Austin Chemical Engineering

Austin Publishing Group

Perspective

Perspectives of Process Systems Engineering

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Received: February 10, 2016; **Accepted:** February 11, 2016; **Published:** February 12, 2016

Perspectives

Process Systems Engineering is a contemporary engineering discipline that emerged with the main purpose to provide the methods, tools and human capacity that allow industry to meet its performance requirements. It deals with the design, modeling, monitoring, optimization, control and operation of all kinds of chemical, physical, and biological processes through the use of systematic computer-aided approaches. Its major challenges are the development of concepts, methodologies and procedures for decision-making and performance improvement of an engineered system. The tasks of process systems engineering have become more challenging in the face of growing demand to meet the requirements of process safety, environmental regulations, energy efficiency, better product quality and optimum utilization of available resources. Process systems engineering approaches find significant applications in a vast range of industries such as chemical, petrochemical, oil and gas, mineral and material processing, specialty chemicals, food, polymer, pharmaceutical, biotechnological, water and energy. This discipline has grown steadily along with the developments in electronics and computing fields. This editorial article appraises the methods and strategies of process systems engineering discipline with special focus on advances in soft sensing, control, monitoring and diagnosis of processes and plants. The knowledge exploited from real life plant operations either in terms of rigorous/semi rigorous mathematical models or data driven models constitutes a basis for these advanced operational strategies.

Soft Sensing or State Estimation is a field that deals with the methods that are used to estimate the unmeasured process variables through the use of known measurements and the process knowledge. The estimated variables by the state estimators are incorporated in process operation schemes such online optimization, fault diagnosis and control to achieve economic optimum. Optimal configuration of measurement sensors is also an important prerequisite for successful state estimation. The approaches for state estimation can be classified into two broad categories [1] as the first principle model based approach and the data driven model based approach. In first principle model based approach, a rigorous/semi-rigorous mathematical model of the process in conjunction with an estimation algorithm is used to build state estimators. In this approach, the principles of filtering and observation in conjunction with the model of the process are used to design the soft sensors. In data driven modeling approach, the heuristic or operational data available from the process can be used to build data driven model based soft sensors. Multivariate statistical tools and artificial neural network techniques can be used to build the data driven model based soft sensors. The field of state estimation provides challenging opportunity to develop novel and efficient methods to aid the monitoring, diagnosis and control schemes.

Process Control Systems play a crucial role in enforcing tighter quality control, higher productivity and enhanced safety. Classical controllers such as the Proportional-Integral (PI) and Proportional-Integral-Derivative (PID) controllers are commonly used in many industrial control systems. They are used as single-loop controllers for Single-Input Single-Output (SISO) systems and multi-loop decentralized or multivariable controllers for Multi-Input Multi-Output (MIMO) processes. The structure of these controllers is simple, their design is fast and the principle is easier to understand. However, conventional controllers may not be effective for plants that operate over a wide range of operating conditions and to those whose nonlinear dynamics changes drastically, and for plants that exhibit unstable, oscillatory and chaotic behavior. Thus a variety of advanced controllers have been developed and applied to meet the control requirement of complex plants [2,3]. These control approaches include Self tuning/Adaptive control, Model Predictive Control (MPC), Dynamic Matrix Control (DMC), optimal control, stochastic control, nonlinear control such as Generic Model Control (GMC), Globally Linearizing Control (GLC) and Nonlinear Internal Model Control (NIMC), intelligent control based on fuzzy reasoning, neural network, machine learning and evolutionary computation. The ever increasing technological developments as well as the growing demand for higher performance, efficiency, reliability and safety considerations of industrial systems creates immense opportunity for research and development on advanced and sophisticated control systems.

Online Optimization deals with the problem of changing the operating conditions of a dynamic process to achieve economic optimum. Several factors such as the process complexities, disturbance dynamics, parameter uncertainties and noisy process variables can severely affect the operating performance of a process. The on-line optimizing control scheme has to take into account of such changes and continuously reevaluate the process operation to maximize its economic production. The selection of model structure as well as online model identification scheme plays an important role in optimizing control scheme. On-line optimization schemes involving adaptive process models are widely to achieve economic operation of plants [4]. Process models based on fundamental physical and chemical laws are preferred for on-line optimization than the empirical input-output models because of their wide range of validity and physically more meaningfulness. Optimizing control provides considerable scope for research and development with the focus of developing efficient methodologies for controlling processes and plants.

Process Monitoring and Fault Diagnosis is an important field in process systems engineering discipline. Fault detection and isolation methods can be broadly classified into three different categories [5,6,7] analytical redundancy approach, knowledge based approach and the

Citation: Venkateswarlu Ch. Perspectives of Process Systems Engineering. Austin Chem Eng. 2016; 3(1): 1022.

data driven modeling approach. Analytical redundancy approach puts emphasis on estimation of process variables and parameters based on a model of the process and it has the ability to detect, locate and identify the fault as soon as it occurs in the plant. This approach can tolerate modeling uncertainties and incompleteness in measurements to certain extent. Methods based on Kalman filters and Luenberger observers and their extensions can be included under the category of analytical redundancy approach. Knowledge based approach utilizes qualitative models of the plant combined with experienced based heuristics for fault inference. This approach requires the construction and maintenance of a comprehensive knowledge base. Techniques like expert systems, neural networks, Petri nets and fuzzy logic can be considered under this category. In data driven modeling approach, the operational data of the plant is treated with different statistical methods to extract the state of the system that enables to detect the abnormal behavior and to identifying an assignable cause for out-of-control status of the process. Different feature extraction methods such as principal component analysis (PCA), partial least squares (PLS), Fisher Discriminant Analysis (FDA) as well as their kernel versions such as Kernel Principal Component Analysis (KPCA), Kernel Partial Least Squares (KPLS), Kernel Fischer Discriminant Analysis (KFDA) and Kernel Scatter Discriminant Analysis (KSDA) belong to the data driven modeling approach. The field of process monitoring and fault diagnosis provides immense opportunity to develop new methods including hybrid techniques thus presents greater scope for research and development.

Fault Tolerant Control System is capable of tolerating the effects of potential faults while maintaining the process stability and desired performance in the event of abnormal process situations [8]. It preserves the stability and pre-specified plant performance with the reconfiguration of controller parameters and incorporating the estimated unmeasured state and uncertain parameters into the operational scheme. The need for such control systems arises in nuclear and chemical plants processing hazardous material where a minor fault could potentially develop into catastrophic event if not corrected in time. This field is evolving with the development of new methodologies in the direction of quantitative, qualitative and data driven model based approaches as well as in the form of hybrid methodologies providing greater scope for research and development.

Modern process industry is undergoing significant changes and the plants are being fully automated with minimal manual intervention. The increased degree of automation and the growing demand for higher performance, efficiency, reliability and safety in industrial systems makes the task of Process Systems Engineering (PSE) more challenging. This article has shown a brief appraisal on the perspectives of process systems engineering discipline focusing on advances in the core fields of soft sensing, optimization, monitoring, diagnosis and control.

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Austin Chem Eng - Volume 3 Issue 1 - 2016
ISSN : 2381-8905 | www.austinpublishinggroup.com

Citation: Venkateswarlu Ch. Perspectives of Process Systems Engineering. Austin Chem Eng. 2016; 3(1): 1022.