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## **Welcome Address**

Welcome to the IPSE conference. This is the first ever Indian conference exclusively in the area of process systems engineering. In keeping with the times, the theme for this edition of the conference is "Re-imagining PSE in the era of big data science and IOT". We believe that the timing is right for this initiative as manufacturing is projected to grow tremendously in India with data science and IOT playing major enabling roles. The idea of the thematic conference is to bring together young PSE faculty and industrial researchers in India and generate enough critical mass to make an impact in this field. It is heartening to note the critical mass of active PSE researchers in India as seen from the number of interesting talks in the conference. It is also a pleasure to host this conference in IIT Madras in the diamond jubilee year of the Institute. We have 5 plenary speakers, 18 invited talks and 33 poster presentations.

Going forward, we hope to develop a larger society to tackle PSE problems of interest, collaboratively. It is our fond wish that industry participate enthusiastically in this initiative. Further, we plan to continue this conference series once every two years at different locations in India. We hope that you have an intellectually stimulating and productive conference.

**Dr. Raghunathan Rengaswamy,  
General Chair, IPSE Conference.  
Institute Chair Professor, Dept. of Chemical Engineering, IIT Madras.**

## **Organizing Committee Members**

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**Plenary Lectures**

**18th August 2019**

**Kallol Roy**

*(Bhavini, India)*

**17:20-18:00**

Systems theoretic and data analytics approaches  
for performance optimization for nuclear plants

**19th August 2019**

**Sachin Patwardhan**

*(IIT Bombay, India)*

**09:00-09:40**

Advances in State and Parameter Estimation and  
Fault-Tolerant Control

**Peter Struss**

*(TU Munich, Germany)*

**11:15-11:55**

Chewing a Mouthful of Sand and Spitting out an  
Intel Chip? - Can Machine Learning Replace  
(Artificial) Intelligence?

**Madhukar Garg**

*(Reliance Industries Limited, India)*

**14:00-14:40**

Advanced Modeling & Deep Characterization:  
Key to Smart & Digital Refining

**B. Ravindran**

*(IIT Madras, India)*

**17:30-18:10**

Reinforcement Learning and MPC



## Abstracts

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## **Energizing chemical engineering community through PSE**

Kannan M. Moudgalya, Dept. of Chemical Engineering, IIT Bombay, Mumbai

### **Abstract**

A major problem facing the chemical engineering graduates from average colleges in a developing country like India is the lack of employment opportunities. Jobs available to them in the IT industry also may also dry up because of the impending automation. On the other hand, most small and medium scale companies don't get any chemical engineering inputs because, while students from good colleges will not join these companies, those from average colleges do not display sufficient skills to be recruited. If only the latter can be trained to use an open source chemical process simulator, savings that can result through just material and energy balances alone can justify their recruitment in small and medium scale companies.

To achieve the above objective, we zeroed in on the open source chemical process simulator DWSIM [1] that comes with CAPE Open compliant thermodynamics. We created 17 Spoken Tutorials on DWSIM, suitable for self learning, and made them available for free access [2]. We wrote to the Heads of all 350 chemical engineering departments in India, telling them about DWSIM based flowsheeting project: a student can take any solved flowsheet from any source, including other commercial simulators, re-solve it in DWSIM, compare the results and upload the solution. After verification of the submission, our project gives them an honorarium, a certificate, and a link on our portal from which their work can be downloaded. This web page summarises this activity [3]. We now have 130 completed DWSIM flowsheets [4], while another 100 are in progress [5], most of them created by students from across India. This large collection also establishes confidence about the capability of the open source simulator. Small and medium scale chemical companies, especially the former, operate mostly in batch mode. To accommodate this need, we need a simulator capable of dynamic simulation, which will be useful also in the high profit margin sectors like speciality chemicals and pharmaceuticals. Our search led us to OpenModelica (OM) [6, 7], an open source general purpose dynamic simulation environment that implements the Modelica language [8]. We ported property databases and thermodynamic correlations to OM [9] from DWSIM. We created a unit operations library in OM [10]. We created Spoken Tutorials using which one can self-learn OM [11]. We are now crowdsourcing flowsheets solved using the equation oriented approach in OM [12].

We plan to build a GUI for chemical process simulation on OM. We plan to build a batch process simulator using OM. These and the solution strategies required for equation oriented simulation are so challenging that some of the best students can be motivated to work in this field. We expect the chemical industry will adopt our open source simulation solutions in a big way, leading to the employment of a large number of chemical engineers, the main objective that triggered this work.

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## **Identification and optimal residual generation for errors-in-variables dynamic processes using DIPCA-EIV-Kalman filter**

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### **Abstract**

Principal Component Analysis (PCA) has been one of the most ubiquitous and effective tools for multivariable data analysis with applications to dimensionality reduction, regression, feature extraction and fault detection. Critical to the success of these applications is a (linear) model that PCA extracts through rank determination (of data matrix) or eigenvalue analysis (of covariance matrix) methods. Estimating this model in presence of (spatially) heteroskedastic measurement errors is a non-trivial problem. In this context, iterative PCA (IPCA) is known to be a highly effective method for simultaneous model determination and error covariance estimation under steady-state conditions. For dynamic processes, however, the problem is challenging and additionally involves the problem of order determination. This talk will present a recently introduced method known as Dynamic IPCA for simultaneous order determination, parameter estimation and error-covariance matrix recovery from measured input-output data (the errors-in-variable or the EIV case) through a two-step process. Further, the talk will present an EIV-Kalman filter-based for obtaining optimal residuals from the DIPCA model. Together, the methods offer a complete, novel optimal and effective solution to the single-input, single-output (SISO) EIV identification and filtering problem. Applications to simulation case studies will be presented to illustrate the effectiveness of the proposed methods.

## Control of batch polymerization using reinforcement learning

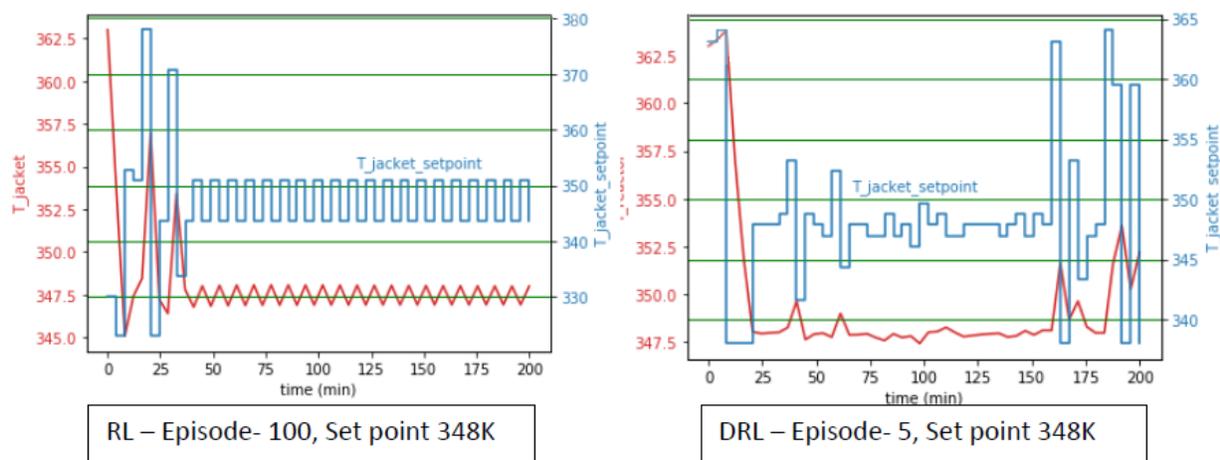
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### Abstract

Control of batch polymerization has been a challenging task. Various traditional controllers like Adaptive and model predictive controller have been used to control the process; still the quality control of polymer product is a challenging task open for further improvement. In this work, we have tried to use Reinforcement Learning (RL), and Deep Reinforcement Learning (DRL) based control to address the existing challenges. RL is a class of machine learning wherein an agent directly interacts with the environment and learns from its past experience. The RL consist of an agent who takes an action, the action changes the state of environment and based on old and new state agent gets a reward, the reward is reinforcement for its action which tells the agent how good or bad the action is for future decisions. The advantage of the RL based controller is that these controllers are model free and they interact directly with the environment to learn a control law that maximizes the desired performance. This features of RL controller makes it applicable in vast range of situations. In this work, we have implemented RL and DRL based control for batch polymerisation of Poly methyl methacrylate (PMMA). The RL controller works with discrete state and action space, limiting the accuracy because of constant approximation. The DRL controller solves some of the limitations by using deep networks to make the action space continuous and improving the accuracy. In both the controllers, the input variable considered was jacket temperature while the reactor temperature was the output variable. Both the controller have been found to achieve the given set point, the DRL controller being faster than the RL controller in terms of the number of episodes. DRL was found to take nearly 10-20 times less number of episodes after proper tuning of neural network parameters. The result for both is shown below along with the number of episodes taken for the result. Further RL and DRL control with risk sensitivity was also carried out to accommodate the process constraints. The agent is made to avoid a particular risk state which hampers the performance or is unfavorable for the reaction.



**Keywords:** Reinforcement learning, Deep reinforcement learning, Risk sensitivity, Batch Polymerisation

## Crude blend compatibility modeling to ensure operational calm

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### Abstract

Refineries typically process blend of crudes so that the resultant feed meets the criteria such as API, Viscosity, TAN etc. Many times, the diet resulting from blending of two or more crudes can face stability issues and unstable diet can pose significant processing challenges resulting in severe fouling in furnaces, tighter emulsion in desalters etc. Such issues may impose severe economic penalties on refineries and at times can also force refineries into unplanned shutdown. Identifying root cause of upset is often a challenging task as it could be resulting from design limitations, unfavorable operating conditions and several unmeasured disturbances. Understanding stability and associated impact on process is generally a labor and time intense process and remains to be an unknown factor either during or post upset condition. CrudePLUS is a proprietary Suez Water Technologies & Solution (SWTS) program which seeks to provide rapid field based crude property indices representing incompatibility, emulsification and fouling. These are described by RIX, ETX and FPX respectively. Figure 1 shows comparison between time consumed by traditional lab-based methods vs CrudePLUS. The latter provides all the information within an hour whereas the traditional method requires around 2 days.

	Turbiscan 4 hours	Static desalter 10 hours	HLPS 28 hours	FTIR 5 min	Hot centrifuge 45 min	Net Time
Indices	RIX	ETX	FPX	IR Fingerprint	TCS, TIS	
Lab Method	✓	✓	✓		✓	~48 hr/ resource
CrudePLUS	✗	✗	✗	✓	✓	~1 hr/ resource

Fig 1 Comparison between CrudePLUS and conventional methods

The proposed CrudePLUS framework essentially uses subject knowledge/expertise blended with the data-science approach. This unique combination leads to development of indices such as RIX, ETX, FPX etc., which vary between 0 to 10 ranging from benign to most aggressive impact respectively. This paper seeks to primarily discuss use of hybrid AIML algorithms which have been used to model under-determined systems resulting from use of crude oil spectral fingerprints. Deciphering formation of highly surface-active molecules during the process of destabilization with the use of advanced algorithms is the key to the development of indices. Efficacy of these algorithms was tested by validating them against inputs, far beyond the training regime. CrudePLUS is being successfully tested and deployed globally across several refineries.

**Keywords:** CrudePLUS, Rapid testing of crude, Predictive analytics, AIML based crude property prediction.

## Artificial Intelligence in automotive product development

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### Abstract

Increased computational speeds and the ability to integrate and handle large data sets has resulted in a renewed thrust in building applications based on Artificial Intelligence (AI) (Venkatasubramanian *et al.*, 2018). The recent promise of AI and related machine learning techniques in solving problems in domains such as game playing, retail consumer experience, autonomous cars, etc. has been instrumental in motivating the engineering community in using AI for solving problems in automotive Product Development (PD) (Winkler, *et al.*, 2019). PD phases including research, design, integration, and testing, all of which, leading up to a vehicle launch are expensive and time consuming. Virtual verification techniques based on physics-based mathematical models have been successful in reducing our reliance on make-test-break “Edisonian” tests that are prevalent in the PD phases. AI techniques could potentially be used to augment and enhance these physics-based modeling approaches.

This presentation will highlight three examples where machine learning techniques augmented by domain knowledge has been used to reduce engineering time. The first example deals with being able to reuse engineering meshes of automotive parts that have been meshed previously. The shapes of the target parts that need meshing are compared to those of the parts in a historical mesh database. Portions of meshes from regions of similar geometry are reused thereby reducing meshing time. The second example highlights how a machine learning algorithm has been able to accurately predict the tire performance metrics. This model has been used to score supplier submissions and has been helpful in reducing the number of physical tests and improve the process of tire design and release process. In the third example, we will show how an automotive catalyst has been modeled with a combination of first principles-based heat and mass balance equations and a data-driven model to capture the kinetics of selective catalytic reduction catalyst (Katare *et al.*, 2007)). Using these three examples we will draw conclusions regarding the use of domain knowledge in the selection of modeling features and improving prediction accuracy while developing robust mathematical models to help reduce engineering time.

**Keywords:** Artificial Intelligence, Product Development, Test Reduction, NOx emissions, Computer Aided Engineering, Tire Modeling

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## Multiple-model approaches to modelling, estimation and control – a tutorial review

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### Abstract

The model based control has gained widespread acceptance in the field of process system engineering to optimally control systems under various constraints. The accuracy of the model has a significant impact on the performance of model based control schemes. The use of multiple linear models weighted using suitable interpolation function has increased in the recent years for modelling of nonlinear systems. Considering the difficulty in the identification of a nonlinear model for the whole operating region of a complex process, the identification of local-linear models and its use to design a bank of state estimators and a bank of model based controllers remains an attractive strategy for the estimation of unmeasured state variables and control of nonlinear process. In this talk, design and development of non-linear state estimation schemes, non-linear control schemes using multiple-model weighted using the fuzzy membership function will be presented. Through extensive Monte Carlo simulation studies, it was observed that the state estimation schemes are able to generate fairly accurate estimates of states and parameters. Through extensive simulation and experimental studies, it was observed that the proposed control schemes provide offset-free servo-regulatory performance.

**Keywords:** Model based Control Scheme, T-S fuzzy model, CSTR, Kalman filters and Inferential control.

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## **Can Process Systems Engineering bridge chemical industry-academia interface in India? – Emerging opportunities and challenges**

Asad Sahir, Dept of Chemical Engineering, IIT Ropar

### **Abstract**

According to an analysis by Invest India, it is expected that the Indian chemicals industry is projected to reach US\$304 billion by 2025 with a rising demand of 9% per annum over the next five years. Chemical Engineering departments worldwide are expected to contribute to building a technical workforce which not only excels in chemical engineering but also can appreciate the opportunities which Process Systems Engineering brings as a discipline and leverage emerging technologies on machine learning, artificial intelligence and process data analytics. From the perspective of a faculty member in a new engineering department at an Indian Institute of Technology with previous industrial research experience; this talk will reflect on the successful academia-industry collaborations in Process Systems Engineering worldwide, and opportunities which can be leveraged in the Indian context, and eventually cater to the emerging need.

## **A systems approach to droplet microfluidics**

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### **Abstract**

Droplet microfluidics is the field that concerns itself with the generation and manipulation of droplets in tiny channels that are as wide as a strand of hair. The idea is to discretize the fluid of interest in another immiscible continuous liquid phase which carries the droplets as it flows. Droplets interact hydrodynamically with the carrying liquid, with other droplets and the boundary (walls) to result in spatio-temporal patterns inside the channel. The motion and pattern formation of these droplets inside the channel are often collective in nature; because understanding the flow and behavior of a single droplet does not shed light into the observed patterns. This can make design and operation of these channels non-intuitive [1]. To systematically approach the problem, there is a need for a modeling framework that not only captures the n-droplet phenomena but is also computationally efficient for the use in design and optimization. We employ an agent-based approach where every droplet is regarded as an agent that interacts with other agents and the surroundings [2]. Simple (approximate and easy to compute) models are used to model the interactions of the agent. And the system as a whole, is simulated to capture the collective droplet phenomena. We show that the framework satisfactorily simulates the observed patterns, which motivates us to extend the analysis to answer some interesting engineering questions of how to design and operate the channel to get the collective behavior of interest, given the application [3].

**Keywords:** Droplet microfluidics, design and optimization, Genetic algorithm, Collective phenomena

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## Integrating data-driven and model-based approaches for process systems

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### Abstract

Development of mathematical models that can accurately predict the profiles of state variables is a key step for carrying out optimal design, control and operation of process systems. While empirical or black-box models provide a good functional representation of input-output variables for complex processes at low computational implementation cost, these have poor predictability outside of the range of the data over which these are developed, and do not provide deep insights into the process. The development of these models usually requires large amount of data. First-principles models, on the other hand, have relatively higher computational cost but have good predictive capabilities, and a deeper understanding of the process can be obtained. Typically, the development of these models requires relatively small amount of data.

Artificial Neural Networks (ANN) provide an effective platform for developing data-driven, input-output models, for large data sets, especially for highly nonlinear functional relationships. Another advantageous feature of ANN models is that these are continuously differentiable and hence can be used to obtain gradient information at low computational cost. In this work, we use this feature for: (i) estimating model parameters for first-principles models given by differential equations, (ii) meshless modelling based control, and (iii) fault-detection. This results in significant reduction in computational cost without compromising accuracy. A number of illustrative examples are presented to demonstrate how synergies between data-driven and model-based approaches can be used to solve process systems engineering problems in computationally efficient and reliable manner.

**Keywords:** Artificial neural networks, parameter estimation, differential equations, meshless modelling, fault-detection

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## **A real-time automated adaptive monitoring approach for a network of SPNDs**

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### **Abstract**

Self Powered Neutron Detectors (SPNDs) are widely used in the nuclear power industry to measure neutron flux in real time. A typical nuclear reactor has hundreds of SPNDs to enable comprehensive monitoring and control of the reactor operations. Over a period of time, SPNDs can develop faults due to a variety of reasons. This in turn can degrade reactor performance if the faults are not detected, identified and compensated for in a timely manner. To ensure that these tasks are performed efficiently in real-time without overburdening the nuclear reactor operation, it is imperative to have an automated, SPND diagnostic system that can perform these tasks in real-time on a continuous basis for varying reactor power levels.

In this work, we develop a data driven monitoring approach that continuously monitors the SPNDs and not only detects failures, identifies faulty detectors but also estimates the magnitude of the sensor fault in real-time. The approach can monitor large number of SPNDs over widely varying reactor power levels. Clustering is used to group the large number of SPNDs in smaller groups of highly correlated SPNDs. Principal Component Analysis (PCA) based models are then used to perform fault detection and diagnosis in each group. Recursive PCA is proposed to ensure that the monitoring system adapts to time varying reactor operating conditions. Reclustering is proposed to deal with significant and sudden variations in the reactor operating conditions. The approach is demonstrated on SPND data obtained from an Indian Pressurized Heavy Water Reactor (PHWR). The monitoring approach used in this work can be extended to monitor various other types of sensor networks.

**Keywords:** SPND, PCA, Clustering, Gross Error Detection

## **Generalized feature set identification for Machine Learning applications in time-series domain**

Srinivasan Ranganathan

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### **Abstract**

Time series measurement representing physical or inferred quantity archived over time are analyzed across several industrial applications, such as: toxic measurements over time indicate the riskiness that is evolving, vibration data from rotating equipment used for failure predictions, process operation data used for identifying process deviations and potential emergence of risks, predictive maintenance of valves, etc.

Underlying to each of these several industrial applications, there are specific time features that are extracted, machine learning algorithms are trained over these extracted features for classification: Valve requires maintenance or not, rotating equipment to be serviced or not, etc. An important point to observe in these industrial applications are that the corresponding features identified are based on some domain knowledge and similar such time series that are seen in other domains are solved differently using different set of time features as seen by those corresponding domain experts.

Hence there is a possibility to create a time-series analysis platform with an objective of a) selecting an appropriate feature for representation, and b) selecting a suitable machine algorithm network. This framework will contain all extracted features that have been developed over several time series application in industrial and beyond.

The advantage of such a generalized time series framework will aid in faster adoption of developing applications quickly in a machine learning framework without too much need of domain specific knowledge to develop predictive analytical applications.

## Process integration approach to production planning

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### Abstract

Production planning starts with the definition of production process then selection of available technologies and appropriate equipments thereafter layout of planned system are to be determined. As demands of various commodities are increasing rapidly therefore production planning is essentially required to achieve sustainable development which reduce environmental effects, improve energy efficiencies and meet forecasted demands of a region[1]. Techniques of process integration can be utilized for solving different aspects of production planning.

In this talk, a graphical approach for minimizing energy consumption and carbon emission while production planning is presented [2]. The methodology is based on pinch analysis that fulfills the demand and considers both objectives in parallel where one of the objectives is constrained within a predefined limit and other is minimized. In other work, a methodology determined for in-between carbon emission capping which provide the limits for carbon emission using pinch analysis while carrying out the production activities[3]. Emission caps for different intervals using Pinch analysis are determined for the entire period of time horizon. Fixing the range of carbon emission for different intervals provide a step-by-step restriction on carbon emission from process industries. It is suggested to the planner to carry out the production activities that matches the limits of carbon emission caps.

Technologies are dynamic in nature and highly market driven. As industrial development and population growth have led to a surge in global demand of energy in recent years, process industries need to implement these energy efficient techniques which incorporate such dynamism in technologies. These energy efficient techniques can also reduce global warming by reducing carbon emission to the environment. Process integration retrofitting of process industries via Best Available Techniques (BAT) is essential as it saves energy. Methodology needs to be derived for implementation of BATs in process industries. Current research is directed towards such issues.

**Keywords:** Production planning, Process integration, Pinch analysis, Carbon emissions, Energy reduction

### Reference

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- [3] R.K. Sinha, N.D. Chaturvedi, Pinch Analysis Approach to Determine In-Between Carbon Emission Caps in Production Planning, *Chem. Eng. Trans.* 70 (2018) 1081–1086. doi:10.3303/CET1870181.

## **Effective deployment of AI/ML in industrial process systems**

Viraj Srivastava

Lead Data Analytics Scientist, Connected Plant, Honeywell Technology Solutions Lab Pvt. Ltd.

### **Abstract**

There is great potential to drive valuable actions via data analytics in industrial processes – the ability to reduce time to market, predict equipment performance, assist in finding root causes for good or bad process performance, and quantify the connections of plant performance to human actions and financial factors. When deployed analytics based solutions will reduce overall operation costs and enable early risk identification.

Industrial solutions built on techniques such as Pattern Recognition and Anomaly Detection in Multi-dimensional data as applied to Industrial Process Systems have the ability to solve key customer challenges such as underperforming assets, unplanned downtime, energy and emissions as well as human capital challenges.

However, developing data analytics in industrial plants often involves both challenges and advantages that are different or amplified from other domains where analytics has achieved traction. Industrial analytics may be characterized by heterogeneous data properties, changing operating conditions, and significant differences between different customers or even between different plants belonging to the same customer. Development of analytic solutions given such constraints requires deep domain expertise in industrial control systems, data management and analysis processes, and innovative out-of-the-box thinking.

Artificial Intelligence and Machine Learning (AI/ML) algorithms produce knowledge that can be used by other systems to solve problems. When developing such solutions is it necessary to identify what they are and their roles within larger systems. This will enable the move away from attempting to build standalone black boxes and instead to developing AI/ML systems that interact with others including humans. In addition, AI/ML based solution that are designed to reach out and touch the customer need to be designed and tested far more thoroughly than conventional solutions.

This session will focus on the potential benefits to be obtained by integrating AI/ML in advanced solution architectures as well as steps to ensure the effective deployment of AI/ML in Industrial Process Systems.

## **Emerging role played by system level modeling in pharmaceutical manufacturing process design**

Pankaj Doshi and Marta Moreno Benito

Drug Product Design, Small Molecule Pharmaceutical Sciences, Worldwide Research and Development, Pfizer Inc.

### **Abstract**

Robust and high-quality manufacturing processes are essential to develop innovative medicines and get them to the market in reduced time. Driven by quality by design (QbD) regulatory guidance and accelerated development cycles, pharmaceutical manufacturing is undergoing a transition with the adoption of many modern technologies like continuous manufacturing platforms, process analytical technology (PAT), real time process control and digital transformation. Concurrent with this technological transition, a systems-based holistic approach for drug development is also begun to emerge. By simultaneously considering drug manufacture and drug performance, it aims to improve the quality of drug products and their manufacturing processes (effectiveness improvements). Moreover, this approach is also helping to reduce the number of iterations required between product formulation and manufacturing process design (efficiency improvements). This systemic approach makes use of digital design methods, based on mechanistic models and targeted experiments, and targets quality improvements in terms of efficacy and robustness.

## A two level hierarchical control configuration for improved operability of wastewater treatment plants

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### Abstract

Wastewater treatment plants are highly complex, nonlinear and slow processes. The intricate nature of the process poses a challenge to the successful implementation of a control system. The challenge lies in the design of a control strategy to reduce operational costs, improve effluent quality and follow the constraints on the effluent variables simultaneously. Sufficient nitrification need to be maintained in the aerobic reactors by controlling the dissolved oxygen (DO) levels at pre-determined set-points. Denitrification in the anoxic reactors needs to be maintained by manipulating internal recirculation flow rate based on nitrate concentration. In this work, model based control strategies are developed based on Benchmark simulation model (BSM)-1 [1] and tested with influent from a real plant data. As the plant model is a complex one with 195 nonlinear ODEs and stiff behavior [2], systematic methodology for identification of the linear state space models using prediction error method for different influent conditions and secondary settler models (Takacs and Burger-Diehl) is developed. A two level hierarchical control architecture is developed by using Ammonia concentration at the higher level as the measured variable for different seasons such as dry, rain and storm weather conditions [3]. Different hierarchical control combinations based on PI-Fuzzy-MPC to address Effluent Quality Index (EQI) and Operational Cost Index (OCI) are analyzed for varied influent behavior. Finally, the importance of sensors and IoT in wastewater treatment plants for flexible and optimal operation are discussed.

**Keywords:** Biological wastewater treatment, Operational cost index, Effluent quality index, Predictor-Error method, Model predictive control

### References:

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## Sparse optimization with applications in system identification

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### Abstract

Sparse constraints appear naturally in many applications in system identification as it is desirable to obtain models with a small number of parameters. For example, the network topology of a process plant, the number of parameters in a dynamic model with unknown delays etc. may be considered sparse. In this talk, an overview of the theory of sparse optimization will be given. Based on these ideas, a few applications such as identification of ordinary, partial differential equation models and sparse networks are presented.

**Keywords:** Sparse optimization, Continuous Time Identification, Tomography, Sparse Networks

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- [4] S. K. Varanasi, and P. Jampana, 2018 " Topology identification of Sparse networks of Continuous Time systems", *IEEE Indian Control Conference, IIT Kanpur*
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## Plantwide control system design for recycle systems

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### Abstract

Material and energy recycle are the hallmark of modern continuous chemical processes. The recycle helps achieve near 100% raw material utilization efficiency with substantial reduction in the plant utility budget (high energy efficiency). On the flip side, the recycle makes the processes highly non-linear with the recycle loops providing multiple paths over which transients can propagate and amplify non-linearly. Many-a-times, there is also the possibility of process instability due to non-linearity induced steady state infeasibility. In this overall context, a robust plantwide regulatory control system that addresses the control issues due to recycle is a pre-requisite for safe and stable process operation.

In this work, qualitative arguments on simple material/energy integrated process modules are used to develop the key guideline of structuring the material/energy inventory control system to transform process variability out of the material/energy recycle loop for robust regulatory control. In energy recycle loops, this requires holding a temperature (pressure for liquid vapour phase change systems) inside the energy recycle loop. In material recycle loops, this requires holding a flow inside the recycle loop and bringing in the fresh feed(s) as make-up streams. The fresh feed(s) should thus NOT be used as the throughput manipulator (TPM) to set the production rate, as is the conventional practice. For the usual case of the bottleneck equipment capacity constraint that limits production being inside the recycle loop, the guideline is further refined to locating the TPM at the bottleneck constraint inside the recycle loop for the tightest possible control of the active constraint. This minimizes the back-off from the hard constraint limit and the associated economic loss. In cases where the bottleneck is not known *a priori*, a flow inside the recycle loop should be used as the TPM as this naturally holds a flow inside the recycle loop and brings in the fresh feed(s) as make-up streams under material balance control.

Application of the guideline on realistic process examples shows that the maximum achieved production can be increased by >20% compared to a conventional control system with the TPM at the process fresh feed. The talk highlights the key role of the regulatory control structure configuration on robust plantwide control.

**Keywords:** Plantwide control, control structure design, throughput maximization

## **Systems Engineering approaches to guide future energy transitions in India**

Prof Rajagopalan Srinivasan, Dr. Laya Das, Mr. Amit Joshi, Ms. Nikita Patel, Dr. Babji Srinivasan  
IIT Gandhinagar

### **Abstract**

Energy systems have been undergoing major transitions throughout the world over the last decade or so, triggered by environmental concerns, new geopolitical realities. Also, there is a significant difference between the energy consumption of developed countries with high human development index (HDI) like United States, Germany, and Netherlands in contrast to less developed ones with low HDI like India. The former group typically has per capita energy consumption about 6000 kWh/person-year while the latter is currently around 1000 kWh/person-year. It is well understood that, for less developed countries, social and economic development is highly correlated with an increase in per-capita energy consumption. However, traditional fossil-fuel based sources (eg. coal) lead to significant environmental and health impacts. Renewable energy sources such as solar and wind offers a promise of clean energy, offer the hope of clean energy; however the heterogeneous (spatial) and sporadic (temporal) nature of their availability leads to many design and operational challenges of the energy grid (technical layer) especially in a large country like India. Experiences in other countries indicate that the appropriate regulatory regime (i.e., one element of the social layer) for integrating renewable and traditional sources, energy diet, may also need to be developed at various time scales. However, one of the major challenges with distributed renewable energy sources is that they are uncertain (depending on climatic conditions) and hence the grid needs to be monitored closely if they are to be integrated. Currently, the distribution data of the grid contains no information on the state of operation during the entire month and is therefore not suitable for monitoring purposes. Grid visibility and situation awareness (SA) on the other hand need to be maintained at all times in order to ensure smooth operation. My talk will address the various challenges involved in improving grid visibility by acquiring informative data from residential users and methods to handle data tsunami from residential grids when AMIs (Advanced Metering Infrastructures) are used.

Specifically the talk will focus on: (i) development & estimation of load profiles of various households using Non-Intrusive Load Monitoring algorithms, (ii) Compressive Sensing approaches to handle data tsunami from Advanced Metering Infrastructures and (iii) Machine learning approaches to improve the compression ratio and its applicability to energy datasets from various continents.

## List of Posters

- | Sl. No. | Title  |
|---------|--|
| 1       | <p><b>Poster Title:</b> Data Science aided first principles modeling of Aluminium smelter<br/><b>Author(s):</b> Venkataraman N V, Danny Raj Masila, Abhishek Sivaram, Raghunathan Rengaswamy.<br/><b>Lead Author's Affiliation:</b> Robert Bosch Centre for Data Science and Artificial Intelligence, IIT Madras, Chennai, India.</p>  |
| 2       | <p><b>Poster Title:</b> Performance analysis of sanitized-teaching learning based optimization and sine cosine algorithm on production planning problem<br/><b>Author(s):</b> Remya Kommadath, Sandeep Singh Chauhan, Gaurav Sharma, Prakash Kotecha<br/><b>Lead Author's Affiliation:</b> Department of Chemical Engineering, Indian Institute of Technology Guwahati, Assam.</p> |
| 3       | <p><b>Poster Title:</b> Use of cross-correlation weighted lag for root cause identification in interactive control loops.<br/><b>Author(s):</b> Mohd. Faheem Ullah, Raghunathan Rengaswamy.<br/><b>Lead Author's Affiliation:</b> Department of Chemical Engineering, Indian Institute of Technology Madras, Chennai, 600036.</p>  |
| 4       | <p><b>Poster Title:</b> Calibration-free modelling of reaction systems using spectroscopic measurements from micro-reactors.<br/><b>Author(s):</b> Manokaran V, Sridharakumar Narasimhan, Nirav Bhatt.<br/><b>Lead Author's Affiliation:</b> Department of Chemical Engineering, IIT Madras, Chennai, India.</p>   |
| 5       | <p><b>Poster Title:</b> Quantifying the effects of disruptions in LNG supply chains through agent-based dynamic simulation.<br/><b>Author(s):</b> Ramanan S V, Rajagopalan Srinivasan.<br/><b>Lead Author's Affiliation:</b> Department of Chemical Engineering, Indian Institute of Technology Madras, Chennai, India.</p>  |

- 6 **Poster Title:** Procurement of LNG under supply and demand uncertainties: Portfolio optimisation studies.  
**Author(s):** Mohd Shahrukh, Rajagopalan Srinivasan.  
**Lead Author's Affiliation:** Department of Chemical Engineering, Indian Institute of Technology Madras, Chennai, India.
- 7 **Poster Title:** Machine Learning approach for blockage detection in pipe using pressure transients.  
**Author(s):** Shubhankar Gurav, Gowri Ramshankar, Prabhat Kumar, Babji Srinivasan, PK Mohapatra.  
**Lead Author's Affiliation:** Indian Institute of Technology Gandhinagar, Palaj Campus, Gandhinagar, Gujarat 382355, India.
- 8 **Poster Title:** Feature selection methods for data driven leak localization in water distribution networks.  
**Author(s):** Rahul Madbhavi, Amit Joshi, Sai Munikoti, Laya Das, Pranab Kumar Mohapatra, Babji Srinivasan.  
**Lead Author's Affiliation:** Dept. of Electrical Engineering, Indian Institute of Technology Gandhinagar, Gujarat, India.
- 9 **Poster Title:** Artificial Intelligence in maritime industry.  
**Author(s):** Rahul D.  
**Lead Author's Affiliation:** Indian Maritime University, Mumbai Port Campus, Marine Engineering and Research Institute, Mumbai-400033, India.
- 10 **Poster Title:** Design and implementation of economic model based control schemes.  
**Author(s):** P Thangaganapathy, J Prakash.  
**Lead Author's Affiliation:** Assistant Engineer, TANGEDCO, NCTPS-II.
- 11 **Poster Title:** Leak detection in intermittently operated water distribution networks.  
**Author(s):** Prasanna Mohan Doss, Sridharakumar Narasimhan, B.S Murty, Shankar Narasimhan.  
**Lead Author's Affiliation:** Department of Chemical Engineering, IIT Madras, Chennai, India.

- Poster Title:** An integrated approach for simulation of complex flowsheets for water and waste water treatment.
- 12 **Author(s):** Sheril Mathew, Deepa Eapen, Sai Varun Aduru, P Vijaysai  
**Lead Author's Affiliation:** Suez Water Technologies and Solutions, JFWTC Bangalore, India.
- Poster Title:** Design and development of a low-cost cantilever based flow sensor.
- 13 **Author(s):** Harija Harikumar, Shankar Narasimhan, Boby George, Arun K. Tangirala  
**Lead Author's Affiliation:** Department of Chemical Engineering, IIT Madras, Chennai, India ; Department of Electrical Engineering, IIT Madras, Chennai, India.
- Poster Title:** Robust scheduling of water distribution networks.
- 14 **Author(s):** Sajay Velmurugan, Varghese Kurian, Shankar Narasimhan, Sridharakumar Narasimhan.  
**Lead Author's Affiliation:** Department of Chemical Engineering, Indian Institute of Technology Madras, Chennai, India.
- Poster Title:** Combined Reinforcement Learning – Model Predictive Control framework (RLMPC).
- 15 **Author(s):** Raghunathan Rengaswamy, Manikandan S.  
**Lead Author's Affiliation:** Department of Chemical Engineering, Indian Institute of Technology Madras, Chennai – 600036.
- Poster Title:** Kinetic Parameter Estimation for ethane pyrolysis in the presence of nitric oxide in a plug flow reactor.
- 16 **Author(s):** Tirthankar Sengupta, Manokaran V, Sridharakumar Narasimhan, Nirav Bhatt.  
**Lead Author's Affiliation:** Department of Chemical Engineering, Robert Bosch Centre for Data Science and Artificial Intelligence, Indian Institute of Technology Madras, Chennai-600036, India.
- Poster Title:** Distributed state estimation of a nonlinear Hybrid dynamic system.
- 17 **Author(s):** M Elenchezhiyan, J Prakash.  
**Lead Author's Affiliation:** Dr. Mahalingam College of Engineering and Technology, Pollachi-642003, India.

- 18 **Poster Title:** Optimal pollutant trading for mercury waste management in water bodies using ABC, SFO and YYPO.  
**Author(s):** Debasis Maharana, Prakash Kotecha.  
**Lead Author's Affiliation:** Department of Chemical Engineering, Indian Institute of Technology Guwahati, Assam.
- 19 **Poster Title:** State Estimation for fully-implicit, index-1 differential algebraic equation systems.  
**Author(s):** Neeraja Srinivasan, Nirav Bhatt, Sridharakumar Narasimhan  
**Lead Author's Affiliation:** Indian Institute of technology, Madras, Chennai, India.
- 20 **Poster Title:** Modelling and optimization of LNG storage tank in regasification terminal.  
**Author(s):** Suraj Prakash Singh, Rajagopalan Sirinivasan.  
**Lead Author's Affiliation:** Department of Chemical Engineering, Indian Institute of Technology Madras, Chennai, India.
- 21 **Poster Title:** IoT enabled monitoring and control of water networks.  
**Author(s):** Saravanan Chinnusamy, Prasanna Mohandoss, Sridharakumar Narasimhan, B S Murty.  
**Lead Author's Affiliation:** Indian Institute of Technology Madras, Chennai, Tamilnadu, India.
- 22 **Poster Title:** Impact of horizon constraint with computational intelligence techniques on job shop scheduling problems.  
**Author(s):** Remya Kommadath, Gaurav Sharma, Prakash Kotecha.  
**Lead Author's Affiliation:** Department of Chemical Engineering, Indian Institute of Technology Guwahati, Assam.
- 23 **Poster Title:** Equitable supply in intermittent water networks.  
**Author(s):** Varghese Kurian, Prasanna Mohandoss, Srinesh Chandrakesha, Saravanan Cinnusamy, Shankar Narasimhan, Sridharakumar Narasimhan.  
**Lead Author's Affiliation:** Department of Chemical Engineering, Indian Institute of Technology Madras, Chennai, India.

- 24 **Poster Title:** Determination of kinetic parameters of an enzymatic reaction using microreactor in tandem with UV-visible spectrophotometer.  
**Author(s):** Shiv Shankar Kumar, Sreeja S Doss, Nirav P Bhatt, Sridharkumar Narasimhan.  
**Lead Author's Affiliation:** Dept. of Chemical Engineering, IIT Madras.
- 25 **Poster Title:** Data-driven Lithium-ion battery prognostics: A supervised learning approach.  
**Author(s):** Sukanya G, Resmi Suresh, Raghunathan Rengaswamy.  
**Lead Author's Affiliation:** Dept. of Chemical Engineering, IIT Madras, India.
- 26 **Poster Title:** Exploring deep networks for system identification.  
**Author(s):** Parameswaran S, Ajsal Shereef PP, Raghunathan R.  
**Lead Author's Affiliation:** Indian Institute of Technology Madras, Chennai.
- 27 **Poster Title:** Towards development of resilient water distribution cyber-physical systems.  
**Author(s):** Jaivik Mankad, Dinesh Borse, Laya Das, Nitin Padhiyar, Babji Srinivasan.  
**Lead Author's Affiliation:** IIT Gandhinagar, Palaj Campus, Gandhinagar 382355.
- 28 **Poster Title:** Variable selection in unlabelled spectroscopic data.  
**Author(s):** Rithik Yadav, S Nandhagopal, Sridharakumar Narasimhan, Nirav P Bhatt.  
**Lead Author's Affiliation:** Indian Institute of Technology Madras, Chennai, India.
- 29 **Poster Title:** Real time monitoring of crude preheat train performance using heat exchanger network tool.  
**Author(s):** Rahul Jagtap, Naveen Agrawal, P Vijaysai.  
**Lead Author's Affiliation:** Suez Water Technologies and Solutions, JFWTC, Bangalore, India.

- 30 **Poster Title:** Modeling of hyaluronic acid production from limited data.  
**Author(s):** Kamakshi C, Kirubhakaran P, Guhan Jayaraman, Nirav Bhatt.  
**Lead Author's Affiliation:** Department of Biotechnology, Indian Institute of Technology Madras, India.
- 31 **Poster Title:** Detection and diagnosis of incipient faults in electrical motors using data driven approaches.  
**Author(s):** Deepesh Agarwal, Manika Kumari, Babji Srinivasan.  
**Lead Author's Affiliation:** IIT Gandhinagar, Palaj Campus, Gandhinagar 382355.
- 32 **Poster Title:** A novel method to detect onset of P-wave in seismic signal using wavelet packet transform.  
**Author(s):** Kanchan Aggarwal, Siddhartha Mukhpopadhya, Arun K Tangirala.  
**Lead Author's Affiliation:** Department of Chemical Engineering, IIT Madras, Chennai, India.
- 33 **Poster Title:** Design and fabrication of autonomous robot drone for agricultural seed sowing  
**Author(s):** D. Venkata Prabhu, N. Yazar  
**Lead Author's Affiliation:** Mahendra College of Engineering, Salem, India.

## Student Demos

Sl. No.

Title

- 1 **Demo Title:** Cylindrical Proton Exchange Membrane Fuel Cell Stack  
**Members:** Prof. Raghunathan Rengaswamy, Mr. Suseendiran S R, Dr. Amit C. Bhosale and Dr. Ramya Ramkumar.
  
- 2 **Demo Title:** IoT enabled Monitoring and Control of Water Networks  
**Members:** Dr. Sankar Narasimhan, Dr. Sridharakumar Narasimhan, Dr. B S Murthy, Mr. N Murali, Mr. C Saravanan, Mr. Prasanna Mohandoss, Mr. Rohit Raphael, Mr. Alif T, Mr. Adityan.
  
- 3 **Demo Title:** "Hyperlocal environmental monitoring through low cost, mobile monitoring network using machine learning framework"  
**Members:** Prof. Raghunathan Rengaswamy, Mr. Sathish Swaminathan, Mr. Abhijeet Ranjan, Mr. Vijaypal Devasoth, Mr. Pruthvi, Mr. Sumeer S.