FAULT DETECTION AND DIAGNOSIS USING UNKNOWN INPUT OBSERVER FOR NON-LINEAR CHEMICAL PROCESSES

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DEDICATION

To Almighty Allah for His Mercy and Blessings

To my beloved parents for their support, supplications, and love.

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ABSTRACT

Advanced automatic control technologies have brought significant benefits to the chemical industry. This is however, hampered by the inefficiency in providing effective detection and diagnosis of process faults that may emerge from various aspects of plant operation. Among the available techniques, unknown input observer (UIO) method has been highlighted as a potentially effective approach as it offers effective capability to deal with residuals between the model estimation and actual measured values of the process variables. UIO modeling strategy creates a specific residual signal that carries information of specific faults, as well as model uncertainties and exogenous disturbances decoupled from fault features. With this characteristic, process faults can be effectively detected, isolated, and identified. The UIO technique was tested on a multi-variable distillation system configured with multiloop feedback control. For this purpose, various scenarios of sensor faults were introduced, and a bank of unknown input observers was designed. Successful results were obtained to detect, isolate, and identify faults. The UIO based fault detection and diagnosis (FDD) system was further tested on case studies involving sensor faults, in open and closed-loop conditions in a non-linear exothermic continuous stirred tank reactor. The proposed FDD scheme was proven robust enough to deal with model uncertainties and exogenous disturbances introduced in the case studies. The results obtained in this study proved the suitability of the UIO modeling approach to be used in FDD system to provide effective early warning feature in process plant alarm management.

ABSTRAK

Teknologi kawalan automatik termaju telah membawa faedah yang ketara kepada industri kimia. Walau bagaimanapun, ia dihalang oleh kegagalan dalam menyediakan pengesanan dan diagnosis ralat proses yang mungkin muncul dari pelbagai aspek operasi loji. Di antara pelbagai teknik yang ada, teknik pemerhati masukan tidak diketahui (UIO) telah ditonjolkan sebagai teknik berkesan yang berpotensi kerana ia menawarkan kemampuan dalam menangani baki di antara nilai yang dianggarkan oleh model dengan nilai sebenar pembolehubah proses yang diukur. Strategi permodelan UIO menghasilkan isyarat baki yang spesifik yang mengandungi maklumat khusus mengenai ralat proses. Dengan ciri-ciri ini, ralat proses akan dapat dikesan, diasing dan dikenalpasti dengan efektif. Teknik UIO ini diuji dengan menggunakan sistem penyulingan berbilang pemboleh ubah yang dilengkapkan dengan kawalan berbilang gelung. Untuk tujuan ini, pelbagai senario kegagalan penderia telah diperkenalkan dan satu bank pemerhati masukan yang tidak diketahui telah direkabentuk. Keputusan yang berjaya telah dicapai bagi mengesan, mengasing dan mengenal pasti kegagalan. Sistem pengesanan dan pengenalpastian (FDD) yang telah dibina seterusnya diuji dengan lebih lanjut dengan kajian kes yang melibatkan kegagalan penderia dalam gelung terbuka dan gelung tertutup pada reaktor tangki teraduk berterusan eksotermik yang tidak lelurus. Keputusan yang diperoleh membuktikan skema FDD yang dicadangkan itu cukup lasak dalam menghadapi ketidakpastian model dan gangguan proses. Penemuan yang diperoleh dalam kajian ini membuktikan kesesuaian pendekatan permodelan UIO untuk digunakan dalam FDD bagi menyediakan sistem amaran awal yang berkesan dalam pengurusan penggera loji proses.

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LIST OF ABBREVIATIONS

ASM	-	Abnormal Situation Management
BTX	-	Benzene, toluene, and xylene
CSTR	-	Continuous Stirred Tank Reactor
CPI	-	Chemical Process Industry
DRGA	-	Dynamic Relative Gain Array
FDD	-	Fault Detection and Diagnosis
FDI	-	Fault Detection and isolation
LQR	-	Linear quadratic regulator
LTI	-	Linear time invariant
MIMO	-	Multi-Input Multi-Output
MVDC	-	Multi-variable distillation column
NI	-	Niederlinski Index
ODE’s	-	Ordinary differential equation
PI		Proportional and integral control
RGA	-	Relative Gain Array
RDX	-	Research Department Formula X
SEM	-	Structural Equation Modelling
SSV	-	Structured Singular Value
SVD	-	Singular value decomposition
TNT	-	Tri-nitro-toluene
UI	-	Unknown input disturbances
UIO	-	Unknown input observer

LIST OF SYMBOLS

$(.)^{+}$	-	Pseudo-inverse of the matrix
α_j	-	Relative volatility of benzene, toluene, and xylene.
δ	-	Tolerance parameter
σ_r	-	Variance of free-fault residuals
τ	-	Time constant for the liquid flow dynamics (min)
τ_c	-	Time constant (min)
ζ	-	The effect of vapour flow on liquid flow
θ	-	Time delay (min)
ΔH_r	-	Enthalpy of reaction (J/mol)
ρ	-	Density of the reacting mixture (g/L)
ρ_j	-	Density of the reacting coolant (g/L)
$\bar{r}$	-	Fault-free residual mean values
$\hat{x}(k)$	-	Observer estimated state vector
$\omega(k)$	-	Unknown input disturbances
$\omega_e(k)$	-	Exogenous disturbance
$\omega_u(k)$	-	Modelling uncertainties
Å	-	Overall heat transfer area (m^2)
B	-	Bottom product flow rate (Kmol/min)
C_{Ain}	-	Inlet feed concentration of component A (mol/L)
C_{Bin}	-	Inlet feed concentration of component B (mol/L)
C_P	-	Heat capacity (J/ (g. K))
C_{PL}	-	Heat capacity of the coolant (J/ (g. K))
CV	-	Controlled variable
D	-	Top product flow rate (Kmol/min)
E	-	Unknown input distribution matrix.
E_a	-	Activation energy (J/mol)
E_e	-	Exogenous disturbance distribution matrix
E_u	-	Modelling uncertainties distribution matrix
$e(k)$	-	Prediction error

e_x	-	State estimation errors
F	-	Feed flow rate (Kmol/min), (L/s)
F_{jin}	-	Inlet coolant flow rate (L/s)
f_s	-	Additive sensor fault
$J(r(k))$	-	Residual evaluation function
K_c	-	The controller gain
K_P	-	Process gain
k_o	-	Arrhenius factor $(L/mole)^{1.28}. s^{-1}$
MV	-	Manipulated variable
M_C	-	Reflux drum level (Kmol)
M_R	-	Reboiler level (Kmol)
min	-	Time domain minute
p	-	Pressure (atm)
Q_C	-	Condenser duty (KJ/min)
Q_R	-	Reboiler duty (KJ/min)
q	-	Number of samples collection
R_L	-	Reflux flow rate (Kmol/min)
$r(k)$	-	Generated residual
S	-	Time domain second
SP	-	Set-point
S_r	-	Binary decision variable
T_C	-	Condenser temperature (K)
T_d	-	Derivative time constant
T_i	-	Integral time constant
T_{in}	-	Feed temperature (K)
T_{jin}	-	Inlet coolant temperature (K)
T_k	-	Residual threshold
T_R	-	Reboiler temperature (K)
U	-	Overall heat transfer coefficient $(w/m^2{\cdot}K)$
$u(k)$	-	Input vector
V_B	-	Vapour boil-up flow rate (Kmol/min)
V_j	-	Volume of the cooling jacket (L)
V_r	-	Volume of the reactor (L)

x(k)	-	Sate vector
X_{Bb}	-	Bottom mole fraction of Benzene (mole %).
X_{Tb}	-	Top mole fraction of Benzene (mole %).
y(k)	-	Output vector
z(k)	-	Observer state vector

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Managing process plant operation involves many challenging tasks including the needs to ensure safety, efficiency, reliability, and profitability, thus requiring all key variables to stay withing specified operating windows. This is exacerbated by the fact that today's process plants are becoming increasingly more complex, highly integrated, and heavily instrumented due to increased demands to achieve higher performance and profitability. In dealing with these complexities, features like fault detection and diagnosis (FDD) are now a necessity. This is to facilitate human interventions whenever needed and to create synergy between operator's action and plant automation.

The key objective of the FDD system is to facilitate plant operators in making decision towards taking the appropriate course of actions when larger deviations emerge. This can be the results of extreme disturbances or failure of certain components of the plant operation system including sensors and actuators. Early detection of these faults is important to avoid the process to drift out of the specified operating window, resulting in hazardous condition and the need to shut down the plant, both of which are very costly. In order to manage process faults efficiently, it is important for the plant operation system to be able to detect and diagnose all potential faults as early as possible. In complex integrated and automated process, ignoring a small fault can lead to terrible consequences (Liu, 2006).

Generally, FDD approaches can be classified into three wide-ranging categories based on a first principle process knowledge such as quantitative based models, qualitative based models, and process history-based methods (Venkatasubramanian et al., 2003c; Venkatasubramanian et al., 2003b;

Venkatasubramanian et al., 2003a). Most of FDD studies for chemical plants are focussed on process history methods using techniques such as artificial neural network, fuzzy logic, statistical process monitoring, and qualitative based models that includes multi-level flow, fault trees analysis, and signed digraphs. These two classes of techniques are relatively easier to apply and develop but limit accuracy and analytical depth. Also, they require a large history data that is specific to the operating condition for which the models were developed (Rahoma, 2021; Tian et al., 2012; Rajaraman, 2006). In order to overcome these weaknesses, the quantitative based models that rely on state-space, input-output, and first-principles models have received more attention in real plants (Patel et al., 2020; Simani et al., 2003). These models have techniques such as parameter estimation, state estimation, and parity relations.

Quantitative model-based methods are based on residual generation from the differences between the measured process variables and their estimates from the model, the fault information could be extracted from the evaluation of this residual (Tangirala, 2018; Wang *et al.,* 2017b). However, this method require theoretical derivation of the process model, which lead to more complexities and can be more computationally intensive if it is compared with process history and qualitative based model approaches (Katipamula and Brambley, 2005). Moreover, the design of an effective and reliable scheme needs to account the modelling uncertainty and the sensitivity of the faults (Yu et al., 2014; Isermann, 2006; Zarei and Poshtan, 2010). Despite these challenges, the urge to have clarity in model predictions that is akin to physical meaning has led to continued developments in this class of FDD approach.

Unknown input observer (UIO) is considered to be among the most popular approaches to achieve decoupling of state estimation error from modelling uncertainties and exogenous disturbances, which makes the residuals insensitive to unknown disturbances, whilst sensitive to the faults (Ahmadizadeh et al., 2014; Hosseini et al., 2020; Guo et al., 2009; Zarei and Poshtan, 2010; Zarei and Poshtan, 2011). This is a powerful feature that can be exploited within the FDD framework to establish better reliability and robustness to avoid false alarms and detection time delay. Examples of similar applications include the work of (Liu, 2016; Sotomayor and Odloak, 2005), in which, the application of UIO in dealing with sensor failures are reported. These early works require further extensions to examine cases involving process systems with larger number of control loops and more process interactions.

Motivated by these considerations, a robust design procedure for FDD using UIO is proposed. The main contributions of this thesis are UI distribution matrix is not known a prior like the previous works and the technique is applied on nonlinear large-scale process (Multivariable distillation column) integrated with PI-control. The robustness and performance of the proposed FDD scheme are investigated and evaluated under several scenarios of abrupt faults occurring in the sensor.

1.2 Objectives of the Study

The main objective of this research is to develop an effective and reliable FDD method as a part of alarm system management for chemical process industry using the advantage of UIO. The objective can be detailed out as follows:

1. To formulate a multi loop feedback control configuration for a multivariable distillation column and evaluate closed loop performances based on set point tracking and disturbance rejection.
2. To evaluate the proposed multi loop control system in managing the abnormal process situation carried out due to sensor failures.
3. To propose a fault detection and diagnosis scheme using unknown input observer (UIO) for sensor fault detection and diagnosis based on the modelling uncertainties and exogenous disturbances in nonlinear process and implement it in the multivariable distillation column as a case study.
4. To study the effects of feedback control on the generated residual of faulty sensors in non-linear CSTR reactor and apply the improved UIO on open-loop non-linear CSTR reactor.

1.3 Scope of the Research

To satisfy and achieve the objectives of this study, the scope and limitations of this research work are as follows:

a. The multi-variable distillation column for aromatic compounds (benzene, toluene, and xylene) was constructed based on mass and energy balance equations, laws of basic thermodynamics, and algebraic energy equations. The relative volatility and pressure inside the column are constant. The hold-up in the vapour phase was neglected.

b. The control configuration selected based on a systematic method called Relative Gains Array (RGA) and the control system are based on multi-loops of PI-control.

c. The unknown input observer (UIO) for fault detection and diagnosis are designed based on modelling uncertainties and exogenous disturbance. By using a bank of UIOs to generate the residuals which are sensitive to the faults and insensitive to modelling uncertainties and exogenous disturbance and are implemented on several sensor fault scenarios with neglected the sensor noise.

d. The non-linear exothermic CSTR reactor was designed based on the data provided by (Liu, 2016) and control system was built on PI-control.

1.4 The Research Contribution

The main contribution of this thesis is improving the design of UIOs via calculated modelling uncertainties and exogenous disturbances distribution matrix from the process plant input and output data and model equations. This procedure should increase the robustness and reliability of the FDD scheme, hence reducing the rate of missing and false alarms. Furthermore, the novelty of this work is applied the designed UIOs to a large-scale chemical process such as a nonlinear multivariable distillation column and nonlinear exothermic CSTR reactor integrated with feedback PI-control.

The improved UIO technique was tested to detect and diagnose the sensor fault occurrence as an abrupt fault. The obtained results have highlighted the robustness, reliability, and efficiency of FDD to track and monitor the process and provide an early warning mechanism to plant operators before the fault reaches a critical situation. Issues associated with generated residuals resulting from the effects of feedback control on the faulty sensor residual are also highlighted.

1.5 Layout of Thesis

Following this introductory chapter, the literature review that outlines key developments in relevant topics is presented as chapter 2. The foundation of the work is established in chapter 3 where the development of mathematical model of a multivariable distillation column is presented. This is followed by the analysis of dynamic response, control loop developments and closed loop performance evaluation. Then process abnormalities are introduced to further evaluate the adequacy of the control system. Then in chapter 4, UIO is introduced and the formulation of an FDD strategy is described. The scheme is implemented on multivariable distillation column. In chapter 5, the robustness of the proposed UIO based FDD is illustrated on a CSTR test bed. Finally, chapter 6 summarises the overall framework of the research, outlines the conclusion and recommends some important extensions of the current works.

Chapter 1:General Introduction

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Chapter 2: Literature Review

- Chemical Plant Faults
- FDD Methods Classification, the capabilities and weaknesses
- Gap analysis

Chapter 3: Managing Process Deviations in Multivariable Distillation Column

- Drived the model of study
- Designed effective and robustness contol system
- Examined the closed-loop system on some abnormal process devaidtion

Chapter 4: Sensor Fault Detection and Diagnosis in a Closed-Loop Nonlinear Multivariable Distillation Process Using Unknown Input Observer (UIO)

- Model Formation of UIO
- UI distribution matrix
- Robust sensor fault detection and diagnosis schemes based on UIOs
- Multivariable distillation column and process control Strategy
- Simulation results and discussion

Chapter 5: Effects of Feedback Control on Residual Generation Via Unknown Input Observer (UIO) For Nonlinear Chemical Process Environment

- Designed CSTR as a Case study
- Control strategy for the nonlinear CSTR system
- Sensor FDD on nonlinear CSTR Oepn-loop using UIO
- Sensor FDD on nonlinear CSTR Closed-loop using UIO

Chapter 6: Thesis conclusions & recommendations

- The summary of thesis with highlithing the significant of the research
- The general conclusion
- Recommendations for future work

Figure 1.1 Thesis Flow chart organization

REFERENCES

Ahmad, A. and Abd Hamid, M. K. (2002). Detection of Multiple Sensor Faults in a Palm Oil Fractionation Plant Using Artificial Neural Network. Regional Symposium on Chemical Engineering (RSCE), Kuala Lumpur, Malaysia. 1805-1811.

Ahmad, A., Samad, A., Fazli, N. A. and Chow, A. W. (2003) . Mathematical Modeling and Analysis of Dynamic Behaviour of a Fed-Batch Penicilin G Fermentation Process. Proceedings of International Conference on Chemical and Bioprocess Engineering. Universiti Malaysia Sabah, 387-394.

Ahmad, M. and Mohd-Mokhtar, R. (2022). A Survey on Model-Based Fault Detection Techniques for Linear Time-Invariant Systems with Numerical Analysis. *Pertanika Journal of Science & Technology*, 30(1).

Ahmadizadeh, S., Zarei, J. and Karimi, H. R. (2014). Robust Unknown Input Observer Design for Linear Uncertain Time Delay Systems with Application to Fault Detection. *Asian Journal of Control*, 16(4)**,** 1006-1019.

Alhelou, H. H., Golshan, M., Hatziargyriou, N. D. and Moghaddam, M. P. (2020). A Novel Unknown Input Observer-Based Measurement Fault Detection and Isolation Scheme for Micro-Grid Systems. *IEEE Transactions on Industrial Informatics*.

Alkhaldi, M., Pathirage, C. and Kulatunga, U. (2017). The Role of Human Error in Accidents within Oil and Gas Industry in Bahrain. 13th International Postgraduate Research Conference (IPGRC): conference proceedings. University of Salford, 822-834.

Alshammari, O., Mahyuddin, M. N. and Jerbi, H. (2018). A Survey on Control Techniques of a Benchmarked Continuous Stirred Tank Reactor. *Journal of Engineering Science and Technology*, 13(10)**,** 3277-3296.

Arkun, Y. and Downs, J. (1990). A General-Method to Calculate Input Output Gains and the Relative Gain Array for Integrating Processes. *Computers & Chemical Engineering*, 14(10)**,** 1101-1110.

Åström, K. J. and Hägglund, T. (2006). *Advanced Pid Control.* ISA-The Instrumentation, Systems and Automation Society.

Attarakih, M., Abu-Khader, M. and Bart, H. J. (2013). Dynamic Analysis and Control of Sieve Tray Gas Absorption Column Using Matalb and Simulink. *Applied Soft Computing*, 13(2)**,** 1152-1169.

Benson, C., Argyropoulos, C. D., Dimopoulos, C., Mikellidou, C. V. and Boustras, G. (2021). Safety and Risk Analysis in Digitalized Process Operations Warning of Possible Deviating Conditions in the Process Environment. *Process Safety and Environmental Protection,* 149**,** 750-757.

Bristol, E. (1979). Recent Results on Interactions in Multivariable Process Control. 71st Annual AIChE Meeting, Houston, USA, 1979.

Buddaraju, D. (2011). *Performance of Control Room Operators in Alarm Management.* Jawaharlal Nehru Technological University.

Bullemer, P. T. and Nimmo, I. (1994). Understanding and Supporting Abnormal Situation Management in Industrial Process Control Environments: A New Approach to Training. Systems, Man, and Cybernetics, 1994.'Humans, Information and Technology'. IEEE International Conference on, 1994. IEEE, 391-396.

Calado, J. and Da Costa, J. (1998). A Hierarchical Fuzzy Neural Network Approach for Multiple Fault Diagnosis. Control'98. UKACC International Conference on (Conf. Publ. No. 455). IET, 1498-1503.

Carrasco, E., Rodrıguez, J., Punal, A., Roca, E. and Lema, J. (2004). Diagnosis of Acidification States in an Anaerobic Wastewater Treatment Plant Using a Fuzzy-Based Expert System. *Control Engineering Practice,* 12(1)**,** 59-64.

Carvalho, P. V., Dos Santos, I. L., Gomes, J. O., Borges, M. R. and Guerlain, S. (2008). Human Factors Approach for Evaluation and Redesign of Human–System Interfaces of a Nuclear Power Plant Simulator. *Displays,* 29(3)**,** 273-284.

Castillo, I., Edgar, T. F. and Dunia, R. (2013). Nonlinear Detection and Isolation of Multiple Faults Using Residuals Modeling. *Industrial & Engineering Chemistry Research*, 53(13)**,** 5217-5233.

Castillo, I. N. (2011). *Nonlinear Model-Based Fault Detection and Isolation: Improvements in the Case of Single/Multiple Faults and Uncertainties in the Model Parameters.* (Doctoral dissertation), University of Texas.

Chen, J. and Patton, R. J. (2012). *Robust Model-Based Fault Diagnosis for Dynamic Systems.* Springer Science & Business Media.

Chou, H. H.-Y. (2000). *Fault Diagnosis of a Heat Exchanger System Using Unknown Input Observers.* (Doctoral dissertation), University of Toronto.

Dai, X. and Gao, Z. (2013). From Model, Signal to Knowledge: A Data-Driven Perspective of Fault Detection and Diagnosis. *IEEE Transactions on Industrial Informatics,* 9(4)**,** 2226-2238.

Daigle, M. J. and Goebel, K. (2013). Model-Based Prognostics with Concurrent Damage Progression Processes. *Systems, Man, and Cybernetics: Systems, IEEE Transactions on,* 43(3)**,** 535-546.

Daroogheh, N., Meskin, N. and Khorasani, K. (2013). Particle Filtering for State and Parameter Estimation in Gas Turbine Engine Fault Diagnostics. American Control Conference (ACC), 2013. IEEE, 4343-4349.

Dash, S. and Venkatasubramanian, V. (2000). Challenges in the Industrial Applications of Fault Diagnostic Systems. *Computers & Chemical Engineering,* 24(2-7)**,** 785-791.

Dash, S. and Venkatasubramanian, V. (2003). Integrated Framework for Abnormal Event Management and Process Hazards Analysis. *Aiche Journal,* 49(1)**,** 124-139.

Dehnert, R., Damaszek, M., Lerch, S., Rauh, A. and Tibken, B. (2022). Robust Feedback Control for Discrete-Time Systems Based on Iterative Lmis with Polytopic Uncertainty Representations Subject to Stochastic Noise. Front. *Control. Eng,* 2**,** 786152.

Ding, S. X. (2008). *Model-Based Fault Diagnosis Techniques: Design Schemes, Algorithms, and Tools.* Springer Science & Business Media.

Ding, S. X. (2012). *Model-Based Fault Diagnosis Techniques: Design Schemes, Algorithms and Tools.* Springer Science & Business Media.

Endsley, M. R. (2018). Automation and Situation Awareness. *Automation and Human Performance: Theory and Applications.* (pp. 163-181). CRC Press.

Frank, P. and Wunnenberg, J. (1989). Robust Fault Diagnosis Using Unknown Input Observer Schemes. *Fault diagnosis in dynamic systems***,** 47-97.

Frank, P. M., Ding, S. X. and Marcu, T. (2000). Model-Based Fault Diagnosis in Technical Processes. *Transactions of the Institute of Measurement and Control,* 22(1)**,** 57-101.

Fruehauf, P. S. and Mahoney, D. P. (2007). Distillation Column Control Design Using Steady State Models: Usefulness and Limitations. *ISA Transactions,* 32(2)**,** 157-175.

Galante, E. B. F., Costa, D. M. B. D., Haddad, A. N. and Santos, I. J. a. L. D. (2014). Risk Assessment for Hexamine Nitration into Rdx. *Journal of Aerospace Technology and Management,* 6(4)**,** 373-388.

Galieriková, A. (2019). The Human Factor and Maritime Safety. *Transportation research procedia,* 40**,** 1319-1326.

Ge, W. and Fang, C. Z. (1988). Detection of Faulty Components Via Robust Observation. *International Journal of Control,* 47(2)**,** 581-599.

Ge, W. and Fang, C. Z. (1989). Extended Robust Observation Approach for Failure Isolation. *International Journal of Control,* 49(5)**,** 1537-1553.

Gertler, J. (1995) Published. Diagnosing Parametric Faults: From Parameter Estimation to Parity Relations. American Control Conference, Proceedings of the 1995. IEEE, 1615-1620.

Gertler, J. and Cao, J. (2004). Pca-Based Fault Diagnosis in the Presence of Control and Dynamics. *AIChE Journal,* 50(2)**,** 388-402.

Gertler, J. J. (2017). *Fault Detection and Diagnosis in Engineering Systems.* New York, NY, USA, CRC press.

Gertler, J. J. and Monajemy, R. (1995). Generating Directional Residuals with Dynamic Parity Relations. *Automatica,* 31(4)**,** 627-635.

Guo, J., Huang, X. and Cui, Y. (2009). Design and Analysis of Robust Fault Detection Filter Using Lmi Tools. *Computers & Mathematics with Applications,* 57(11-12)**,** 1743-1747.

Halvorsen, I. J. and Skogestad, S. (2003). Minimum Energy Consumption in Multicomponent Distillation. 3. More Than Three Products and Generalized Petlyuk Arrangements. *Industrial & Engineering Chemistry Research,* 42(3)**,** 616-629.

Hammouri, H. and Tmar, Z. (2010). Unknown Input Observer for State Affine Systems: A Necessary and Sufficient Condition. *Automatica,* 46(2)**,** 271-278.

Hosseini, I., Fiacchini, M., Karimaghaee, P. and Khayatian, A. (2020). Optimal Reset Unknown Input Observer Design for Fault and State Estimation in a Class of Nonlinear Uncertain Systems. *Journal of the Franklin Institute,* 357(5)**,** 2978-2996.

Hou, M. and Muller, P. C. (1995). Design of a Class of Luenberger Observers for Descriptor Systems. *Ieee Transactions on Automatic Control,* 40(1)**,** 133-136.

Hui, S. and Zak, S. H. (2005). Observer Design for Systems with Unknown Inputs. *International Journal of Applied Mathematics and Computer Science,* 15(4)**,** 431-446.

Hwang, I., Kim, S., Kim, Y. and Seah, C. E. (2010). A Survey of Fault Detection, Isolation, and Reconfiguration Methods. *Ieee Transactions on Control Systems Technology,* 18(3)**,** 636-653.

Isermann, R. (1997). Supervision, Fault-Detection and Fault-Diagnosis Methods—an Introduction. *Control engineering practice,* 5(5)**,** 639-652.

Isermann, R. (2005). Model-Based Fault-Detection and Diagnosis–Status and Applications. *Annual Reviews in control,* 29(1)**,** 71-85.

Isermann, R. (2006). *Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerance.* Springer Science & Business Media.

Isermann, R. (2011). *Fault-Diagnosis Applications: Model-Based Condition Monitoring: Actuators, Drives, Machinery, Plants, Sensors, and Fault-Tolerant Systems.* Berlin, Springer Science & Business Media.

Isermann, R. and Balle, P. (1997). Trends in the Application of Model-Based Fault Detection and Diagnosis of Technical Processes. *Control Engineering Practice,* 5(5)**,** 709-719.

Jelali, M. (2012). *Control Performance Management in Industrial Automation: Assessment, Diagnosis and Improvement of Control Loop Performance.* Springer Science & Business Media.

Kanev, S. K. (2004). *Robust Fault-Tolerant Control.* Ph.D. Thesis, University of Twente, The Netherlands.

Kano, M. and Ogawa, M. (2010). The State of the Art in Chemical Process Control in Japan: Good Practice and Questionnaire Survey. *Journal of Process Control,* 20(9)**,** 969-982.

Katipamula, S. and Brambley, M. R. (2005). Review Article: Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems—a Review, Part I. *HVAC&R Research,* 11(1)**,** 3-25.

Khaki-Sedigh, A. and Moaveni, B. (2009). *Control Configuration Selection for Multivariable Plants.* Berlin Heidelberg, Springer.

Khodja, M. A., Tadjine, M., Boucherit, M. S. and Benzaoui, M. (2017). Tuning Pid Attitude Stabilization of a Quadrotor Using Particle Swarm Optimization (Experimental). *International Journal for Simulation and Multidisciplinary Design Optimization,* 8**,** A8.

Kiliç, E. (2005). *Fault Detection and Diagnosis in Nonlinear Dynamical Systems.* (Doctoral dissertation), Middle East Technical University.

Kiyak, E. and Ermeydan, A. (2016). Fault Diagnosis for a Uav Using Unknown Input Observer. *International Journal of Sustainable Aviation,* 2(4)**,** 309-326.

Koenig, D. (2006). Observer Design for Unknown Input Nonlinear Descriptor Systems Via Convex Optimization. *Ieee Transactions on Automatic Control,* 51(6)**,** 1047-1052.

Kordestani, M., Samadi, M. F., Saif, M. and Khorasani, K. (2018). A New Fault Diagnosis of Multifunctional Spoiler System Using Integrated Artificial Neural Network and Discrete Wavelet Transform Methods. *IEEE Sensors Journal,* 18(12)**,** 4990-5001.

Kuphaldt, T. R. (2012). Lessons in Industrial Instrumentation. *URL: http://www. pacontrol. com/industrial-instrumentation. html*.

Laurentys, C., Bomfim, C., Menezes, B. and Caminhas, W. M. (2011). Design of a Pipeline Leakage Detection Using Expert System: A Novel Approach. *Applied Soft Computing,* 11(1)**,** 1057-1066.

Lavasani, M. S., Ardali, N. R., Sotudeh-Gharebagh, R., Zarghami, R., Abonyi, J. and Mostoufi, N. (2021). Big Data Analytics Opportunities for Applications in Process Engineering. *Reviews in Chemical Engineering*.

Leung, D. and Romagnoli, J. (2000). Dynamic Probabilistic Model-Based Expert System for Fault Diagnosis. *Computers & Chemical Engineering,* 24(11)**,** 2473-2492.

Li, R. K. and Olson, J. H. (1991). Fault-Detection and Diagnosis in a Closed-Loop Nonlinear Distillation Process - Application of Extended Kalman Filters. *Industrial & Engineering Chemistry Research,* 30(5)**,** 898-908.

Li, Z. T. and Dahhou, B. (2007). Fault Isolation for Nonlinear Dynamic Systems Based on Parameter Intervals. *International Journal of Systems Science,* 38(7)**,** 531-547.

Lieftucht, D., Kruger, U. and Irwin, G. W. (2006). Improved Reliability in Diagnosing Faults Using Multivariate Statistics. *Computers & chemical engineering,* 30(5)**,** 901-912.

Ling, H., Cai, Z., Wu, H., Wang, J. and Shen, B. (2011). Remixing Control for Divided-Wall Columns. *Industrial & engineering chemistry research,* 50(22)**,** 12694-12705.

Ling, H. and Luyben, W. L. (2009). Temperature Control of the Btx Divided-Wall Column. *Industrial & Engineering Chemistry Research,* 49(1)**,** 189-203.

Liu, L. (2006). *Robust Fault Detection and Diagnosis for Permanent Magnet Synchronous Motors.* (Ph.D. thesis), The Florida State University, USA.

Liu, Q. (2016). *Observer-Based Fault Diagnosis: Applications to Exothermic Continuous Stirred Tank Reactors.* Master's thesis, Texas A & M University.

Luenberger, D. (1971). An Introduction to Observers. *IEEE Transactions on automatic control,* 16(6)**,** 596-602.

Mak, W. Y. and Ibrahim, K. A. (2012). Fault Detection and Diagnosis Using Correlation Coefficients between Variables. *Jurnal Teknologi,* 50(1)**,** 1–13.

Malwatkar, G. M., Sonawane, S. H. and Waghmare, L. M. (2009). Tuning Pid Controllers for Higher-Order Oscillatory Systems with Improved Performance. *ISA Trans,* 48(3)**,** 347-53.

Manum, H. and Scali, C. (2006). Closed Loop Performance Monitoring: Automatic Diagnosis of Valve Stiction by Means of a Technique Based on Shape Analysis Formalism. Proceedings of the 2006 ANIPLA International Congress on Methodologies for Emerging Technologies in Automation.

Marlin, T. E. (2000). *Process Control : Designing Processes and Control Systems for Dynamic Performance*. (2nd ed. ed). Boston [etc.] :, McGraw-Hill.

Maurya, M. R., Rengaswamy, R. and Venkatasubramanian, V. (2005). Fault Diagnosis by Qualitative Trend Analysis of the Principal Components. *Chemical Engineering Research & Design,* 83(A9)**,** 1122-1132.

Mazzoleni, M., Di Rito, G. and Previdi, F. (2021). Fault Diagnosis and Condition Monitoring Approaches. *Electro-Mechanical Actuators for the More Electric Aircraft.* (pp. 87-117). Springer.

Meel, A. and Seider, W. D. (2006). Plant-Specific Dynamic Failure Assessment Using Bayesian Theory. *Chemical engineering science,* 61(21)**,** 7036-7056.

Monroy Chora, I. (2012). *An Investigation on Automatic Systems for Fault Diagnosis in Chemical Processes.* PhD Thesis, Universitat Politècnica de Catalunya, Barcelona, Spain.

Nabeshima, K., Suzudo, T., Seker, S., Ayaz, E., Barutcu, B., Türkcan, E., Ohno, T. and Kudo, K. (2003). On-Line Neuro-Expert Monitoring System for Borssele Nuclear Power Plant. *Progress in Nuclear Energy,* 43(1)**,** 397-404.

Nazari, S. (2015). A Review of the Unknown Input Observer with Examples. *arXiv preprint arXiv:1504.07300*.

Noura, H., Theilliol, D., Ponsart, J.-C. and Chamseddine, A. (2009). *Fault-Tolerant Control Systems: Design and Practical Applications.* Springer London Science & Business Media.

Olivier-Maget, N., Hetreux, G., Le Lann, J. M. and Le Lann, M. V. (2009). Model-Based Fault Diagnosis for Hybrid Systems: Application on Chemical Processes. *Computers & Chemical Engineering,* 33(10)**,** 1617-1630.

Omana, M. and Taylor, J. H. (2007). Fault Detection and Isolation Using the Generalized Parity Vector Technique in the Absence of an a Priori Mathematical Model. 2007 IEEE International Conference on Control Applications. IEEE, 970-975.

Othman, M., Ali, M. W. and Kamsah, M. Z. (2003). Process Fault Detection and Diagnosis Using Boolean Representation on Fatty Acid Fractionation Column. *International Conference on Chemical and Bioprocess Engineering, Sabah*.

Othman, M. R., Ali, M. W. and Kamsah, M. Z. (2012). Process Fault Detection Using Hierarchical Artificial Neural Network Diagnostic Strategy. *Jurnal Teknologi,* 46(1)**,** 11–26.

Özbay, Y., Ceylan, R. and Karlik, B. (2011). Integration of Type-2 Fuzzy Clustering and Wavelet Transform in a Neural Network Based Ecg Classifier. *Expert Systems with Applications,* 38(1)**,** 1004-1010.

Park, Y.-J., Fan, S.-K. S. and Hsu, C.-Y. (2020). A Review on Fault Detection and Process Diagnostics in Industrial Processes. *Processes,* 8(9)**,** 1123.

Patel, N., Nease, J., Aumi, S., Ewaschuk, C., Luo, J. and Mhaskar, P. (2020). Integrating Data-Driven Modeling with First-Principles Knowledge. *Industrial & Engineering Chemistry Research,* 59(11)**,** 5103-5113.

Patton, R. J. and Chen, J. (1997). Observer-Based Fault Detection and Isolation: Robustness and Applications. *Control Engineering Practice,* 5(5)**,** 671-682.

Patton, R. J., Frank, P. M. and Clark, R. N. (2013). *Issues of Fault Diagnosis for Dynamic Systems.* Berlin, Germany, Springer Science & Business Media.

Pierri, F., Paviglianiti, G., Caccavale, F. and Mattei, M. (2008). Observer-Based Sensor Fault Detection and Isolation for Chemical Batch Reactors. *Engineering Applications of Artificial Intelligence,* 21(8)**,** 1204-1216.

Qian, H. M., Fu, Z. D., Li, J. B. and Yu, L. L. (2013). Robust Fault Diagnosis Algorithm for a Class of Lipschitz System with Unknown Exogenous Disturbances. *Measurement,* 46(8)**,** 2324-2334.

Qin, S. J. (2006). An Overview of Subspace Identification. *Computers & chemical engineering,* 30(10)**,** 1502-1513.

Qu, C. (2009). *Nonlinear Estimation for Model Based Fault Diagnosis of Nonlinear Chemical Systems.* PhD thesis, Texas A&M University.

Ragini, A. H., Rajesh, K. and Krishna, B. H. (2013). Effective Open-Loop Transfer Function Method for Design of Multi-Loop Pi/Pid Controller for Interacting Multivariable Processes. *International Journal of Electronics,* 2(1)**,** 206-215.

Rahoma, A. A. (2021). *Fault Detection and Root Cause Diagnosis Using Sparse Principal Component Analysis (Spca).* PhD diss., Memorial University of Newfoundland.

Rajaraman, S. (2006). *Robust Model-Based Fault Diagnosis for Chemical Process Systems.* PhD Thesis, Texas A&M University, Houston, TX, USA,.

Rajaraman, S., Hahn, J. and Mannan, M. S. (2004). A Methodology for Fault Detection, Isolation, and Identification for Nonlinear Processes with Parametric Uncertainties. *Industrial & engineering chemistry research,* 43(21)**,** 6774-6786.

Rauh, A. and Romig, S. (2021). Linear Matrix Inequalities for an Iterative Solution of Robust Output Feedback Control of Systems with Bounded and Stochastic Uncertainty. *Sensors (Basel),* 21(9)**,** 3285.

Rengaswamy, R., Hagglund, T. and Venkatasubramanian, V. (2001). A Qualitative Shape Analysis Formalism for Monitoring Control Loop Performance. *Engineering Applications of Artificial Intelligence,* 14(1)**,** 23-33.

Richter, J. H., Weiland, S., Heemels, W. and Lunze, J. (2009). Decoupling-Based Reconfigurable Control of Linear Systems after Actuator Faults. 2009 European Control Conference (ECC). IEEE, 2512-2517.

Rothenberg, D. H. (2009). *Alarm Management for Process Control: A Best-Practice Guide for Design, Implementation, and Use of Industrial Alarm Systems.* USA, NY, New York:Momentum Press.

Ruiz, D., Nougues, J. M., Calderon, Z., Espuna, A. and Puigjaner, L. (2000). Neural Network Based Framework for Fault Diagnosis in Batch Chemical Plants. *Computers & Chemical Engineering,* 24(2-7)**,** 777-784.

Sabbaghian-Bidgoli, F. and Farrokhi, M. (2021). Sensor and Actuator Fault-Tolerant Control Based on Fuzzy Unknown Input Observer: A Polynomial Fuzzy Approach. *Applied Soft Computing,* 110**,** 107747.

Scali, C. and Ghelardoni, C. (2008). An Improved Qualitative Shape Analysis Technique for Automatic Detection of Valve Stiction in Flow Control Loops. *Control Engineering Practice,* 16(12)**,** 1501-1508.

Scenna, N. J. (2000). Some Aspects of Fault Diagnosis in Batch Processes. *Reliability Engineering & System Safety,* 70(1)**,** 95-110.

Schubert, U., Kruger, U., Wozny, G. and Arellano-Garcia, H. (2012). Input Reconstruction for Statistical-Based Fault Detection and Isolation. *AIChE Journal,* 58(5)**,** 1513-1523.

Seborg, D. E., Mellichamp, D. A., Edgar, T. F. and Doyle Iii, F. J. (2010). *Process Dynamics and Control.* John Wiley & Sons.

Sharma, V., Sharma, B. and Nath, R. (2018). Unknown Input Reduced Order Observer Based Synchronization Framework for Class of Nonlinear Systems. *International Journal of Dynamics and Control,* 6(3)**,** 1111-1125.

Simani, S. and Fantuzzi, C. (2006). Dynamic System Identification and Model-Based Fault Diagnosis of an Industrial Gas Turbine Prototype. *Mechatronics,* 16(6)**,** 341-363.

Simani, S., Fantuzzi, C. and Patton, R. J. (2003). Model-Based Fault Diagnosis Techniques. *Model-Based Fault Diagnosis in Dynamic Systems Using Identification Techniques.* (pp. 19-60). London, UK: Springer-Verlag.

Skogestad, S. (1997). Dynamics and Control of Distillation Columns: A Tutorial Introduction. *Chemical Engineering Research and Design,* 75(6)**,** 539-562.

Skogestad, S. (2007). The Dos and Don'ts of Distillation Column Control. *Chemical Engineering Research and Design,* 85(1)**,** 13-23.

Skogestad, S., Lundstrom, P. and Jacobsen, E. W. (1990). Selecting the Best Distillation Control Configuration. *Aiche Journal,* 36(5)**,** 753-764.

Smuts, J. F. (2011). Process Control for Practitioners: How to Tune Pid Controllers and Optimize Control Loops. *League City, TX: OptiControls Inc***,** 27-30.

Sotomayor, O. a. Z. and Odloak, D. (2005). Observer-Based Fault Diagnosis in Chemical Plants. *Chemical Engineering Journal,* 112(1-3)**,** 93-108.

Sun, B., Wang, J., He, Z., Zhou, H. and Gu, F. (2019). Fault Identification for a Closed-Loop Control System Based on an Improved Deep Neural Network. *Sensors (Basel),* 19(9)**,** 2131.

Sun, X. (2013). *Unknown Input Observer Approaches to Robust Fault Diagnosis.* Doctoral dissertation, University of Hull.

Tahraoui, S., Meghabbar, A. and Boubekeur, D. (2017). Unknown Input Observer Based on Lmi for Robust Generation Residuals. *Turkish Journal of Electrical Engineering and Computer Sciences,* 25(1)**,** 95-107.

Tang, D., Chen, L. and Hu, E. (2014). A Novel Unknown-Input Estimator for Disturbance Estimation and Compensation. Proceedings of Australasian Conference on Robotics and Automation. 116-1-116-8.

Tangirala, A. K. (2018). *Principles of System Identification: Theory and Practice.* Boca Raton, FL, USA:CRC Press.

Taqvi, S. a. A., Zabiri, H., Tufa, L. D., Fatima, S. A. and Maulud, A. H. S. (2019). Distillation Column: Review of Major Disturbances. 9th IEEE International Conference on Control System, Computing and Engineering (ICCSCE), 2019. IEEE, 168-171.

Tian, W. D., Guo, Q. J. and Sun, S. L. (2012). Dynamic Simulation Based Fault Detection and Diagnosis for Distillation Column. *Korean Journal of Chemical Engineering,* 29(1)**,** 9-17.

Tong, C., El-Farra, N. H., Palazoglu, A. and Yan, X. (2014). Fault Detection and Isolation in Hybrid Process Systems Using a Combined Data-Driven and Observer-Design Methodology. *AIChE Journal*.

Vázquez, F. and Morilla, F. (2002). Tuning Decentralized Pid Controllers for Mimo Systems with Decouplers. *IFAC Proceedings Volumes,* 35(1)**,** 349-354.

Venkatasubramanian, V., Rengaswamy, R. and Kavuri, S. N. (2003a). A Review of Process Fault Detection and Diagnosis: Part Ii: Qualitative Models and Search Strategies. *Computers & Chemical Engineering,* 27(3)**,** 313-326.

Venkatasubramanian, V., Rengaswamy, R., Kavuri, S. N. and Yin, K. (2003b). A Review of Process Fault Detection and Diagnosis Part Iii: Process History Based Methods. *Computers & Chemical Engineering,* 27(3)**,** 327-346.

Venkatasubramanian, V., Rengaswamy, R., Yin, K. and Kavuri, S. N. (2003c). A Review of Process Fault Detection and Diagnosis: Part I: Quantitative Model-Based Methods. *Computers & chemical engineering,* 27(3)**,** 293-311.

Vu, T. N. L. and Lee, M. (2010). Multi-Loop Pi Controller Design Based on the Direct Synthesis for Interacting Multi-Time Delay Processes. *Isa Transactions,* 49(1)**,** 79-86.

Wang, H., Kropholler, H. and Daley, S. (1993). Robust Observer Based Fdi and Its Application to the Monitoring of a Distillation Column. *Transactions of the Institute of Measurement and Control,* 15(5)**,** 221-227.

Wang, J., Ge, W., Zhou, J., Wu, H. and Jin, Q. (2017a). Fault Isolation Based on Residual Evaluation and Contribution Analysis. *Journal of the Franklin Institute,* 354(6)**,** 2591-2612.

Wang, J. and Qin, S. J. (2006). Closed-Loop Subspace Identification Using the Parity Space. *Automatica,* 42(2)**,** 315-320.

Wang, K., Chen, J. and Song, Z. (2017b). Data-Driven Sensor Fault Diagnosis Systems for Linear Feedback Control Loops. *Journal of Process Control,* 54**,** 152-171.

Watanabe, K. and Himmelblau, D. M. (1982). Instrument Fault-Detection in Systems with Uncertainties. *International Journal of Systems Science,* 13(2)**,** 137-158.

Wiegmann, D. A. and Shappell, S. A. (2017). *A Human Error Approach to Aviation Accident Analysis: The Human Factors Analysis and Classification System*. (1st edition ed). Routledge, London.

Xu, S., Adhitya, A. and Srinivasan, R. (2014). Hybrid Model-Based Framework for Alarm Anticipation. *Industrial & Engineering Chemistry Research,* 53(13)**,** 5182-5193.

Yang, F. and Wilde, R. W. (1988). Observers for Linear-Systems with Unknown Inputs. *Ieee Transactions on Automatic Control,* 33(7)**,** 677-681.

Yang, Q. (2004). *Model-Based and Data Driven Fault Diagnosis Methods with Applications to Process Monitoring.* PhD thesis, Case Western Reserve University.

Yang, S.-F., Ho, H.-W. and Rahim, M. A. (2007). Effects of Measurement Error on Controlling Two Dependent Process Steps. *Economic Quality Control,* 22(1)**,** 127-139.

Yi, C. K. and Luyben, W. L. (1995). Evaluation of Plant-Wide Control-Structures by Steady-State Disturbance Sensitivity Analysis. *Industrial & Engineering Chemistry Research,* 34(7)**,** 2393-2405.

Yoon, S. and Macgregor, J. F. (2000). Statistical and Causal Model-Based Approaches to Fault Detection and Isolation. *AIChE Journal,* 46(9)**,** 1813-1824.

Yoon, S. and Macgregor, J. F. (2001). Fault Diagnosis with Multivariate Statistical Models Part I: Using Steady State Fault Signatures. *Journal of process control,* 11(4)**,** 387-400.

Yu, D. L., Shields, D. N. and Daley, S. (1996). A Bilinear Fault Detection Observer and Its Application to a Hydraulic Drive System. *International Journal of Control,* 64(6)**,** 1023-1047.

Yu, Y., Woradechjumroen, D. and Yu, D. (2014). A Review of Fault Detection and Diagnosis Methodologies on Air-Handling Units. *Energy and Buildings,* 82**,** 550-562.

Zarei, J. and Poshtan, J. (2010). Design of Nonlinear Unknown Input Observer for Process Fault Detection. *Industrial & Engineering Chemistry Research,* 49(22)**,** 11443-11452.

Zarei, J. and Poshtan, J. (2011). Sensor Fault Detection and Diagnosis of a Process Using Unknown Input Observer. *Mathematical and Computational Applications,* 16(1)**,** 31.

Zarei, J. and Shokri, E. (2014). Robust Sensor Fault Detection Based on Nonlinear Unknown Input Observer. *Measurement,* 48**,** 355-367.

Zhai, S., Wang, W. and Ye, H. (2015). Fault Diagnosis Based on Parameter Estimation in Closed-Loop Systems. *IET Control Theory & Applications,* 9(7)**,** 1146-1153.

Zhang, Q. and Delyon, B. (2001). A New Approach to Adaptive Observer Design for Mimo Systems. American Control Conference, 2001. Proceedings of the 2001. IEEE, 1545-1550.

Zhong, M., Du, X., Song, Y., Xue, T. and Ding, S. X. (2021). Event-Triggered Parity Space Approach to Fault Detection for Linear Discrete-Time Systems. *IEEE*

Transactions on Systems, Man, and Cybernetics: Systems, 52(no. 8)**,** pp. 4813-4822.

Zhou, Y. (2004). *Data Driven Process Monitoring Based on Neural Networks and Classification Trees.* PhD dissertation, Texas A&M University.

LIST OF PUBLICATIONS

Journal with Impact Factor

1. **Al-Shatri, A. H.**, Ahmad, A., Abdullah, N., Oladokun, O., Al-Shanini, A., & Khalil, M. (2015). Control and optimization of aromatic compounds in multivariable distillation column. *Chemical engineering transactions*, *45*, 469-474. **(Q2, IF:1.006)**

Indexed Journal

1. **Al-Shatri, A. H.,** Ahmad, A., Oladokun, O., Nyakuma, B. B., & Al-shanini, A. (2019). Dynamic Control of Sensor and Actuator failures in Multivariable Distillation Column. *Journal of Energy and Safety Technology (JEST)*, *2*(2). (**Indexed by SCOPUS**)

Non-indexed Journal

1.

Indexed Conference Proceedings

1. **Al-Shatri, A. H.,** Arshad, A., Olagoke, O., & Nyakuma, B. B. (2019). Unknown input observer design for fault detection and diagnosis in a continuous stirred-tank reactor. In *E3S Web of Conferences* (Vol. 90, p. 02004). EDP Sciences. (**Indexed by SCOPUS**)

Non-Indexed Conference Proceedings

1.