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Multiscale subspace identification of nuclear reactor using wavelet basis function

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ABSTRACT

This paper introduces a methodology of multiscale system identification using wavelet basis functions. Being specific, it deals with subspace identification, for approximation of any multiscale process by employing a number of linear time invariant models at different scales. The idea is to estimate low dimensional state-space models in projection space at appropriate scales. The efficacy of proposed approach has been demonstrated by modeling a nuclear reactor coupled with thermal hydraulics in prediction as well as in simulation framework. Outcome of the multiscale subspace modeling approach is compared with that in single scale to bring out the advantage of the proposed method at different signal to noise ratios. In case of multiscale subspace process identification, the mean squared error in output prediction is found to be small, which suggests improvement in modeling.

1. Introduction

The ease in availability and the presence of an enormous amount of data from nuclear power plants popularize the design of data-driven system modeling (Polifke, 2014). The traditional approach of deriving reactor model description is from first principles through the application of physics laws. However, underlying simplifying assumptions, complexity, and high order often make the first principle model unsuitable for control applications (Human, 2009; Gabor et al., 2011). In contrast, data-driven modeling which is a systematic way of constructing simple mathematical model of a dynamical system from the recorded input–output data (Ljung, 1999), is more appropriate for obtaining an acceptable representation of the process. Usually, the identified model is employed for performing process-related tasks like output prediction, state estimation, fault detection, or design of model-based control laws.

For multivariable processes, state-space representation offers better tractability in controller synthesis and implementation (Gabor et al., 2011). Thus, it is preferred to transfer function or impulse response descriptions. Subspace identification (SID) is a time-domain system identification methodology for estimating a state-space model directly from measurements (Ljung, 1999). System states are determined from the row space of Hankel matrix representation of measurements through projection and then least squares estimates of parameters are obtained from its column space. This notion of first state calculation and then parameter estimation can be viewed as input-state-output modeling and it makes subspace identification different from usual identification of input–output model e.g. prediction error methods (PEM) (Qin, 2006). Subspace techniques are robust and computationally efficient as they are based on numerically stable QR decomposition and Singular Value Decomposition (SVD) algorithms. SID being non-iterative is free from non-convergence or local minima problems. Further, the algorithm possesses better numerical properties of parametrization over traditional PEM methods (Ljung, 1999).

In practice, measurement dataset is obtained during operation of a nuclear reactor in which different complex time-varying processes exist possibly with inherent non-linear characteristics. However, various multiscale features may not be clearly visible in measurement domain. Therefore, it is imperative to have the transformation of data and visualization in a multiresolution framework around a proper set of scales. Wavelet bases are generalized basis functions especially preferred for modeling and analysis of non-stationery time-varying systems (Abuhamdia and Taheri, 2017). System description using wavelet basis functions offers several merits over the single-scale (measurement space) approach of modeling. For example, the estimated projection space

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models have lower order due to the excellent approximation ability of compactly supported wavelet basis functions. Such models are suitable for designing model-based control laws in multiresolution. Further, systems with nonlinearity can be approximated by a set of linear time invariant models in projection space. Thus, the estimated model shows significantly better output prediction (Basseville et al., 1992).

In the literature of system theory, multiple perspectives exist for introducing wavelets in modeling and identification, e.g. function approximation, filter banks, *etc.* (Abuhamdia and Taheri, 2017). The earliest work by Basseville et al. (1992), proposed the notion of stochastic modeling for auto-regressive processes. The system is represented by different nodes of homogeneous trees. Chou et al. (1994) constructed a class of multiscale dynamic state-space models on dyadic trees for handling multiscale data structure and discussed Kalman filter on trees. However, these algorithms seem to model process dynamics across the scales rather than along them and tend to ignore evolution of modes with time. Tsatsanis and Giannakis (1993) and Doroslovacki and Fan (1996) adopt the function approximation route of modeling where the Linear Time-Varying (LTV) parametric impulse response function is approximated by wavelet basis functions. Zhao and Bentsman (2001) extended the methodology using biorthogonal wavelet functions. These works assume local time invariance in the formulation which may not be valid for fast changing systems. Besides, the selection of basis function is rather difficult for such a system and one needs to know certain aspects of a process a priori defeating the notion of true black-box system identification. The LTV parameter estimation of a dynamical system described by differential equation is studied by Ghanem and Romeo (2000) and Chen et al. (2012). Nevertheless, these approaches completely ignored the effective way of inverse wavelet transform for mapping output in projection space to that in measurement space.

The filter bank aspects of wavelets are employed in Bakshi (1998), Carrier and Stephanopoulos (1998), Vana and Preisig (2012), Billings and Wei (2005), Reis (2009), Mukhopadhyay and Tiwari (2010), Nounou and Nounou (2007), Vajpayee et al. (2016) utilizing the computationally efficient implementation of wavelets. The work by Bakshi (1998) developed multiscale Principal Component Analysis (PCA) and motivated for combining filtering with identification. Carrier and Stephanopoulos (1998) advocated frequency domain approach where the estimation of reduced order models over a specific range of frequencies is proposed. This viewpoint is further emphasized in Vana and Preisig (2012) and it discussed several theoretical aspects while working with wavelets. A general multiscale nonlinear polynomial model structure is designed by Billings and Wei (2005). However, the model is not suitable for designing simple multiscale control laws. Reis (2009) proposed an algorithm to handle multiscale data structure in prediction framework. The work by Mukhopadhyay and Tiwari (2010) employs the notion of consistency in output estimate and developed models at all scales for the liquid zone control system. However, validation through simulation (infinite-step-ahead prediction) model is missing in most of the works. Nounou and Nounou (2007) used the multiscale representation ability of wavelets to improve the prediction accuracy of empirical models, particularly that of Auto Regressive with Exogenous input (ARX) models by estimating parameters only at an appropriate scale. Despite this, their work lacks two important aspects of modeling: 1) information of detail subspace is discarded thereby losing the advantage of multiscale modeling naturally provided by the wavelet basis function, 2) modeling only at one scale is rather limiting in the sense that most of the processes like a nuclear reactor have multiple time-scale behaviour. On the other hand, the approach of Mukhopadhyay and Tiwari (2010) suffers with increase in cost for model estimation. It is therefore felt that a balance between two approaches is necessary and the same calls for having models only at significant scales.

Subspace-based methods have found several applications in nuclear science (Shiguo et al., 2004; Previdi et al., 2007; Abdel-Khalik et al., 2008; Wu et al., 2012; Wu and Abdel-Khalik, 2013). In nuclear spectroscopy, subspace approaches are employed for identifying the poles of a system (Shiguo et al., 2004). In the work of Previdi et al. (2007), the methodology is used for the identification of light charged particles. Abdel-Khalik et al. (2008) proposed efficient subspace-based algorithm for sensitivity analysis, uncertainty quantification, and data assimilation in reactor physics calculation. Wu et al. (2012, 2013) integrated the subspace approach with hybrid Monte Carlo method for variance reduction in Monte Carlo simulations in reactor analysis. However, application of subspace methods for modeling of nuclear reactor is not common and the approach undertaken in this paper can be considered as the first such attempt.

In last two decades, wavelet-based techniques have been widely applied to nuclear engineering for transient detection (Paredea et al., 2007), noise removal (Shimazu, 2000; Heo et al., 2000; Park et al., 2004), signal/system monitoring and analysis (Mukhopadhyay and Tiwari, 2010; Antonopoulos-Domis and Tambouratzis, 1998; Tambouratzis and Antonopoulos-Domis, 2004; Patra and Saha Ray, 2014). Transient instability phenomenon like neutronic power oscillation has been studied in wavelet domain for a Boiling Water Reactor (BWR) (Paredea et al., 2007). Estimation and monitoring of reactivity coefficients like moderator temperature coefficient using wavelet denoising technique is proposed by Shimazu (2000). Heo et al. (2000) proposed a wavelet-PCA based multi-step denoising technique for the estimation of reactor thermal power under degraded flowmeter. Park et al. (2004) demonstrated that the application of wavelet denoising improves water level control of steam generators. A system identification methodology is developed during a transient via wavelet MRA by Antonopoulos-Domis and Tambouratzis (1998). Estimation of system characteristics is obtained using spectral analysis technique followed by wavelet denoising. In the work of Tambouratzis and Antonopoulos-Domis (2004), a similar technique combining wavelet MRA with auto-correlation function has been employed to estimate system parameters for the evaluation of stability of a BWR. In the recent works of Patra and Saha Ray (2014), authors demonstrated the application of Haar wavelet in solving the point-kinetics model and to further study the behaviour of neutron density.

The proposed work integrates wavelet based modeling approach with subspace identification technique. It estimates empirical models at significant scales in both prediction and simulation framework. The efficacy of the proposed multiscale subspace identification technique is illustrated by modeling a nuclear reactor coupled with thermal hydraulics in the presence of feedbacks from fuel and coolant temperatures. Two case studies with different validation datasets show the advantage of multiscale subspace identification (ms-SID) over the classical approach of measurement space modeling for e.g. ARX, SID, Box–Jenkins (BJ) and the multiscale ARX (ms-ARX) modeling. Further, to draw statistically valid argument, Monte Carlo simulations are performed at different noise levels as well as at various decomposition depths.

The rest of the paper is arranged as follows. Section 2 presents the theory of wavelets, subspace identification, and reviews the essential fundamentals of system identification with wavelet basis functions. The methodology of multiscale subspace identification of a system is presented in Section 3 and useful insights on wavelet applications are also discussed. Application of the proposed technique to the nuclear reactor system coupled with thermal hydraulics is presented in Section 4. Finally, Section 5 concludes the paper indicating major contributions.