Proposal of open invited track for IFAC World Congress 2023, Yokohama, Japan

Session code: 58mj9

Proposers

Name and surname	**University**	**Contact**	**PIN**
Prof. Mirko Mazzoleni	University of Bergamo (Italy)	mirko.mazzoleni@unibg.it	81903
Prof. Silvio Simani	University of Ferrara (Italy)	silvio.simani@unife.it	26223
Dr. Mayank Shekhar JHA	University of Lorraine (France)	mayank-shekhar.jha@univ-lorraine.fr	121850
Ir. Jacques Noom	Delft University of Technology (Netherlands)	j.noom@tudelft.nl	152478
Prof. Horst Schulte	HTW Berlin - University of Applied Sciences (Germany)	horst.schulte@htw-berlin.de	25706
Prof. Michel Verhaegen	Delft University of Technology (Netherlands)	m.verhaegen@tudelft.nl	10146
Prof. Didier Theilliol	University of Lorraine (France)	didier.theilliol@univ-lorraine.fr	27295

Choice of IFAC Technical Committee for Evaluation

TC 6.4. Fault Detection, Supervision & Safety of Technical Processes

Title

Intelligent data-driven fault diagnosis, prognostics and health aware control

Abstract

The complexity of modern industrial plants, along with the major investment in process data collections, have increased the attention towards data-driven methods for diagnosis and prognostic, as a fundamental tool to implement predictive maintenance schemes. Along the same line, safety-critical plants need robustness against process faults and deteriorations. The recent concept of health aware control is rapidly emerging as a way to include system health information into the control actions. This open invited track aims to face current challenges in data-driven diagnosis, prognostics and health aware control, discussing methodologies and applications.

Detailed description of the topic

In a survey conducted by the IFAC industry committee to their members in 2018 to determine the current and future impact of several control technologies, intelligent control and fault diagnosis placed in the two top positions, with an increment of +30% from "high current impact" to "high future impact" responses (Samad, et al., 2020). At the same time of the previous paper publication, industry 4.0 national development plans are fostering manufacturing companies to research and develop solutions for gathering and analyzing data from the production process towards a "smart" manufacturing concept (Ding, et al., 2020), where intelligence is leveraged for both control and diagnosis. The new concept of industrial artificial intelligence (industrial AI), combining AI technologies with the domain knowledge of standard industrial processes, is rapidly emerging (Lee, Davari, Singh, & Pandhare, 2018). Anomaly detection in Cyber-Physical Systems (CPS) through watermarking techniques (Ferrari & Teixeira, 2021) is another recent and thriving field of application for AI methods.

AI and, more generally, statistical methods, are key elements for diagnostic algorithms in knowledge-based (or data-driven) approaches. While model-based and signal-based methods require some prior information, a knowledge-based method is expected to automatically detect and recognize the health states of the machines by discovering fault symptoms from process and production data, oftentimes in contexts where unlabeled or imbalanced data are present. Even though production research is oriented towards a fully autonomous industrial plant (Gamer, Hoernicke, Kloepper, Bauer, & Isaksson, 2020) the above limits hinder the applicability of pure-AI methods to the diagnosis field, where the physical knowledge of the components inner mechanisms is of extreme value for fault diagnosis. In the last years, researchers have worked in parallel directions to improve diagnostic methods by relying on process data, examples of which are: (i) data-driven design of residual generators (Wang, Ma, Ding, & Li, 2011); (ii) data-driven fault estimation methods (Wan, Keviczky, Verhaegen, & Gustafsson, 2016); (iii) process monitoring methods (Yin, Wang, & Gao, 2016); (iv) transfer learning with deep neural networks (Lei, et al., 2020); (v) fuzzy and neural networks diagnosis approaches (Farsoni, Simani, & Castaldi, 2021) (Yu, Fu, Li, & Zhang, 2018).

On the other hand, prognostics and health management (PHM) focuses on accurate and reliable prediction of failure (remaining useful life) at component as well as system level (Mayank Shekhar Jha, Dauphin-Tanguy, and Ould-Bouamama 2016). Hybrid approaches, that combine model-based and data-driven methods, have garnered significant attention recently and seek efficient ways to combine approximate degradation models with various signal estimation techniques (Kanso et al.

2022). Moreover, the past decade has seen significant explosion in Deep Learning based approaches for accurate prognostics either in supervised (Suh et al. 2020) or unsupervised manner (de Beaulieu et al. 2022).

The intersection of diagnosis and control has been vastly considered in the Fault Tolerant Control (FTC) topic (Schulte & Gauterin, 2015) (Zhang, Parisini, & Polycarpou, 2004). New endeavors are being made in the domain of FTC and adaptive control to address the issues associated at the cross-sections component reliability and system performance. To this end, academic as well as industrial practitioners are developing novel methods that lie at the intersection of FTC and PHM for synthesis of adaptive control. In this context, HAC has recently emerged as the domain wherein control design is sought based upon current state of health and failure prognostics (Escobet, Puig, & Nejjari, 2012) (Karimi Pour, Theilliol, Puig, & Cembrano, 2021) as well as system reliability-based indicators (Salazar Cortés et al. 2016). On the other hand, recent advances in the field of Reinforcement Learning (RL) have brought in remarkable breakthroughs in data-driven learning and execution of (near) optimal control policies in absence of model knowledge (i.e., using a model free approach). In recent years, RL based algorithms have seen a rapid surge in research mainly due to their ability to learn optimal control policies offline as well as online based on interactions with the environment, in model-based as well as model-free settings leading to their successful application in several domains such as robotics, power control, autonomous systems, and health aware control (Mayank Shekhar Jha et al. 2019).

Summarizing, the aim of this invited session is to foster the discussion and collaboration on algorithmic methodologies that leverage the production process data for fault diagnosis, estimation, condition monitoring, prognostics, and health-aware control. The session includes, but is not limited to, the following topics:

- Data-driven methods for designing residual generators for fault detection and isolation
- Data-driven methods for fault estimation
- Data-driven methods for prognostics and remaining useful life (RUL) estimation
- Health-aware control schemes and applications
- Transfer learning approaches to fault diagnosis
- Approaches for the inclusion of qualitative diagnostic information and operator experience
- Anomaly detection approaches in presence of unlabeled or unsecure data
- Reinforcement learning based approaches for control design of systems under deterioration.

References

Ding, H., Gao, R., Isaksson, A., Landers, R., Parisini, T., & Yuan, Y. (2020). State of ai-based monitoring in smart manufacturing and introduction to focused section. **IEEE/ASME Transactions on Mechatronics**, 2143-2154. doi: 10.1109/TMECH.2020.3022983

Escobet, T., Puig, V., & Nejjari, F. (2012). Health aware control and model-based prognosis. **20th IEEE Mediterranean Conference on Control & Automation (MED)**, Barcelona, 691-696. doi: 10.1109/MED.2012.6265718

Farsoni, S., Simani, S., & Castaldi, P. (2021). Fuzzy and Neural Network Approaches to Wind Turbine Fault Diagnosis. **Applied sciences**, 11, 5035. doi: 10.3390/app11115035

Ferrari, R. M., & Teixeira, A. M. (2021). A Switching Multiplicative Watermarking Scheme for Detection of Stealthy Cyber-Attacks. **IEEE Transactions on Automatic Control**, 66(6), 2558-2573, June 2021. doi: 10.1109/TAC.2020.3013850

Gamer, T., Hoernicke, M., Kloepper, B., Bauer, R., & Isaksson, A. (2020). The autonomous industrial plant – future of process engineering, operations and maintenance. **Journal of Process Control**(88), 101-110. doi: 10.1016/j.jprocont.2020.01.012

Karimi Pour, F., Theilliol, D., Puig, V., & Cembrano, G. (2021). Health-aware control design based on remaining useful life estimation for autonomous racing vehicle. **ISA Transactions**, 196-209. doi: 10.1016/j.isatra.2020.03.032

Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial artificial intelligence for industry 4.0-based manufacturing systems. **Manufacturing Letters**(18), 20-23. doi: 10.1016/j.mfglet.2018.09.002

Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. **Mechanical Systems and Signal Processing**, 138, 106587. doi: 10.1016/j.ymssp.2019.106587

Samad, T., Bauer, M., Bortoff, S., Di Cairano, S., Fagiano, L., Odgaard, P., Sosseh, R. (2020). Industry engagement with control research: Perspective and messages. **Annual Reviews in Control**, 49, 1-14. doi: 10.1016/j.arcontrol.2020.03.002

Schulte, H., & Gauterin, E. (2015). Fault-tolerant control of wind turbines with hydrostatic transmission using Takagi–Sugeno and sliding mode techniques. **Annual Reviews in Control**, 82-92. doi: 10.1016/j.arcontrol.2015.08.003

Wan, Y., Keviczky, T., Verhaegen, M., & Gustafsson, F. (2016). Data-driven robust receding horizon fault estimation. **Automatica**, 71, 210-221. doi: 10.1016/j.automatica.2016.04.020

Wang, Y., Ma, G., Ding, S. X., & Li, C. (2011). Subspace aided data-driven design of robust fault detection and isolation systems. **Automatica**, 2474-2480. doi: 10.1016/j.automatica.2011.05.028

Yin, S., Wang, G., & Gao, H. (2016). Data-Driven Process Monitoring Based on Modified Orthogonal Projections to Latent Structures. **IEEE Transactions on Control Systems Technology**, 24(4), 1480-1487. doi: 10.1109/TCST.2015.2481318

Yu, X., Fu, Y., Li, P., & Zhang, Y. (2018). Fault-Tolerant Aircraft Control Based on Self-Constructing Fuzzy Neural Networks and Multivariable SMC Under Actuator Faults. **IEEE Transactions on Fuzzy Systems**, 26(4), 2324-2335. doi: 10.1109/TFUZZ.2017.2773422

Zhang, X., Parisini, T., & Polycarpou, M. (2004). Adaptive fault-tolerant control of nonlinear uncertain systems: an information-based diagnostic approach. **IEEE Transactions on Automatic Control**, 49(8), 1259-1274. doi: 10.1109/TAC.2004.832201

Beaulieu, Martin Hervé de, Mayank Shekhar Jha, Hugues Garnier, and Farid Cerbah (2022). Unsupervised Remaining Useful Life Prediction through Long Range Health Index Estimation Based on Encoders-Decoders. **11th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes (SAFEPROCESS)**, IFAC-PapersOnLine 55 (6): 718–23. doi: 10.1016/j.ifacol.2022.07.212

Jha, Mayank Shekhar, D. Theilliol, G. Biswas, and P Weber (2019). Approximate Q-Learning Approach for Health Aware Control Design. **4th International Conference on Control and Fault-Tolerant Systems (SYSTOL)**, 18-20 September 2019, Casablanca, Morocco. doi: 10.1109/SYSTOL.2019.8864756

Jha, Mayank Shekhar, G Dauphin-Tanguy, and B Ould-Bouamama (2016). Particle Filter Based Hybrid Prognostics for Health Monitoring of Uncertain Systems in Bond Graph Framework. **Mechanical Systems and Signal Processing** 75: 301–29. doi: 10.1016/j.ymssp.2016.01.010.

Kanso, Soha, Mayank Shekhar Jha, Marco Galeotta, and Didier Theilliol (2022). Remaining Useful Life Prediction with Uncertainty Quantification of Liquid Propulsion Rocket Engine Combustion Chamber. **11th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes (SAFEPROCESS).** IFAC-PapersOnLine 55 (6): 96–101. doi: 10.1016/j.ifacol.2022.07.112

Salazar Cortés, Jean Carlo, Fatiha Nejjari Akhi-Elarab, Ramon Sarrate Estruch, Philipe Weber, and Didier Theilliol (2016). Reliability Importance Measures for a Health-Aware Control of Drinking Water Networks. **IEEE 3rd Conference on Control and Fault-Tolerant Systems (SYSTOL)**, Barcelona, Spain, Sept. 7-9, 557–563. doi: 10.1109/SYSTOL.2016.7739810

Suh, S., J. Jang, S. Won, Mayank Shekhar Jha, and Y.O. Lee (2020). Supervised Health Stage Prediction Using Convolutional Neural Networks for Bearing Wear." **Sensors** (Switzerland) 20 (20) doi: 10.3390/s20205846.