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14. ABSTRACT
Recent advances in simulation and computation call for innovative modeling and design approaches for engineered systems that can account for the complexities and uncertainties in the system description in design processes. In this research we consider the problem of optimal design of uncertain complex systems.
A framework has been developed for the optimal design of complex dynamical systems that incorporates model uncertainties directly into the design objective. A class of systems that exhibit complex behavior that can be approximated by a hybrid system is considered. The discrete behavior evolves on a slow time scale and can be modeled as a hidden Markov process. A model reduction technique that captures all critical aspects of the discrete component has been developed. Data driven identification techniques have been developed for identification of the hidden Markov model. Furthermore, system identification is used for the characterization of fast time scale dynamics of the hybrid components resulting in reduced models that are suitable for design. The novelty of the approach lies in hybrid system modeling approach.

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Final Report:
Optimal Design of Uncertain Complex Dynamical Systems
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Abstract

Great advances in the last decade in computer and network technologies as well as demands for higher levels of performance and functionality often results in complex engineered systems that can exhibit complicated dynamic behavior that had not been anticipated during the design process and is difficult to control.

Recent advances in simulation and computation call for innovative modeling and design approaches that can account for the complexities and uncertainties in the system description in design processes. In this research we consider the problem of optimal design of uncertain complex systems.

We are developing a framework for the optimal design of complex dynamical systems that incorporates model uncertainties directly into the design objective. We consider a class of systems that exhibit complex behavior that can be approximated by a hybrid system. The discrete behavior evolves on a slow time scale and can be modeled as a hidden Markov process. We have developed model reduction techniques that capture all critical aspects of the discrete component. Furthermore, system identification is used for the characterization of fast time scale dynamics of the hybrid components resulting in reduced models that are suitable for design. The novelty of the approach lies in hybrid system modeling approach.

1 Accomplishments

The research achievements of the project are summarized in the following pages.

1.1 Uncertainty Analysis

Uncertainty analysis is a topic of research that has received much attention in recent years. Indeed, the increased use of physics based models in the study of the dynamical behavior of systems in a wide range of applications calls for the analysis and quantification of model predictions in terms of uncertainties in model descriptions and model operating environments [4]. In this research we considered systems that can be modeled by discrete maps and studied, abstractly, uncertainty propagation in such systems, following an approach for measure propagation developed in [6], [3], [7]. In particular, we were interested in uncertainty analysis of systems that are far from linearity, may have multiple steady states and exhibit purely nonlinear behavior such as bifurcations that depend on the uncertain parameters of the system. We developed an approach that involved defining uncertainty propagation in the system through the invariant measures of the system and defining uncertainty as a worst case distance from a certain system in a space of output measures.

1.1.1 Uncertainty Measures In [8] a new measure is introduced for measuring the effect of uncertainty in dynamical systems that may exhibit complex behavior. The new measure is compared to other existing measures for quantifying uncertainty. An operator based approach is also introduced for the propagation of uncertainty in complex dynamical systems that have both initial condition and parametric uncertainty but may also have dynamic induced uncertainties.

The new uncertainty measures were considered as performance measures for robust (i.e. in the presence of uncertainty) design of dynamical systems and the newly developed techniques demonstrated through illustrative examples.

1.1.2 Computational Methods In [13] an efficient approach for calculating stationary (or invariant) distribution in uncertain dynamical systems is developed. The approach is based on Random Dynamical Systems [1] and is based on novel computational techniques for nonlinear dynamics developed in [2], [3].

1.2 Model Reduction and Simplification of Complex Dynamical Systems

In this part of the research effort we consider the problem of finding a low dimensional approximate model for a complex dynamical system that can be represented as a nonreversible Markov process. This problem is of particular interest in systems that exhibit a so-called metastable behavior, i.e. there exists a decomposition of the state space into a finite number of components that have the characteristic that once the systems enters one of the components it spends a long period of time there but eventually transitions to one of the other components where the behavior repeats itself. Systems that exhibit this kind of behavior arise for instance in complex dynamical systems that have many stable limit sets and are perturbed by a small noise process. For complex systems that exhibit such metastable behavior a model simplification in the form of a hybrid system may be of considerable interest. A first step in the model simplification process is the characterization of the metastable behavior. This is the problem was considered using two different techniques in the research.

1.2.1 Proper Orthogonal Decomposition in a Function Space In [10], [11] and [12] a novel method based on Proper Orthogonal Decomposition of for identifying clustering components in complex dynamic systems. The novelty of the approach lies in the construction of a finite dimensional approximation of the expectation operator for the Markov process (i.e. Koopman operator for the dynamical system) using proper orthogonal approximation techniques.

1.2.2 Decomposition of Nonreversible Markov Chains In [14] an approach for the identification of clustering components (so-called metastable or almost invariant sets) in complex dynamical systems based on the spectral properties of an associated transfer operator is considered. We consider complex dynamical systems whose transfer operator can be approximated by a (high dimensional) Markov chain. Following an approach developed for reversible Markov chains in [5], [9] an approach for nonreseversible Markov chains is developed and applied for the construction of an operator that capture the multi-modal behavior in the underlying complex dynamical system.

1.3 Identification of Complex Dynamical Systems

In [15] the identification of complex dynamical systems that exhibit multi-modal behavior is considered. It is assumed that the system is autonomous and only noisy output data is available for the identification. The approach is partially based on the techniques in [14] but involves also a novel approach for the modeling of the system as Hidden Markov Model (HMM).

1.4 Filtering of Multi-modal Dynamical Systems

In [17] and [16] the problem of filtering of multi-modal complex systems is considered. This problem is an integral part of the problem of identification of complex systems model as multi-modal systems. An computationally efficient and highly accurate approach is developed by an appropriate intelligent mixture of high and low accuracy filtering algorithms. The approach is illustrated through a tracking example.

1.5 Power System Simplification

In [18] the multi-model clustering techniques developed in other phases of the research effort was applied for the analysis of wind farm with a large number of turbine/generator units. It was found that the units can be grouped into few representative groups and this grouping or clustering of the units can be of great benefits in the design of control and scheduling algorithms for wind farm operation.

2 Personnel Supported

Faculty: Thordur Runolfsson

Partially supported postdoctoral Fellows: Prasanth Alluvada, Junk-Uk Lim

Partially supported Graduate Students: Chenxi Lin, Yong Ma, Yuzhen Xue

3 Interactions/transitions

3.1 Year 1

The PI gave an invited presentation on the topics of research described here at the Lawrence Berkeley National Laboratory.

3.2 Year 2

The PI gave an invited presentation on the topics of research described here at the University of California Santa Barbara and Caltech.

3.3 Year 3

The PI and his students collaborated with a power systems colleague at the University of Oklahoma and staff at Oklahoma Gas and Electric in the application of the techniques developed in the research to analysis and simplification of response of a large wind farm.

The analysis was based on real data provided by OGE and provided very valuable insight into the dynamic behavior of wind farms that may lead to improved operational strategies.

References

[1] L. Arnold. *Random Dynamical Systems.* Springer, Berlin, 1998.

[2] M. Dellnitz and O. Junge. On the approximation of complicated dynamical behavior. *SIAM Journal on Numerical Analysis*, 36:491–515, 1999.

[3] M. Dellnitz and O.Junge. Set oriented numerical methods for dynamical systems. In *B. Fiedler, G. Iooss and N. Kopell (eds.): Handbook of Dynamical Systems II: Towards Applications*, pages 221–264. World Scientific, 2002.

[4] J.C. Helton. Treatment of uncertainty in performance assessments for complex systems. *Risk Analysis*, 14(4):483–511, 1994.

[5] W. Huisinga and B. Schmidt. Metastability and dominant eigenvalues of transfer operators. *'Advances in Algorithms for Macromolecular Simulation', Lecture Notes in Computational Science and Engineering*, 2005.

[6] A. Lasota and M. C. Mackey. *Chaos, Fractals and Noise.* Springer-Verlag, New York, 1994.

[7] I. Mezic and A. Banaszuk. Comparison of complex systems. 2002. Submitted.

[8] I. Mezic and T. Runolfsson. Uncertainty propagation in nonlinear systems. *Automatica*, 2008.

[9] Boaz Nadler, Stéphane Lafon, Ronald R. Coifman, and Ioannis G. Kevrekidis. Diffusion maps, spectral clustering and eigenfunctions of fokker-planck operators. In *in Advances in Neural Information Processing Systems 18*, pages 955–962. MIT Press, 2005.

[10] T. Runolfsson. Model reduction of uncertain complex dynamical systems. *Proceedings of IEEE 2006 CCA/CACSD/ISIC*, 2006.

[11] T. Runolfsson. Towards hybrid systems modeling of uncertain complex dynamical systems. *International Conference of Hybrid Systems and Applications*, 2006.

[12] T. Runolfsson. Towards hybrid systems modeling of uncertain complex dynamical systems. *Nonlinear Analysis: Hybrid Systems*, 2:383–392, 2008.

[13] T. Runolfsson and C. Lin. Computation of uncertainty distributions in complex dynamical systems. *submitted to the 2009 American Control Conference (ACC)*, 2008.

[14] T. Runolfsson and Y. Ma. Model reduction of nonreversible markov chains. *Proceedings of the 2007 IEEE Conference on Decision and Control*, 2007.

[15] T. Runolfsson and Y. Xue. Identification of multi-modal behavior in complex dynamic systems from output data. *submitted to the 2009 American Control Conference (ACC)*, 2008.

[16] Y. Xue and T. Runolfsson. Efficient estimation of hybrid systems with applications to tracking. *submitted to IEEE Trans on Aerospace and Electronic Systems*, 2008.

[17] Y. Xue and T. Runolfsson. State estimation and mode detection for stochastic hybrid system. *Proceedings of the 2008 IEEE MSC*, pages 625–630, 2008.

[18] John N. Jiang Yong Ma and Thordur Runolfsson. Cluster analysis of wind turbines of large wind farm. *to appear Proceedings of the 2009 IEEE PES Power Systems Conference Exposition*, 2008.