Complex Systems Monitoring, Modeling and Analysis

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1. Research Overview

Dr. Yang and his research team at USF aim to create a *rigorous* knowledge body for sensor-based complex systems monitoring, modeling and analysis. The research will ultimately contribute to a new paradigm where a complex system is autonomized and optimized at all scales. As shown in Figure 1, industry in the 21st century is investing in a variety of sensor networks and dedicated data centers to increase information visibility in both engineering and healthcare domains. Real-time sensing brings the proliferation of big data (i.e., dynamic, nonlinear, nonstationary, high dimensional) that contains a wealth of information on the condition and status of a product, process or a system. Big Data presents a ‘gold mine’ of this era (21st century). Innovations in industrial and systems engineering in this century will be highly dominated by “new methods and tools” to mine the big data and harness its power for new product development, problem solving and system optimization.

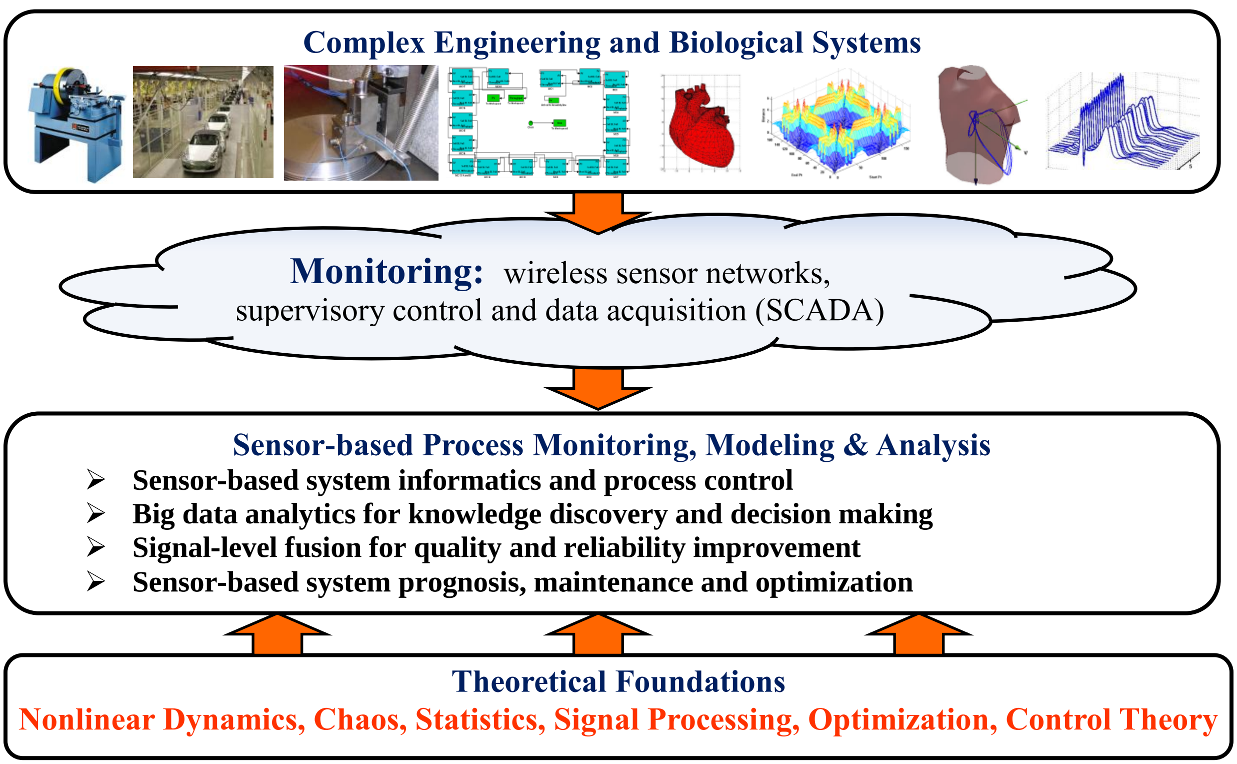

Fig. 1. Research Roadmap of Complex Systems Monitoring, Modeling and Analysis Lab

2. Nonlinear Dynamics and Chaos

Engineering and physiological systems (e.g., nanoscale machining and human heart) involve greater levels of complexity and technical challenge. Much of the complexity emerges from *nonlinear dynamics* of the underlying process. In order to cope with system complexity and dynamic environments, modern industries are investing in a variety of sensors and data acquisition systems. However, most of existing approaches adopt linear methods and tools for sensor information processing. Traditional linear approaches interpret the regular structure, e.g., dominant frequencies in the data, and have encountered certain difficulties to capture nonlinearity, nonstationarity and high-order variations [1]. In contrast, complex engineering and biological systems exhibit aperiodic, strange and irregular behaviors. Dealing with nonlinear dynamics is a general problem facing both the traditional and next-generation innovation practices in the engineering field. However, little has been done to develop the rigorous body of knowledge on sensor-based complex systems monitoring, modeling and analysis.

Nonlinear dynamics theory has emerged as an important methodology for complex systems modeling and analysis. For decades, it has been primarily studied in the society of mathematics and physics. The basic idea is to model the state evolution of underlying processes by a set of nonlinear differential equations, i.e., $\dot{\boldsymbol{X}} = \frac{dX}{dt} = F(\boldsymbol{X}, \boldsymbol{\theta}), F \in \mathbb{R}^n \rightarrow \mathbb{R}^n$, where $\boldsymbol{X}$ is a multi-dimensional state variable, F is the nonlinear function, and $\boldsymbol{\theta}$ is model parameters. Thus, the solution, i.e., $\boldsymbol{X} = f(\boldsymbol{X}(0), t)$, generates a trajectory representing the flow of state evolution for a given initial condition $\boldsymbol{X}(0)$. When there is a small perturbation in $\boldsymbol{\theta}$ or $\boldsymbol{X}(\boldsymbol{0})$, the dynamics of a nonlinear process undergo abrupt changes and reveal complex characteristics, including chaos, recurrences, fractals and bifurcations.

Notably, recurrence (i.e., approximate repetitions of a certain event) is one of the most common phenomena in natural and engineering systems. The human heart is near-periodically beating to maintain vital living organs [2-4]. Stamping machines are cyclically forming sheet metals during production [5]. Rapid technological advances bring the proliferation of sensing data gathered from complex processes. This offers an unprecedented opportunity to exploit recurrence dynamics underlying the data for system informatics, monitoring, and control.

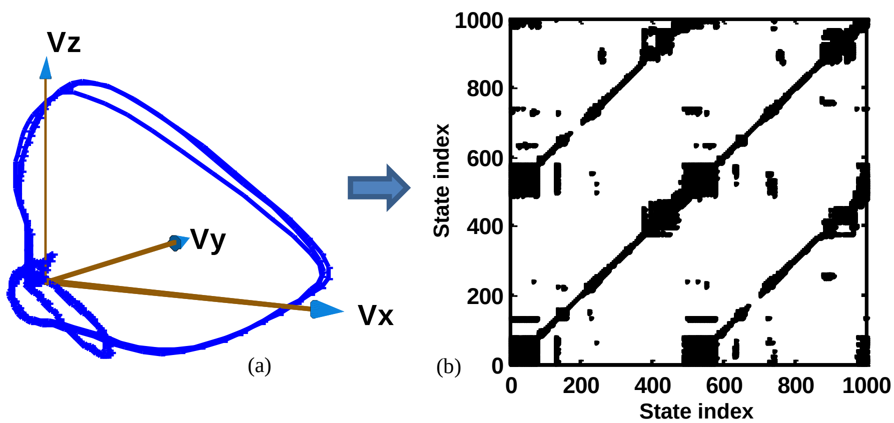

Fig. 2. Graphical illustration of a vectorcardiogram (VCG) state space (a) and its recurrence plot (b). The recurrence plot characterizes the proximity of two state vectors $\vec{\boldsymbol{s}}(i)$ and $\vec{\boldsymbol{s}}(j)$, i.e., $\boldsymbol{R}(\boldsymbol{i},\boldsymbol{j}) \coloneqq \boldsymbol{\Theta}(\varepsilon - \|\vec{\boldsymbol{s}}(i) - \vec{\boldsymbol{s}}(j)\|)$, where $\boldsymbol{\Theta}$ is the Heaviside function, ε is the threshold and $\|\cdot\|$ is a distance measure.

Process monitoring of disease conditions or manufacturing quality is more concerned with aperiodic recurrences and recurrence variations in nonlinear and nonstationary systems. As shown in Fig. 2, vectorcardiogram (VCG) signal waveform at different segments changes significantly within one cycle, corresponding to different stages of cardiac operations [6, 7]. In addition, the waveform in one cycle is similar to others but with variations between cycles [8, 9]. The approach of nonlinear recurrence analysis characterizes recurrence behaviors in the high-dimensional state space. As shown in Fig. 2b, it captures topological relationships in the state space as a 2D image. If two states are located close to each other in the m-dimensional state space (e.g., 3D space in Fig. 2a), the color code is black (Fig. 2b). If they are located farther apart, the color is white. The structure of recurrence plot has distinct topology and texture patterns (Fig. 2b). The ridges locate the nonstationarity and/or the switching between local behaviors. The parallel diagonal lines indicate the near-periodicity of system behaviors.

Dr. Yang and his research team have developed a series of novel nonlinear recurrence methods for real-time system informatics, monitoring, and control. Specifically, the developed methodologies are demonstrated in both healthcare and manufacturing applications. First, we developed a novel multiscale framework to quantify recurrence dynamics in complex systems [10, 11] and resolve computational issues for large-scale datasets [1]. As opposed to traditional single-scale recurrence analysis, we characterize and quantify recurrence dynamics in multiple wavelet scales. As a result, multiscale recurrence analysis facilitates the prominence of hidden recurrence properties that are usually buried in a single scale. Second, we developed a novel approach of heterogeneous recurrence analysis [5, 12] that utilizes a new fractal representation to delineate heterogeneous recurrence states, including the recurrences of both single states and multi-state sequences. Third, we collaborated with General Motors and developed a local recurrence model [13] for the prognosis of nonlinear and nonstationary evolution of manufacturing operational conditions.

3. System Dynamics Modeling and Simulation

Discrete event simulation (DES) has usually been a common practice in manufacturing system analysis. However, multistage manufacturing systems consist of multifariously interdependent entities and their interactions give rise to nonlinear and nonstationary behaviors (Fig. 3). For instance, the rate of change in the ith buffer stock dL_i/dt can be described as the differences between the throughput rates of upstream and downstream machines, i.e., $dL_i/dt = u_{\text{up}} - u_{\text{down}}$. Because the quantity of buffer stock often has lower and upper bounds, linearity is lost when these bounds are reached [13-16]. Furthermore, internal and external disruptions that require control actions occur throughout the manufacturing process, from material procurement to the transportation of finished goods. It should also be noted that inter-release time scales of working parts are becoming smaller and smaller in the mass manufacturing setting. For example, a stamping machine is capable of stroking 2000 samples per minute. As a result, traditional DES methods are time-consuming and computational intractable due to the modeling of individual entities and their activities.

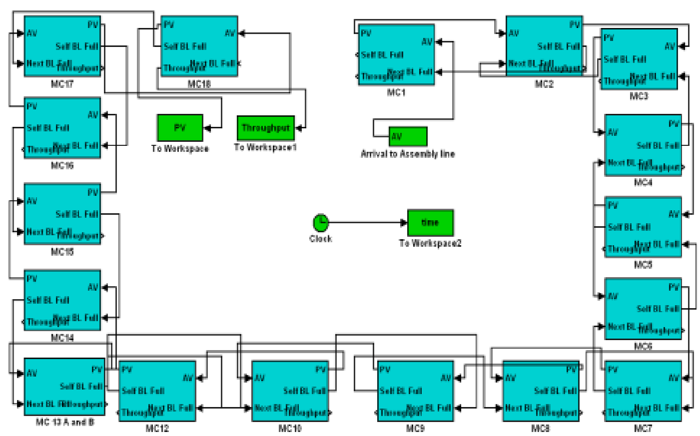

Fig. 3. Simulation model of a multi-stage assembly line [13-16].

To increase flexibility and responsiveness, a typical assembly line contains numerous sensors that provide dynamically-evolving information of manufacturing stations. Examples of state variables include the machine throughput, downtime, buffer levels and their coupled temporal dynamics. Harnessing multi-sensor signals, in the form of tractable models to predict dynamic behaviors, is essential to support day-to-day manufacturing planning and control decisions [13, 14]. This provides an unprecedented opportunity to develop nonlinear system dynamics simulation models (NSDS) of multistage manufacturing systems that use a series of buffer stocks and product flows, in which the state changes are continuous. This enables fast estimation and prediction of aggregated dynamic behaviors of manufacturing processes.

Dr. Yang and his research team developed a sensor-driven NSDS modeling approach [13-16] to simulate operational dynamics of a multistage assembly line. The movement of entities is treated as a fluid flow, buffer stocks are water tanks, the conveyor belt is water pipe and manufacturing stations are the valves which control the rates of flow. The NSDS models were parameterized using sensor data from a real-world manufacturing system. Experimental results showed that NSDS models enable faster and more accurate prediction of aggregate manufacturing performance than discrete-event simulation (DES) counterparts.

3. Physical-Statistical Modeling and Optimization

Large-scale simulation models such as the 3D tissue and whole heart models are computationally very expensive (see Fig. 4). For example, one simulation of the whole heart can take up to two weeks in a 3.2 GHz desktop computer. This limits the utility of the models in real-time medical decision making, where the models need to optimized over a potentially large number of decision variables. As shown in Fig. 4, we tackle this computational challenge by approximating the complex cardiac models using statistical metamodels.

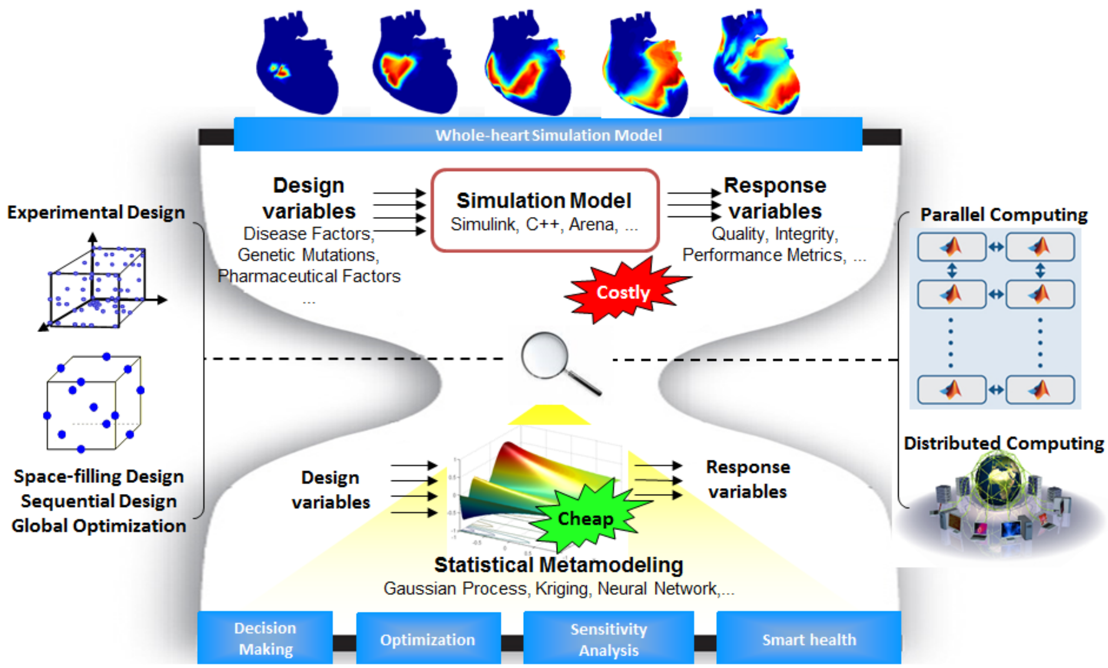

Fig. 4. Research roadmap of physical-statistical modeling and optimziation.

Dr. Yang and his research team developed physical-statistical models of cardiovascular systems for optimizing medical decision making in spatiotemporal disease processes [17, 18]. Multi-scale computer models are developed to improve the understanding of disease-altered cardiac electrical dynamics. In particular, the modeling is done in multiple physical levels starting with ion channels, then cells, then tissues, and finally an anatomically realistic heart. Physics-based models are statistically calibrated and adjusted so as to make more realistic predictions. Furthermore, an easy-to-evaluate statistical surrogate model has been developed for faster approximation, prediction and optimization, thereby facilitating real-time medical decision making. Physical-statistical models are used in conjunction with sensor-based data fusion to optimize cardiovascular diagnostics. The simulation-based optimization approach provides a unique opportunity to search the optimal medical decisions with the "virtual" heart, as opposed to traditional "experience-based" and "trial-and-error" decisions in the real-world heart.

The results of this research will yield a fundamental understanding of the progression of cardiac diseases that is so vitally needed to improve preventive healthcare services. This research has the potential to make a paradigm shift in healthcare, i.e., from reactive care to preventive and proactive care, from experience-based to evidence-based cardiac care services. The early identification of cardiovascular diseases will decrease mortality rates, promote the timely delivery of life-saving interventions, and reduce healthcare cost (e.g., preventive care in lieu of expensive surgical interventions). This will positively impact cardiovascular patients, the largest population at risk of death in the US and in the world.

References

[1] Y. Chen and H. Yang, "Multiscale recurrence analysis of long-term nonlinear and nonstationary time series," *Chaos, Solitons & Fractals,* vol. 45, pp. 978-987, 2012, Link: http://dx.doi.org/10.1016/j.chaos.2012.03.013.

[2] Y. Chen and H. Yang, "A comparative analysis of alternative approaches for exploiting nonlinear dynamics in the heart rate time series," in *Proceedings of 2013 IEEE Engineering in Medicine and Biology Society Conference (EMBC),* Osaka, Japan, 2013, pp. 2599 - 2602, PMID: 24110259, Link: http://dx.doi.org/10.1109/EMBC.2013.6610072.

[3] Y. Chen and H. Yang, "Wavelet packet analysis of disease-altered recurrence dynamics in the long-term spatiotemporal vectorcardiogram (VCG) signals," in *Proceedings of 2013 IEEE Engineering in Medicine and Biology Society Conference (EMBC),* Osaka, Japan, 2013, pp. 2595-2598, PMID: 24110258, Link: http://dx.doi.org/10.1109/EMBC.2013.6610071.

[4] H. Yang, S. T. S. Bukkapatnam and R. Komanduri, "Nonlinear adaptive wavelet analysis of electrocardiogram signals," *Physical Review E,* vol. 76, pp. 026214, 2007, PMID: 17930128, Link: http://dx.doi.org/10.1103/PhysRevE.76.026214.

[5] H. Yang and Y. Chen. Heterogeneous recurrence monitoring and control of nonlinear stochastic processes. *Chaos: An Interdisciplinary Journal of Nonlinear Science 24(1),* 2014, Link: http://dx.doi.org/10.1063/1.4869306.

[6] H. Yang, S. T. S. Bukkapatnam and R. Komanduri, "Spatio-temporal representation of cardiac vectorcardiogram (VCG) signals," *Biomedical Engineering Online,* vol. 11, pp. 16, 2012, PMID: 22463593, Link: http://dx.doi.org/10.1186/1475-925X-11-16.

[7] D. Dawson, H. Yang, M. Malshe, S. T. S. Bukkapatnam, B. Benjamin and R. Komanduri, "Linear affine transformations between 3-lead (Frank XYZ leads) vectorcardiogram (VCG) and 12-lead electrocardiogram (ECG) signals," *Journal of Electrocardiology,* vol. 42, pp. 622-630, 2009, PMID: 19608193, Link: http://dx.doi.org/10.1016/j.jelectrocard.2009.05.007.

[8] Y. Chen and H. Yang, "Self-organized neural network for the quality control of 12-lead ECG signals," *Physiological Measurement,* vol. 33, pp. 1399, 2012, PMID: 22902675, Link: http://dx.doi.org/10.1088/0967-3334/33/9/1399.

[9] H. Yang, S. T. S. Bukkapatnam, T. Le and R. Komanduri, "Identification of myocardial infarction (MI) using spatio-temporal heart dynamics," *Medical Engineering & Physics,* vol. 34, pp. 485-497, 2011, PMID: 21940193, Link: http://dx.doi.org/10.1016/j.medengphy.2011.08.009.

[10] H. Yang, "Multiscale Recurrence Quantification Analysis of Spatial Cardiac Vectorcardiogram (VCG) Signals," *Biomedical Engineering, IEEE Transactions on,* vol. 58, pp. 339-347, 2011, PMID: 20693104, Link: http://dx.doi.org/10.1109/TBME.2010.2063704.

[11] H. Yang, "Multiscale recurrence analysis of complex physiological rhythmic dynamics," in *Proceedings of the 2010 Industrial Engineering Research Conference (Best Track Paper Award in Computers and Information Systems),* Cancun, Mexico, 2010, Link: http://www.iienet2.org/Details.aspx?id=21458.

[12] H. Yang and G. Liu, "Self-organized topology of recurrence-based complex networks," *Chaos: An Interdisciplinary Journal of Nonlinear Science,* vol. 23, pp. 043116, 2013, PMID: 24387555, Link: http://dx.doi.org/10.1063/1.4829877.

[13] H. Yang, S. T. S. Bukkapatnam and L. G. Barajas, "Local recurrence based performance prediction and prognostics in the nonlinear and nonstationary systems," *Pattern Recognit,* vol. 44, pp. 1834-1840, 2011, Link: http://dx.doi.org/10.1016/j.patcog.2011.01.010.

[14] H. Yang and S. T. S. Bukkapatnam, "Recurrence based performance prediction and prognostics in complex manufacturing systems," in *Proceedings of the 2009 Industrial Engineering Research Conference (Best Track Paper Award),* Miami, FL, 2009, Link: http://www.iienet2.org/annual2/details.aspx?id=15532.

[15] H. Yang, S. T. S. Bukkapatnam and L. G. Barajas, "Continuous flow modelling of multistage assembly line system dynamics," *Int. J. Comput. Integr. Manuf.,* vol. 26, pp. 401-411, 2013, Link: http://dx.doi.org/10.1080/0951192X.2012.719085.

[16] U. Mittal, H. Yang, S. T. S. Bukkapatnam and L. G. Barajas, "Dynamics and performance modeling of multistage manufacturing systems using nonlinear stochastic differential equation models," in *Proceedings of the 4th Annual IEEE Conference in Automation Science and Engineering,* Washington DC, 2008, pp. 498-503, Link: http://dx.doi.org/10.1109/COASE.2008.4626530.

[17] D. Du, H. Yang, S. Norring and E. Bennett, "In-Silico Modeling of Glycosylation Modulation Dynamics in hERG Ion Channels and Cardiac Electrical Signals," *IEEE Journal of Biomedical and Health Informatics,* vol. 18, pp. 205-214, 2013, PMID: 24403418, Link: http://dx.doi.org/10.1109/JBHI.2013.2260864.

[18] D. Du, H. Yang, S. Norring and E. Bennett, "Multi-Scale Modeling of Glycosylation Modulation Dynamics in Cardiac Electrical Signaling," *Engineering in Medicine and Biology Society (EMBC), 2011 Annual International Conference of the IEEE (Placed First in the IBM Best Student Paper Competition),* pp. 104-107, 2011, PMID: 22254261, Link: http://dx.doi.org/10.1109/IEMBS.2011.6089907.

Author Biography

Hui Yang is an Assistant Professor of Industrial and Management Systems Engineering and the Director of Complex Systems Monitoring, Modeling and Analysis Laboratory at the University of South Florida. Dr. Yang received his BS and MS degrees in Electrical and Computer Engineering with honors from China University of Mining and Technology (Beijing) in 2002 and 2005, respectively, and his Ph.D. degree in Industrial Engineering and Management from Oklahoma State University in 2009. His research focuses on sensor-based modeling and analysis of complex systems for process monitoring/control, system diagnostics/prognostics, quality improvement, and performance optimization, with special focus on nonlinear stochastic dynamics, and the resulting chaotic, recurrence, multifractal, self-organizing behaviors. His research is highlighted in the website homepage of IEEE Journal of Biomedical and Health Informatics, and in the cover of the journal - Physiological Measurement. His lab has received several research awards such as the IBM Best Paper Award in 2011 IEEE Annual Conference of Engineering in Medicine and Biology Society, and the IERC Conference Best Paper Awards (Manufacturing and Design Track in 2009, Computer and Information Systems Track in 2010, Computer and Information Systems track in 2014). Currently, he is the board member of Data Mining section and Quality, Statistics and Reliability section of INFORMS, Also, he is the guest editor for IEEE Intelligent Systems and Information Systems and e-Business Management (Springer), and a professional member of IEEE, IIE, AHA, ASEE and INFORMS.

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