practical to adopt physics based calculations for real-time reactor control. In this context, machine learning based surrogate mathematical model is utilized here. It is adopted for constructing the prediction module in order to avoid time-consuming systematic analyses. Machine learning and other Artificial Intelligence (AI) algorithms based methodology has been introduced in nuclear engineering for years and in various aspects, especially in the area of operation and maintenance of nuclear power plants. Conventional applications mostly focused on online monitoring, fault detection and diagnosis of plant components and systems such as noise analysis (Olma, 2004), online calibration monitoring of sensors (Ma et al., xxxx; Garvey et al., xxxx), transient identification and fault diagnostics (Kim et al., 2015; Embrechts and Benedek, 2004; Zio and Baraldi, 2005), etc. Algorithms involved include Artificial Neural Network (ANN), fuzzy logic, Support Vector Machine (SVM) and etc. Such AI based algorithms are preferred due to their superior adaptation to various processes and operational envelopes (Hashemian, 2011). Recently, machine learning algorithms have also been introduced into reactor analysis area to formulate surrogate models for complex physics based numerical codes or models. In some computationally expensive occasions where the time-consuming physics based numerical model is to be run for significant amount of times (e.g. sampling based uncertainty analysis, reliability assessment for rare events, Bayesian calibration of analysis codes, and etc.); whereas machine learning models can be trained to emulate the behavior of the input/output relationship of the numerical model using a relatively small sample of input/output pairs (Yurko et al., 2015). Overall, the introduction of machine learning surrogate models largely improves the computational efficiency. As a pure mathematical model, surrogate models can run much faster than original models, allowing the large scale sampling to be completed in a more acceptable time range (refer to Yurko et al. (2015), Pedroni et al. (2010) Cadini et al. (2014), Fynan and Ahn (2016) for applications of surrogate models).

In this paper, we created a machine learning base system performance prediction model for the TFHR using support vector regression (SVR). The latter is a widely-used algorithm, which features flexible nonparametric regression for multivariate problems. As shown in Fig. 1, training data is generated by multiple

numerical runs, where "best-estimated" point kinetics reactor system analysis code RELAP5-3D (The RELAP5-3D© Code Development Team, 2012) is adopted as the multi-physics solver. The trained machine learning model is capable of predicting core behavior in the following time steps, and self-adjustment according to instrument measurements. The predictions are then passed to the decision module to provide information for autonomous control decision-making. It should be noted that the multi-physics solver, i.e. RELAP5-3D, is selected for the considerations of convenient implementation. It could be potentially replaced with high performance computational codes, once the framework is confirmed to be functionary.

2. Methodology

2.1. Model description

The machine learning based system performance prediction model consists of two sub-models: a reactor physics model and a thermal-hydraulic model, as shown in Fig. 2. The reactor physics model takes inputs from flux/power history, fuel and coolant temperatures, and reactivity variations to predict reactor flux/power in the next time step. The latter, in turn, feeds into the thermal-hydraulic model, which computes the temperatures with given reactor system parameters, such as coolant mass flow rate, heat

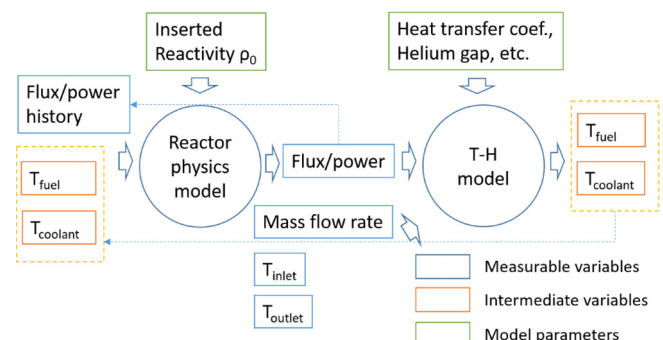


Fig. 2. Framework of machine learning based system performance prediction model.

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