



 **IFAC** Papers  
Online  
CONFERENCE PAPER ARCHIVE





# IFAC-PapersOnLine

<p><b>COUNTRY</b></p> <p>Austria</p> <div style="background-color: #333; color: white; padding: 5px; margin-bottom: 5px;">  Universities and research institutions in Austria         </div> <div style="background-color: #333; color: white; padding: 5px;">  Media Ranking in Austria         </div>	<p><b>SUBJECT AREA AND CATEGORY</b></p> <p>Engineering</p> <ul style="list-style-type: none"> <li>Control and Systems Engineering</li> </ul>	<p><b>PUBLISHER</b></p> <p>IFAC Secretariat</p>	<p><b>H-INDEX</b></p> <h1 style="font-size: 48px; margin: 0;">76</h1>
<p><b>PUBLICATION TYPE</b></p> <p>Journals</p>	<p><b>ISSN</b></p> <p>24058963</p>	<p><b>COVERAGE</b></p> <p>2002-2021</p>	<p><b>INFORMATION</b></p> <p><a href="#">Homepage</a></p>

**SCOPE**

All papers from IFAC meetings are published, in partnership with Elsevier, the IFAC Publisher, in the IFAC-PapersOnLine proceedings series hosted at the ScienceDirect web service. This series includes papers previously published in the IFAC website. The main features of the IFAC-PapersOnLine series are: -Online archive including papers from IFAC Symposia, Congresses, Conferences, and most Workshops. -All papers accepted at the meeting are published in PDF format - searchable and citable. -All papers published on the web site can be cited using the IFAC PapersOnLine ISSN and the individual paper DOI (Digital Object Identifier). The site is Open Access in nature - no charge is made to individuals for reading or downloading. Copyright of all papers belongs to IFAC and must be referenced if derivative journal papers are produced from the conference papers. All papers published in IFAC-PapersOnLine have undergone a peer review selection process according to the IFAC rules.

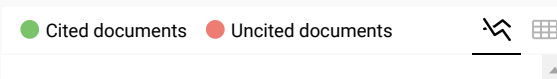
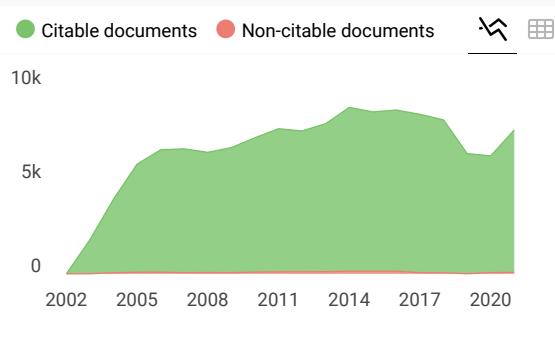
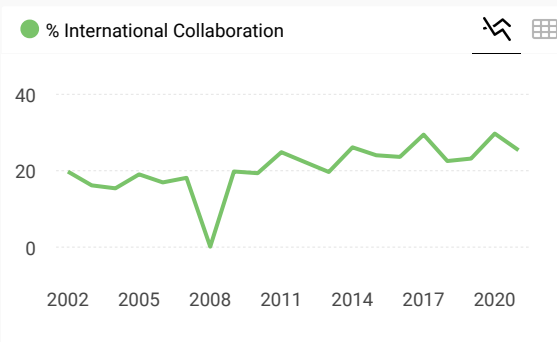
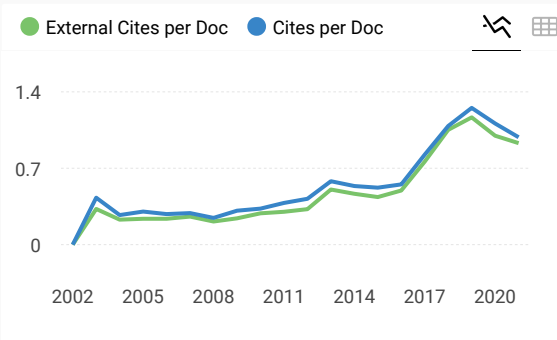
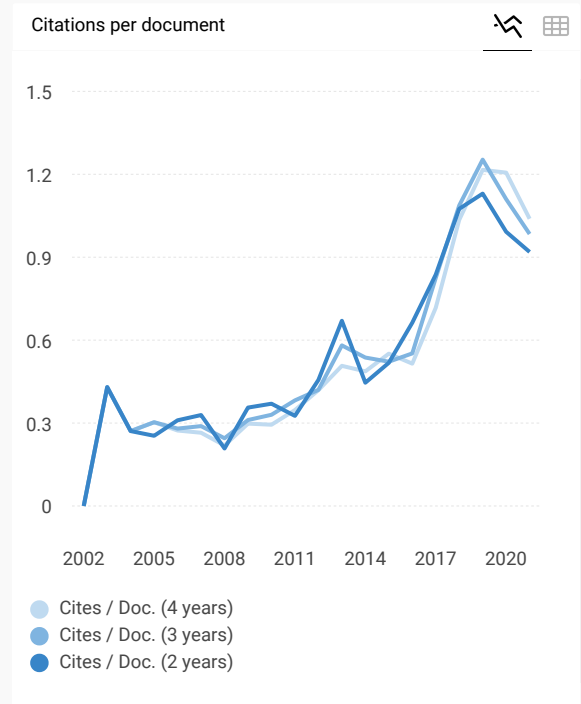
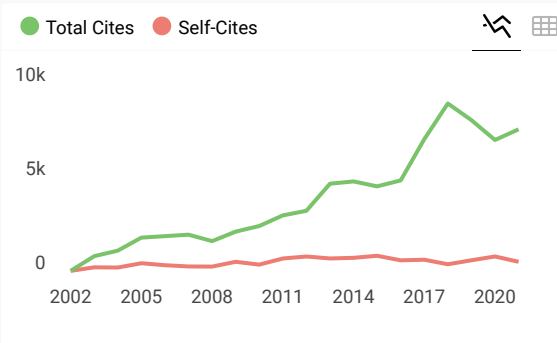
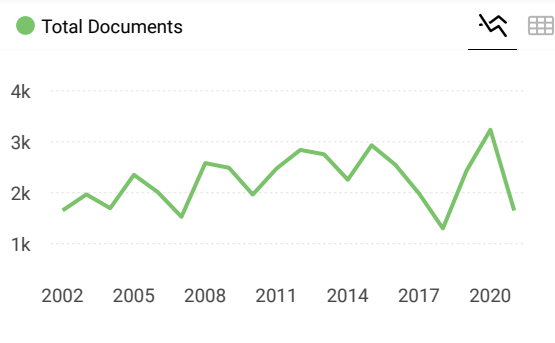
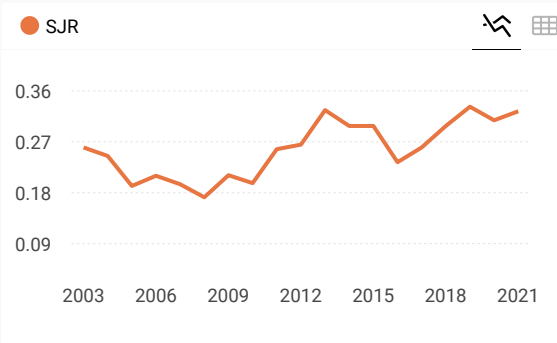
Join the conversation about this journal

Quartiles

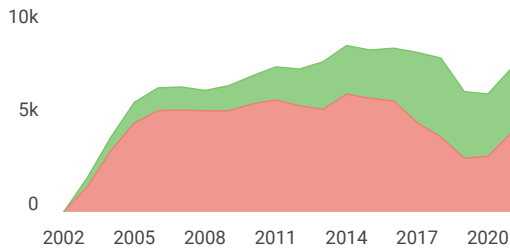


FIND SIMILAR JOURNALS ?

<p>1 <b>Annual Reviews in Control</b> GBR <b>75%</b> similarity</p>	<p>2 <b>Automatisierungstechnik</b> DEU <b>59%</b> similarity</p>	<p>3 <b>Optimal Control Applications and Methods</b> GBR <b>55%</b> similarity</p>	<p>4 <b>IEEE/CAA J. Automatica</b> USA <b>5</b> s</p>
-------------------------------------------------------------------------------------	-----------------------------------------------------------------------------------	----------------------------------------------------------------------------------------------------	-----------------------------------------------------------------------



Show this widget in your own website



**IFAC-PapersOnLine**

Q3 Control and Systems Engineering best quartile

SJR 2021 0.32

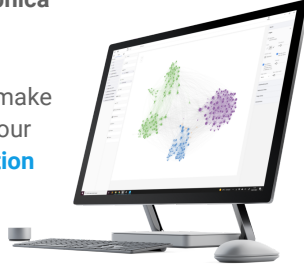
powered by scimagojr.com

← Just copy the code below and paste within your html code:

```
<a href="https://www.scimagojr.com" data-bbox="630 96 780 109">
```

**SCImago Graphica**

Explore, visually communicate and make sense of data with our **new data visualization tool**.



Metrics based on Scopus® data as of April 2022



**Adolfo Escobar** 5 months ago

Does Scopus define the coverage? For this publication, the Scimago coverage is 2002-2021 while in Scopus it is 2002-2020. Why?

<https://www.scopus.com/sourceid/21100456158>

← reply



**Melanie Ortiz** 5 months ago

SCImago Team

Dear Adolfo, thank you very much for your comment. We always suggest you consult the Scopus database directly. Keep in mind that the SJR is a static image (the update is made one time per year) of a database (Scopus) which is changing every day.

The Scopus' update list can also be consulted here:

<https://www.elsevier.com/solutions/scopus/how-scopus-works/content>

Best Regards, SCImago Team

**Leave a comment**

Name

Email

(will not be published)

I'm not a robot reCAPTCHA  
Privacy - Terms

Submit

The users of Scimago Journal & Country Rank have the possibility to dialogue through comments linked to a specific journal. The purpose is to have a forum in which general doubts about the processes of publication in the journal, experiences and other issues derived from the publication of papers are resolved. For topics on particular articles, maintain the dialogue through the usual channels with your editor.

Developed by:



Powered by:



Follow us on @ScimagoJR

Scimago Lab, Copyright 2007-2022. Data Source: Scopus®

EST MODUS IN REBUS

Horatio (Satire 1,1,106)

[Cookie settings](#)

[Cookie policy](#)

- > Aims and scope
- > **Editorial board**
- > Abstracting & indexing
- > News

### Editorial board by country/region

66 editors and editorial board members in 24 countries/regions

- 1 France (10)
- 2 Germany (7)
- 3 Italy (7)

> [See more editors by country/region](#)

### Editorial board



---

Polytechnic University of Valencia, Spain

## Advisor

Carlos Eduardo Pereira

Federal University of Rio Grande do Sul, Brazil

## Editors

### Systems and Signals

Hideaki Ishii

Tokyo Institute of Technology, Japan

### Design Methods

Laura Menini

University of Rome Tor Vergata, Italy

### Computers, Cognition and Communication

Thierry Marie Guerra

Polytechnic University Hauts-de-France, France

### Mechatronics, Robotics and Components

Andreas Kugi



---

Research Center for Automatic Control of Nancy, Vandoeuvre Les Nancy, France

## Manufacturing and Logistics Systems

Dmitry Ivanov

Berlin School of Economics and Law, Germany

## Process and Power Systems

Jay H. Lee

Korea Advanced Institute of Science and Technology, South Korea

## Transportation and Vehicle Systems

Lars Eriksson

Linköping University, Sweden

## Bio & Ecological Systems

Ronald R. van Nooijen

Delft University of Technology, Netherlands

## Social Systems

Lawrence Stapleton





---

Alessandro Chiuso

University of Padua, Department of Information Engineering, Italy

Adaptive and Learning Systems

Tiago Roux Oliveira

Rio de Janeiro State University, Brazil

Discrete Event and Hybrid Systems

Carla Seatzu

University of Cagliari, Italy

Stochastic Systems

Yilin Mo

Tsinghua University, China

Networked Systems

Maurice Heemels

Eindhoven University of Technology, Netherlands

Control Design



---

Silviu-Iulian Niculescu

CentraleSupélec, France

Non-Linear Control Systems

Christophe Prieur

GIPSA-lab Control Department, France

Optimal Control

Eric Kerrigan

Imperial College London, United Kingdom

[View full biography](#)

Robust Control

Mario Sznaier

Northeastern University, United States of America

Distributed Parameter Systems

Yann Le Gorrec

Franche-Comté Electronics Mechanics Thermics and Optics Sciences and Technologies, Department of Optics, France

Computers for Control



---

Kevin Guelton

Reims Champagne-Ardenne University, France

Telematics: Control via Communication Networks

Lei Ma

Southwest Jiaotong University, China

Mechatronic Systems

Tsu-Chin Tsao

University of California Los Angeles, United States of America

Robotics

Ivan Petrović

University of Zagreb, Faculty of Electrical Engineering and Computing, Croatia

Human Machine Systems

Jianhua Zhang

Oslo Metropolitan University, Norway

Manufacturing Plant Control



---

Dmitry Ivanov

Berlin School of Economics and Law, Germany

Enterprise Integration and Networking

Georg Weichhart

Profactor GmbH, Austria

Large Scale Complex Systems

Wei Ren

University of California Riverside, United States of America

Chemical Process Control

Rolf Findeisen

Otto von Guericke University, Germany

Mining, Mineral and Metal Processing

Chris Aldrich

Curtin University, Australia

Power and Energy Systems



---

Vicenç Puig

Polytechnic University of Catalonia, Spain

Automotive Control

Per Tunestål

Lund University, Department of Energy Sciences, Sweden

Marine Systems

Roberto Galeazzi

Technical University of Denmark, Denmark

Aerospace

Antonios Tsourdos

Cranfield University, United Kingdom

Transportation Systems

Tankut Acarman

Galatasaray University, Turkey

Intelligent Autonomous Vehicles



---

Manoj Karkee

Washington State University, Department of Biological Systems Engineering, United States of America

Biological and Medical Systems

Thomas Desaive

University of Liege, Belgium

Modelling and Control of Environmental Systems

Marialuisa Volta

University of Brescia, Italy

Biosystems and Bioprocesses

Alejandro Vargas Casillas

National Autonomous University of Mexico, Mexico

Economic, Business, and Financial Systems

Fei-Yue Wang

Chinese Academy of Sciences Institute of Automation, China

Systems and Control for Societal Impact



---

Qing-Shan Jia

Tsinghua University, Department of Automation, China

Control Education

Antonio Visioli

University of Brescia, Italy

Technology, Culture and International Stability

Peter Kopacek

TU Wien University, Austria

All members of the Editorial Board have identified their affiliated institutions or organizations, along with the corresponding country or geographic region. Elsevier remains neutral with regard to any jurisdictional claims.



Copyright © 2023 Elsevier B.V. or its licensors or contributors.  
ScienceDirect® is a registered trademark of Elsevier B.V.





ScienceDirect®

# IFAC-PapersOnLine

1.5  
CiteScore

[Guide for authors ↗](#)

☰ Menu

🔍 Search in this journal

## Modeling, Estimation and Control Conference MECC 2021 Austin, Texas, USA, 24-27 October 2021

Edited by Junmin Wang, Hosam Fathy, Qian Wang, Beibei Ren

Volume 54, Issue 20,

Pages 1-934 (2021)

[← Previous vol/issue](#)

[Next vol/issue >](#)

Receive an update when the latest issues in this journal are published



[Sign in to set up alerts](#)

● Full text access

Contents

Pages i-viii



[View PDF](#)

FEEDBACK



Research article ● Full text access

## A Digital Twin Framework for Mechanical System Health State Estimation

Maxwell Toothman, Birgit Braun, Scott J. Bury, Michael Dessauer, ... Kira Barton

Pages 1-7



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Weighted expectation-maximisation algorithm for parameter estimation of misspecified dynamical models: application to vehicle dynamics

Jules Matz, Abderazik Birouche, Benjamin Mourllion, Fethi Bouziani, Michel Basset

Pages 8-13



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Iterative Learning Control Strategy for a Furuta Pendulum System with Variable-Order Linearization

Ricardo Binz, Stanislav Aranovskiy

Pages 14-19



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Realization of Excavator Loading Operation by Nonlinear Model Predictive Control with Bucket Load Estimation

Shinji Ishihara, Akira Kanazawa, Ryu Narikawa

Pages 20-25



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Fast Allan Variance (FAVAR) and Dynamic Fast Allan Variance (D-FAVAR) Algorithms for both Regularly and Irregularly Sampled Data

Satya Prasad Maddipatla, Hossein Haeri, Kshitij Jerath, Sean Brennan

Pages 26-31



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Modelling vortex-induced loads using Recurrent Neural Networks

Joshua A. Foster, Tim De Troyer, Mark C. Runacres, Jan Decuyper

Pages 32-37



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Long Short-term Memory Neural Network-based System Identification and Augmented Predictive Control of Piezoelectric Actuators for Precise Trajectory Tracking

Mayur S. Patil, Bharat Charuku, Juan Ren

Pages 38-45



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Learning-based Robust Model Predictive Control for Sector-bounded Lur'e Systems

Katrine Seel, Mark Haring, Esten I. Grøtli, Kristin Y. Pettersen, Jan T. Gravdahl

Pages 46-52



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Fault Cause Assignment with Physics Informed Transfer Learning

Furkan Guc, YangQuan Chen

Pages 53-58



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Cautious Nonlinear Covariance Steering using Variational Gaussian Process Predictive Models

Alexandros Tsolovikos, Efstathios Bakolas

Pages 59-64



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## A Gaussian Process Based Approach to Estimate Wind Speed Using SCADA Measurements from a Wind Turbine

Eduardo B.R.F. Paiva, Hoai-Nam Nguyen, Olivier Lepreux, Delphine Bresch-Pietri

Pages 65-71



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Extended Capture Point and Optimization-based Control for Quadrupedal Robot Walking on Dynamic Rigid Surfaces

Amir Iqbal, Yan Gu

Pages 72-77



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Mixed Use of Analytical Derivatives and Algorithmic Differentiation for NMPC of Robot Manipulators

Alejandro Astudillo, Justin Carpentier, Joris Gillis, Goele Pipeleers, Jan Swevers

Pages 78-83



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Disturbance Attenuation Through Real-Time Optimization of PD Gains for a Two-Link Robot

Alexander Bertino, Hashem Ashrafiuon, Peiman Naseradinmousavi

Pages 84-89



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Robust Deep Reinforcement Learning for Quadcopter Control

Aditya M. Deshpande, Ali A. Minai, Manish Kumar

Pages 90-95



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Model Predictive Control of Biomechanical Sit-to-Stand

Kamran Iqbal

Pages 96-101



[View PDF](#)

Article preview

Research article ● Full text access

## Variance Reduction of Quadcopter Trajectory Tracking in Turbulent Wind

Asma Tabassum, Rohit K.S.S. Vuppala, He Bai, Kursat Kara

Pages 102-107



[View PDF](#)

Article preview

Research article ● Full text access

## Adaptive Parameter Estimation of a Steerable Drifter

Eric Gaskell, Xiaobo Tan

Pages 108-113



[View PDF](#)

Article preview

Research article ● Full text access

## Averaged Modeling of Pectoral Fin-Actuated Robotic Fish

Maria L. Castaño, Xiaobo Tan

Pages 114-121



[View PDF](#)

Article preview

Research article ● Full text access

## Model-based estimation of the line tension in a fishing reel

Federico Dettù, Marco Centurioni, Simone Formentin, Sergio Matteo Savaresi

Pages 122-127



[View PDF](#)

Article preview

Research article ● Full text access

## Burrowing Locomotion via Crack Propagation of a Bio-inspired Soft Robot

John P. Lathrop, Derek A. Paley

Pages 128-133



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Robust control of rotation-floating space robots with flexible appendages for on-orbit servicing

Sofiane Kraïem, Mathieu Rognant, Jean-Marc Biannic, Yves Brière

Pages 134-140



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## A Twisted String Actuator-Driven Soft Robotic Manipulator

David Bombara, Ryan Coulter, Revanth Konda, Jun Zhang

Pages 141-146



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Real-Time Adaptive Threshold Adjustment for Lane Detection Application under Different Lighting Conditions using Model-Free Control

Yujing Zhou, Zejiang Wang, Junmin Wang

Pages 147-152



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Safety-Guaranteed Driving Control of Automated Vehicles via Integrated CLFs and CDBFs

Yiwen Huang, Yan Chen

Pages 153-159



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## A Three-Phase Framework for Global Path Planning for Nonholonomic Autonomous Vehicles on 3D Terrains

Congkai Shen, Siyuan Yu, Tulga Ersal

Pages 160-165



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Adaptive and Reference Shaping Control for Steer-By-Wire Vehicles in High-Speed Maneuvers

Srivatsan Srinivasan, Matthias J. Schmid, Venkat Krovi

Pages 166-171



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## A Safety Guaranteed Control Framework to Integrate Actuator Dynamics via Control-Dependent Barrier Functions

Yiwen Huang, Yan Chen

Pages 172-178



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## A Novel IDS-based Control Design for Tire Blowout

Ao Li, Yan Chen, Wen-Chiao Lin, Xinyu Du

Pages 179-184



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Electromagnetic energy harvesting from train induced railway bridge vibrations

Jia Mi, Mingyi Liu, Qiaofeng Li, Xiaofan Li, Lei Zuo

Pages 185-190



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## On the Problem of On–Board Early Detection of Hunting on Rail Vehicles: an exploratory study

Kiriakos Kritikakos, Spilios D. Fassois, John S. Sakellariou, Ilias Chronopoulos, ... Georgios Vlachospyros

Pages 191-197



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Control Co-design and Characterization of a Power Takeoff for Wave Energy Conversion based on Active Mechanical Motion Rectification

Lisheng Yang, Jianuo Huang, Nob Congpuong, Shuo Chen, ... Lei Zuo

Pages 198-203



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Closed-form solutions of bending-torsion coupled forced vibrations of a piezoelectric energy harvester under a fluid vortex

X. Zhao, W.D. Zhu, Y.H. Li

Pages 204-211



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Multi-resonance Phenomena in Stochastic Resonance Energy Harvesting: Influence of Periodic Signal Magnitude and Noise Intensity to the Dynamics

Hongjip Kim, Lei Zuo

Pages 212-217



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Intelligent Autonomous Navigation of Car-Like Unmanned Ground Vehicle via Deep Reinforcement Learning

Shathushan Sivashangaran, Minghui Zheng

Pages 218-225

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Improved Motor Imagery Classification Using Regularized Common Spatial Pattern with Majority Voting Strategy

Md Ferdous Wahid, Reza Tafreshi

Pages 226-231

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Control-Theoretic Modeling and Prediction of Blood Clot Viscoelasticity in Trauma Patients

Damon E. Ghetmiri, Miguel E. Perez Blanco, Mitchell J. Cohen, Amor A. Menezes

Pages 232-237

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Design and Control of an Autonomous Robot for Mobility-Impaired Patients

Aarya Deb, Zachery Wypych, Jess Lonner, Hashem Ashrafiuon

Pages 238-243

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Electromyographic Classification to Control the SPAR Glove

John E. Britt, Marcia K. O'Malley, Chad G. Rose

Pages 244-250

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Estimation of the Basic Reproduction Number for the COVID-19 Pandemic in Minnesota

H. Movahedi, A. Zemouche, R. Rajamani

Pages 251-257



[View PDF](#)[Article preview](#)

Research article ● Full text access

## Physical Human-UAV Interaction with Commercial Drones using Admittance Control

Christopher Banks, Antonio Bono, Samuel Coogan

Pages 258-264

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Parameter Optimization for Variable Admittance Control of Haptic Systems

Antonio Moualeu, Jun Ueda

Pages 265-270

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Safe Human-Robot Coetaneousness Through Model Predictive Control Barrier Functions and Motion Distributions

Mohammadreza Davoodi, Joseph M. Cloud, Asif Iqbal, William J. Beksi, Nicholas R. Gans

Pages 271-277

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Control of a Bipedal Walker Under Foot Slipping Condition Using Whole-Body Operational Space Framework

Marko Mihalec, Jingang Yi

Pages 278-283

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Human Gesture Robot Control Using a Camera/Accelerometer-in-Palm Sensor

Jared Floersch, Perry Y. Li

Pages 284-289

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Invariant Extended Kalman Filtering for Hybrid Models of Bipedal Robot Walking

Yuan Gao, Chengzhi Yuan, Yan Gu

Pages 290-297

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Noninvasive Systemic Vascular Resistance Estimation using a Photoplethysmogram and a Piezoelectric Sensor

Zixiao Zhang, Sardar Ansari, Lu Wang, Keith D. Aaronson, ... Kenn R. Oldham

Pages 298-303

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Control-oriented Nonlinear Modeling of Polyvinyl Chloride (PVC) Gel Actuators

Mohammed Al-Rubaiai, Xinda Qi, Zachary Frank, Ryohei Tsuruta, ... Xiaobo Tan

Pages 304-309

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Observer Design and Analysis for Non-Invasive Hemorrhage Detection

Xin Jin, Yekanth Ram Chalumuri, Ali Tivay, Jin-Oh Hahn

Pages 310-315

[View PDF](#)[Article preview](#)

Research article ● Full text access

## AI Guided Measurement of Live Cells Using AFM

Jaydeep Rade, Juntao Zhang, Soumik Sarkar, Adarsh Krishnamurthy, ... Anwesha Sarkar

Pages 316-321

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Analysis of epidemic spread dynamics using a PDE model and COVID-19 data from Hamilton County OH USA

Faray Majid, Aditya M. Deshpande, Subramanian Ramakrishnan, Shelley Ehrlich, Manish Kumar

Pages 322-327



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Actin Cytoskeleton Morphology Modeling Using Graph Embedding and Classification in Machine Learning

Yi Liu, Juntao Zhang, Charuku Bharat, Juan Ren

Pages 328-333



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Robust State Estimations in Controlled ARMA Processes with the Non-Gaussian Noises: Applications to the Delayed Dynamics

Vadim Azhmyakov, Jose Perea Arango, Moises Bonilla, Raymundo Juarez del Toro, Stefan Pickl

Pages 334-339



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Model Segmentation in Single Particle Tracking

Boris I. Godoy, Nicholas A. Vickers, Sean B. Andersson

Pages 340-345



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## System Identification for Safe Controllers using Inverse Optimization

Jaskaran Grover, Changliu Liu, Katia Sycara

Pages 346-353



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Indirect Adaptive Inverse Control Design Based on the FASS-NLMS Algorithm

Rodrigo Possidônio Noronha

Pages 354-359



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Safe Adaptation with Multiplicative Uncertainties Using Robust Safe Set Algorithm

Charles Noren, Weiye Zhao, Changliu Liu

Pages 360-365



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Reinforced Optimal Estimator

Wenhan Cao, Jianyu Chen, Jingliang Duan, Shengbo Eben Li, ... Yuhang Zhang

Pages 366-373



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## A control oriented comprehensive degradation model for battery energy storage system life prediction

Yaqi Zhu, Tazdik Plateau, Brody Riemann, Robert Landers, Jonghyun Park

Pages 374-380



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Clustering-based Sensor Placement for Thermal Fault Diagnostics in Large-Format Batteries

Sara Sattarzadeh, Tanushree Roy, Satadru Dey

Pages 381-386



[View PDF](#)

[Article preview](#) ✓

Research article ● Full text access

## Airflow and Power-Split Control Strategy for a Fuel Cell Hybrid Powered Robot

Miriam Figueroa-Santos, Valentin Sulzer, Youngki Kim, Jason Siegel, ... Denise M. Rizzo

Pages 387-392



[View PDF](#)

[Article preview](#) ▼

Research article ● Full text access

## Online energy management for intermittent operation of hybrid electric vehicles at low temperatures

Florian Meier, Luigi del Re

Pages 393-398



[View PDF](#)

[Article preview](#) ▼

Research article ● Full text access

## Lithium-Sulfur Battery Discharge Optimization using a Thermally-Coupled Equivalent Circuit Model

Chu Xu, Mahsa Doosthosseini, Hosam K. Fathy

Pages 399-405



[View PDF](#)

[Article preview](#) ▼

Research article ● Full text access

## Input-output Data-driven Modeling and MIMO Predictive Control of an RCCI Engine Combustion

Behrouz Khoshbakht Irdmousa, Jeffrey Donald Naber, Javad Mohammadpour Velni, Hoseinali Borhan, Mahdi Shahbakhti

Pages 406-411



[View PDF](#)

[Article preview](#) ▼

Research article ● Full text access

## Nonlinear Model Predictive Planning and Control for High-Speed Autonomous Vehicles on 3D Terrains

Siyuan Yu, Congkai Shen, Tulga Ersal

Pages 412-417

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Optimization of Charging Schedule for Battery Electric Vehicles Using DC Fast Charging Stations

Kuo Yang, Pinggen Chen

Pages 418-423

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Automatic Extrinsic Rotational Calibration of LiDAR Sensors and Vehicle Orientation Estimation

Stephanie W. Meyer, Howard Chen, David M. Bevy

Pages 424-429

[View PDF](#)[Article preview](#)

Research article ● Full text access

## RSS Model Calibration and Evaluation for AV Driving Safety based on Naturalistic Driving Data

Yiwen Huang, Maria Soledad Elli, Jack Weast, Yingyan Lou, ... Yan Chen

Pages 430-436

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Collaborative Manipulation of Spherical-Shape Objects with a Deformable Sheet Held by a Mobile Robotic Team

Kyle Hunte, Jingang Yi

Pages 437-442

[View PDF](#)[Article preview](#)

Research article ● Full text access

## Learning Energy Efficient Jumping Strategies for Flexible-Legged Systems

Andrew Albright, Joshua Vaughan

Pages 443-448



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Utilizing Hidden Markov Models to Classify Maneuvers and Improve Estimates of an Unmanned Aerial Vehicle

Amy K. Strong, Scott M. Martin, David M. Bevly

Pages 449-454



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Developing Equations of Motion for a Planar Biped Walker with Nonuniform Foot Shape

Claire H. Rodman, Anne E. Martin

Pages 455-462



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Modeling and Control of a Tethered Tilt-Rotor Quadcopter with Atmospheric Wind Model

Rumit Kumar, Shubham R. Agarwal, Manish Kumar

Pages 463-468



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## PLDI-Based Convexification for Roll-to-Roll Dry Transfer Control

C. Martin, Q. Zhao, S. Bakshi, D. Chen, W. Li

Pages 469-474



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## A High-Fidelity Modeling Framework for Near-Field Electrohydrodynamic Jet Printing

Nazanin Farjam, Isaac A. Spiegel, Kira Barton

Pages 475-481



[View PDF](#)

[Article preview](#)

Research article Full text access

## Construction of Spatial Filtering Matrices for Norm-Optimal ILC in Single Point Incremental Forming

Joseph D. Fischer, Mitchell R. Woodside, Douglas A. Bristow, Robert G. Landers

Pages 482-487



[View PDF](#)

[Article preview](#)

Research article Full text access

## Dynamic Resource Allocation Using Multi-Agent Control for Manufacturing Systems

Mingjie Bi, Ilya Kovalenko, Dawn M. Tilbury, Kira Barton

Pages 488-494



[View PDF](#)

[Article preview](#)

Research article Full text access

## Control Logic Synthesis for Manufacturing Systems Using Markov Decision Processes

Changmin Lee, Jehyun Park, Jongeun Choi, Jaebok Ha, Sangyeong Lee

Pages 495-502



[View PDF](#)

[Article preview](#)

Research article Full text access

## Intelligent Scan Sequence Optimization for Uniform Temperature Distribution in Laser Powder Bed Fusion using a Control Theoretic Approach

Keval S. Ramani, Chinedum E. Okwudire

Pages 503-508



[View PDF](#)

[Article preview](#)

Research article Full text access

## Modeling of Lithium-ion Batteries via Tensor-Network-Based Volterra Model



Yangsheng Hu, Raymond A. de Callafon, Ning Tian, Huazhen Fang

Pages 509-515



[View PDF](#)

[Article preview](#)

Research article Full text access

## Optimal Health-Conscious Fast Charging of Lithium Ion Batteries

Zachary Salyer, Matilde D'Arpino, Marcello Canova, Yann Guezennec

Pages 516-521



[View PDF](#)

[Article preview](#)

Research article Full text access

## An Algorithmic Safety VEST For Li-ion Batteries During Fast Charging

Peyman Mohtat, Sravan Pannala, Valentin Sulzer, Jason B. Siegel, Anna G. Stefanopoulou

Pages 522-527



[View PDF](#)

[Article preview](#)

Research article Full text access

## Modeling Li-ion Battery First Venting Events Before Thermal Runaway

Ting Cai, Vivian Tran, Anna G. Stefanopoulou, Jason B. Siegel

Pages 528-533



[View PDF](#)

[Article preview](#)

Research article Full text access

## Impact of Data Sampling Methods on the Performance of Data-driven Parameter Identification for Lithium ion Batteries

Gyouho Cho, Youngki Kim, Jaerock Kwon, Wencong Su, Mengqi Wang

Pages 534-539



[View PDF](#)

[Article preview](#)

Research article Full text access

## Robust Control for a Class of Nonlinearly Coupled Hierarchical Systems with Actuator Faults

Sina Ameli, Olugbenga Moses Anubi

Pages 540-546



[View PDF](#)

[Article preview](#)

Research article Full text access

## Information-Theoretic Approach for Model Reduction Over Finite Time Horizon

Punit Tulpule, Umesh Vaidya

Pages 547-553



[View PDF](#)

[Article preview](#)

Research article Full text access

## Extended Kalman Filter for Index-2 Nonlinear Differential Algebraic Equation Systems

Jalesh L. Purohit

Pages 554-559



[View PDF](#)

[Article preview](#)

Research article Full text access

## Semistability and Stochastic Semistability for Switched Nonlinear Systems by Means of Fixed Point Theory: Application to Constrained Distributed Consensus over Random Networks

S. Sh. Alaviani, A.G. Kelkar

Pages 560-565



[View PDF](#)

[Article preview](#)

Research article Full text access

## Comparing Linear Systems with Gaussian Mixture Model Additive Uncertainties Using Kullback-Leibler Rate

Aditya Karumanchi, Punit Tulpule

Pages 566-572



[View PDF](#)

[Article preview](#)

Research article Full text access

## A data-driven approach to MIMO PID tuning via LMI constraints

Anna Paula V de A Aguiar, George Acioli, Péricles R Barros, Angelo Perkusich

Pages 573-578



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Non-minimum Phase Zeros of Two-DoF Damped Flexible Systems

Siddharth Rath, Shorya Awtar

Pages 579-585



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Efficient Path Planning of Soft Robotic Arms in the Presence of Obstacles

Preston R. Fairchild, Vaibhav Srivastava, Xiaobo Tan

Pages 586-591



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Modeling and $H_\infty$ Position Control of a Spreader in the Gantry Crane

Zeshen Chen, Zheng Chen, Bin Yao

Pages 592-597



[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Fast Multi-Robot Motion Planning via Imitation Learning of Mixed-Integer Programs

Mohit Srinivasan, Ankush Chakrabarty, Rien Quirynen, Nobuyuki Yoshikawa, ... Stefano Di Cairano

Pages 598-604





[View PDF](#)

[Article preview](#)

Research article ● Full text access

## Fuzzy Logic Force-Torque Feedback Controller For Multi-Drone Cooperative Transport With Offset CG

Shraddha Barawkar, Manish Kumar  
Pages 605-610

 [View PDF](#) Article preview 

Research article ● Full text access

## Time Optimal Control for a Non-Linear Planar Vehicle Subject to Disturbances

Ayal Taitler, Ilya Ioslovich, Erez Karpas, Per-Olof Gutman  
Pages 611-616

 [View PDF](#) Article preview 

Research article ● Full text access

## A Hybrid Lateral Dynamics Model Combining Data-driven and Physical Models for Vehicle Control Applications

Zhisong Zhou, Yafei Wang, Qinghui Ji, Daniel Wellmann, ... Chengliang Yin  
Pages 617-623

 [View PDF](#) Article preview 

Research article ● Full text access

## Robust Control Design for a Single-Wheel Module Operating in an Off-Road Terrain with Uncertain and Stochastic Attributes


Masood Ghasemi, Vladimir V. Vantsevich, David J. Gorsich, Lee Moradi  
Pages 624-631

 [View PDF](#) Article preview 

Research article ● Full text access

## Robust Control of a Three-Phase Synchronous In-wheel Motor

Răzvan Mocanu, Alexandru Onea  
Pages 632-637

 [View PDF](#) Article preview 

[< Previous vol/issue](#)

[Next vol/issue >](#)

ISSN: 2405-8963

Copyright © 2023 International Federation of Automatic Control. Published by Elsevier Ltd.



Copyright © 2023 Elsevier B.V. or its licensors or contributors.  
ScienceDirect® is a registered trademark of Elsevier B.V.



# An Energy Balance Model Parameter Estimation with an Extended Kalman Filter

Auralius Manurung\* Lisa Kristiana\*\* Dwi Aryanta\*\*

\* Universitas Pertamina, Jakarta, Indonesia (e-mail: [auralius.manurung@ieee.org](mailto:auralius.manurung@ieee.org))

\*\* Institut Teknologi Nasional Bandung, Bandung, Indonesia (e-mail: [\[lisa,dwiaryanta\]@itenas.ac.id](mailto:[lisa,dwiaryanta]@itenas.ac.id))

**Abstract:** This paper presents modeling and parameter estimation of a thermal system, which is often nonlinear, with nonlinearities found in its parameters. As a result, it requires an additional online parameter estimation. In this paper, we implement an Extended Kalman Filter for modeling and parameter identification of such a device. The thermal device that we use is an educational device developed in-house. First, we derive the device's mathematical model using a zero-order energy balance model as the template model. Next, we find the model's best parameters by performing an optimization process. Finally, we implement an Extended Kalman Filter technique to accommodate the possibility that those parameters may change over time. Our experiments show that when we have reliable measurements and a reliable system model, the Kalman filtering technique can perform well as an online parameter estimator and act as a basis to build an adaptive model.

Copyright © 2021 The Authors. This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0/>)

**Keywords:** Recursive identification, process modeling and identification, embedded computer control systems and applications.

## 1. INTRODUCTION

Heat transfer modeling on thermal systems is a essential since it provides engineers better insights into the system processes and allows sophisticated control implementations. However, this modeling task can be challenging since a thermal system's nonlinear behaviors are commonly found in the model parameters. In contrast, the used model itself is linear (see Jonsson and Palsson (1994)). As a result, the model performance may deteriorate if the parameters are assumed to be constant at all times.

In a situation where the nonlinear behaviors are found in the system's parameters or where the parameters are actually changing as functions of time, online parameter estimation can be used as one of the solutions. For this purpose, a Kalman filtering technique can be used, such as found in the works by Song et al. (2017), Kim et al. (2016), Jonsson and Palsson (1994), Mutambara and Al-Haik (1999) and Yanou et al. (2016). In general, a Kalman filtering technique is used for state estimation. However, it can also be used to perform parameter estimation by extending the system's state model with the model parameters that we want to estimate (see Blanchard et al. (2007) and Walker (2006)). As the result, the Kalman filter will estimate both the state variables and the added model parameters.

To model a thermal system, an energy balance model can be used as a template model. An energy balance model is most common in environmental science where it is used to model the climate systems (see Roques et al. (2014)).

In this paper, we use a zero-dimensional energy balance model. The term zero-order is used to describe that there is no spatial variable in the model. Such model is the simplest form of an energy balance model. Park et al. (2020) also use a zero-order energy balance model in their work, although they do not include time delay in their energy balance equations. As for the model parameters, we use an optimization process to find their best values.

In order to test the proposed concept, we have developed a thermal device that is originally developed for teaching purpose (see Section II). Recently, educational thermal devices have become more widely used in several engineering courses, such as in Park et al. (2020), Tran et al. (2019), and Barbosa (2020). Besides teaching, the same devices can also be used for research, such as as test devices for control system developments (see Cui et al. (2020)). These educational devices are typically compact in size, low-cost, and easy to build. Since the thermal process is generally slow, it does not require a high-performance control computer and data acquisition system.

This paper takes the references above and investigates the use of a Kalman filtering technique to enhance a thermal system modeled by using an energy balance model with delayed input and an already optimized set of parameters. Our contribution will be the overall investigation process that we introduce in this paper. Here we demonstrate that if noises do not significantly contaminate the state variables, a Kalman filtering technique should perform very satisfactorily as an online parameter estimator. Additionally, we also contribute to the application of a Kalman

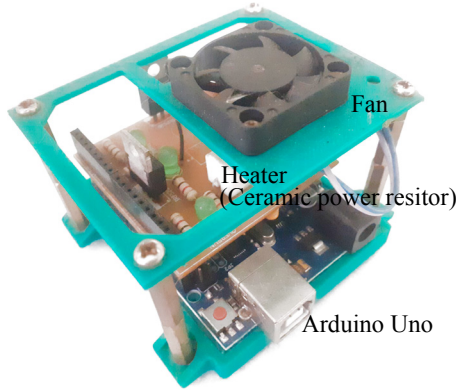


Fig. 1. The developed temperature control device.

filtering technique in heat transfer science. To the best of the authors' knowledge, a Kalman filtering technique is not very common in heat transfer science. Moreover, using a Kalman filtering technique for parameter estimation is not as common as using it for state estimation.

This paper organizes as follows. In Section 2, we describe the hardware design of the thermal test device. In Section 3, we perform system modeling. In Section 4, we implement and test the online parameter estimation procedures. In Section 5, we evaluate the estimation results. Finally, we present our conclusion in Section 6.

## 2. HARDWARE DESCRIPTION

The thermal device that we use for testing purpose in this paper is shown in Fig. 1. The device is compact in size and stacked on top of an Arduino Uno (Arduino AG, Italy) board. To program the Arduino, we use MATLAB Simulink (MathWorks Inc., USA) software in the control computer. The Arduino Uno acts only as an input-output server. The main control program, written with Simulink, runs in the control computer with a sampling frequency of 10 Hz.

The developed device is equipped with one heater (a 27  $\Omega$ /5 W ceramic power resistor) and one small fan. Both the heater's temperature and the fan's speed can be controlled by sending Pulse-Width-Modulation (PWM) signals. An external 12 V / 2 A power supply powers both the heater and the fan. To measure the temperature of the heater, an analog temperature sensor is attached to the heater (LM35).

## 3. PHYSICAL MODELING AND PARAMETER OPTIMIZATION

To model the temperature test-bench, we deployed an energy balance model with a time delay in its input. In an energy balance model, the amount of heat received by a system equals the amount of heat dissipated by that system added with the amount of heat stored in that system. The dissipated heat occurs through both convective and radiative heat losses.

Taking into account the heat loss due to the running fan, we introduce to the model two convective losses: the normal convective loss and the forced convective loss. As

Table 1. Parameter constraints and the optimized parameters.

	Constraints		Optimized Values
	Upper	Lower	
$h_1$	100	10	41.563
$h_2$	200	10	99.955
$\varepsilon$	1	0.9	0.950
$c_r$	2000	1	1599.672
$\theta$	15	5	10.002

a result, the governing dynamic equation of the proposed thermal test device can be expressed as follows:

$$\underbrace{\alpha(t-\theta)P_{\max}}_{\text{Generated heat}} = \underbrace{mc_r \frac{dT_r(t)}{dt}}_{\text{Stored heat}} + \underbrace{h_1(T_r(t) - T_\infty)}_{\text{Normal convective loss}} + \underbrace{\varepsilon\sigma A(T_r(t)^4 - T_\infty^4)}_{\text{Radiative loss}} + \underbrace{\gamma(t)h_2(T_r(t) - T_\infty)}_{\text{Forced convective loss}} \quad (1)$$

The nomenclature for Equation 1 is as follows:

- $c_r$  is the heat capacity of the power resistor (in J/(kg K)).
- $h_1$  and  $h_2$  are the normal and forced convective heat transfer coefficients, respectively (in W/(m<sup>2</sup>K)).
- $T_r$  and  $T_\infty$  are the power resistor's temperature and the ambient temperature, respectively (in Kelvin).
- $\varepsilon$  is the emissivity (unitless).
- $\sigma$  is the Stefan-Boltzmann constant ( $5.67 \times 10^{-8}$  W/(m<sup>2</sup>K<sup>4</sup>)).
- $\gamma$  is the applied PWM input to the fan (from 0 to 1, unit-less).
- $\alpha$  is the PWM input applied to the heater (from 0 to 1, unit-less).
- $\theta$  is the input time delay (in seconds).
- $P_{\max}$  is the maximum power that can be delivered to the power resistor ( $P_{\max} = 5.3$  W).

Additionally, there are several parameters whose values are approximated from measurements by using a ruler and a weight scale. They are the mass ( $m = 0.005$  kg) and the surface area ( $A = 0.0008$ m<sup>2</sup>) of the ceramic power resistor.

Once we have established the template model, the next step is to find the unknown parameters' values, which are  $h_1$ ,  $h_2$ ,  $\varepsilon$ ,  $c_r$ , and  $\theta$ , using an optimization technique. To do this, we stimulated the test device with arbitrary PWM signals for both inputs while at the same time we recorded the resulting temperature (the top plot in Figure 2). After that, we then performed an optimization process to find the optimal values of the parameters mentioned above using the collected data (the center plot in Figure 2). Here, we use a MATLAB built-in `fmincon` command, a nonlinear optimization technique with predefined parameter constraints. Details on this topic can be found in Kristiana and Manurung (2021).

The predefined constraints and the resulting optimized parameters are shown in Table 1. In Figure 2, we compare the output from the optimized model with the actual measurements. The optimized energy balance model fits the actual measurements nicely with a maximum absolute error of 5 degrees centigrade.



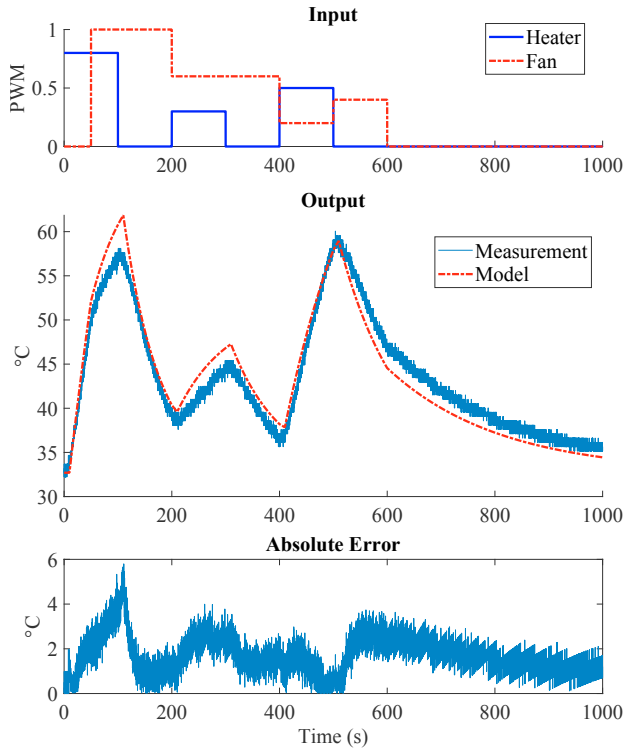


Fig. 2. Comparison between the actual temperature and the temperature calculated by the optimized model.

#### 4. EXTENDED KALMAN FILTER DESIGN

An EKF is a type of Kalman filter for a nonlinear system. From Equation 1, we notice that the system's nonlinearity comes from the radiative term. However, the contribution of this radiative term is minimal when compared to the other two convective terms. Thus, the nonlinearity most certainly comes from the model's parameters, not from the model itself.

In this section, we first generate a new state-space model that includes the four parameters we want to estimate, which are  $T_\infty$ ,  $h_1$ ,  $h_2$  and  $c_r$ . After that, we apply the EKF procedure to estimate the values of those parameters.

##### 4.1 The Parametrization

To implement the EKF, we must first formulate the energy balance model in Equation 1 into its canonical state-space model. First, Equation 1 can be rewritten as follows:

$$\frac{dT_r(t)}{dt} = \frac{1}{mc_r} \left\{ \alpha(t - \theta)P_{\max} + h_1(T_\infty - T_r(t)) + \gamma(t)h_2(T_\infty - T_r(t)) + \varepsilon\sigma A(T_\infty^4 - T_r(t)^4) \right\} \quad (2)$$

Next, by using a finite difference method, we can discretize Equation 2 as follows:

$$\frac{dT(t)}{dt} = \frac{T_r(t + \Delta t) - T_r(t)}{\Delta t} \quad (3)$$

$$T_r(t + \Delta t) = \frac{dT(t)}{dt} \Delta t + T_r(t)$$

where  $\Delta t$  is the discretization sampling time. Substituting Equation 2 to Equation 3 will give us:

$$T_r(t + \Delta t) = \frac{\Delta t}{mc_r} \left\{ \alpha(t - \theta)P_{\max} + h_1(T_\infty - T_r(t)) + \gamma(t)h_2(T_\infty - T_r(t)) + \varepsilon\sigma A(T_\infty^4 - T_r(t)^4) \right\} + T_r(t) \quad (4)$$

After that, we selected four model parameters that we want to estimate by using the EKF. They are the ambient temperature ( $T_\infty$ ), the normal convective heat transfer coefficient ( $h_1(t)$ ), the forced convective heat transfer coefficient ( $h_2(t)$ ) and the power resistor heat capacity ( $c_r(t)$ ). From this point, those four parameters are now functions of time. Let us now introduce new state variables  $\mathbf{z}(k)$  as follows:

$$\mathbf{z}(k) = [z_1(k) \ z_2(k) \ z_3(k) \ z_4(k) \ z_5(k)]^T = [T_r(k) \ T_\infty(k) \ h_1(k) \ h_2(k) \ c_r(k)]^T \quad (5)$$

where  $k = 0, 1, 2, \dots$  and  $t = k\Delta t$ . In total, there are five new variables: one state variable and four parameters.

Let us consider an input vector  $\mathbf{u}(k) = [u_1(k) \ u_2(k)]^T = [\alpha(k) \ \gamma(k)]^T$ . Thus, we can complete the state-space form as follows:

$$z_1(k+1) = \frac{\Delta t}{m z_5(k) z_1(k)} \left\{ u_1 \left( k - \frac{\theta}{\Delta t} \right) P_{\max} + z_3(k)(z_2(k) - z_1(k)) + u_2(k)z_4(k)(z_2(k) - z_1(k)) + \varepsilon\sigma A(z_2(k)^4 - z_1(k)^4) \right\} + z_1(k) + v_1(k) \quad (6)$$

$$z_2(k+1) = z_2(k) + v_2(k)$$

$$z_3(k+1) = z_3(k) + v_3(k)$$

$$z_4(k+1) = z_4(k) + v_4(k)$$

$$z_5(k+1) = z_5(k) + v_5(k)$$

where  $\mathbf{v}(k) = [v_1(k) \ v_2(k) \ v_3(k) \ v_4(k) \ v_5(k)]^T$  is the additive process noise. Since the only measurable output is  $z_1(k)$ , the output becomes a scalar and its equation can be written as follows:

$$\mathbf{y}(k) = [1 \ 0 \ 0 \ 0 \ 0] \mathbf{z}(k) + \mathbf{w}(k) \quad (7)$$

where  $\mathbf{y}(k) \in \mathbb{R}$  is the output vector and  $\mathbf{w}(k) \in \mathbb{R}$  is the additive measurement noise vector. Both  $\mathbf{v}(k)$  and  $\mathbf{w}(k)$  are assumed to be zero-mean white Gaussian distribution.

##### 4.2 The Extended Kalman Filter Procedure

First, let us reformulate Equation 6 and Equation 7 into their formal short forms.

$$\mathbf{z}(k) = f(\mathbf{z}(k-1), \mathbf{u}(k-1)) + \mathbf{v}(k-1) \quad (8)$$

$$\mathbf{y}(k) = h(\mathbf{z}(k)) + \mathbf{w}(k)$$

Next, we will implement the EKF procedure for the two equations above, which consists of two repetitive procedures (see Chui and Chen (2017)): time update and measurement update.

*Time Update* Let us introduce  $\hat{\mathbf{z}}_p(k)$  and  $\hat{\mathbf{z}}(k)$  as the prior and posterior estimate of  $\mathbf{z}(k)$ , respectively. Hence, the



time update procedure of the EKF can then be written as follows:

$$\begin{aligned}\hat{\mathbf{z}}_p(k) &= f(\hat{\mathbf{z}}(k-1), \mathbf{u}(k-1)) + \mathbf{v}(k-1) \\ \mathbf{P}_p(k) &= \mathbf{F}(k)\mathbf{P}(k-1)\mathbf{F}^T(k) + \mathbf{Q}\end{aligned}\quad (9)$$

where  $\mathbf{P}_p(k) \in \mathbb{R}^{5 \times 5}$  and  $\mathbf{P}(k) \in \mathbb{R}^{5 \times 5}$  are the prior and posterior error covariance matrix, respectively; and  $\mathbf{Q} \in \mathbb{R}^{5 \times 5}$  is the covariance matrix of  $\mathbf{v}(k)$ .  $\mathbf{F}(k) \in \mathbb{R}^{5 \times 5}$  is the Jacobian of  $f(\hat{\mathbf{z}}(k))$  and can be calculated as follows:

$$\mathbf{F}(k) = \frac{\partial f(\hat{\mathbf{z}}(k-1), \mathbf{u}(k-1))}{\partial \hat{\mathbf{z}}(k-1)} \quad (10)$$

Equation 10 is solved numerically by using a finite difference method.

Before the first iteration, we initialize  $\hat{\mathbf{z}}(0)$  and  $\mathbf{P}(0)$  as follows:

$$\begin{aligned}\hat{\mathbf{z}}(0) &= [32.7 \ 32.7 \ 41.563 \ 99.955 \ 1599.672]^T \\ \mathbf{P}(0) &= \mathbf{I} \in \mathbb{R}^{5 \times 5}\end{aligned}\quad (11)$$

where  $\mathbf{I}$  is an identity matrix. The initial value for  $\hat{z}_1(0)$  and  $\hat{z}_2(0)$  are set to be close to the current room temperature. While for the remaining, their initial values are the optimal values that we have already found in the previous section (see Table 1).

*Measurement Update* Let us introduce  $\mathbf{K}(k) \in \mathbb{R}$  as the Kalman gain,  $\mathbf{R} \in \mathbb{R}$  as the covariance matrix of  $\mathbf{w}$ , and  $\mathbf{I} \in \mathbb{R}^{5 \times 5}$  as an identity matrix. The measurement update is implemented as follows:

$$\begin{aligned}\mathbf{K}(k) &= \mathbf{P}_p(k)\mathbf{H}^T(k) \left( \mathbf{H}(k)\mathbf{P}_p(k)\mathbf{H}^T(k) + \mathbf{R} \right)^{-1} \\ \hat{\mathbf{z}}(k) &= \hat{\mathbf{z}}_p(k) + \mathbf{K}(k) \left( \mathbf{z}(k) - \mathbf{H}(k)\hat{\mathbf{z}}_p(k) \right) \\ \mathbf{P}(k) &= \left( \mathbf{I} - \mathbf{K}(k)\mathbf{H}(k) \right) \mathbf{P}_p(k)\end{aligned}\quad (12)$$

where  $\mathbf{H} \in \mathbb{R}^{1 \times 5}$  is the Jacobian of  $h(\hat{\mathbf{z}}(k))$  and can be calculated as follows:

$$\mathbf{H}(k) = \frac{\partial h(\hat{\mathbf{z}}_p(k))}{\partial \hat{\mathbf{z}}_p(k)} \quad (13)$$

Similar to Equation 10, we also solve Equation 13 numerically by using a finite difference method.

### 4.3 Estimation Results

For a preliminary test, we ran the EKF procedure offline for 1000 seconds, with a sampling time of 0.1 seconds, using the same dataset as in Figure 2. Matrices  $\mathbf{Q}$  and  $\mathbf{R}$  are heuristically set to be as follows:

$$\begin{aligned}\mathbf{Q} &= 0.4 \times \mathbf{I} \in \mathbb{R}^{5 \times 5} \\ \mathbf{R} &= 10\end{aligned}\quad (14)$$

where  $\mathbf{I}$  is an identity matrix.

The power resistor's estimated temperature is presented in Figure 3, along with the measured temperature. Estimated model parameters:  $T_\infty$ ,  $h_1$ ,  $h_2$ , and  $c_r$  are presented in Figure 4, Figure 5, Figure 6, and Figure 7, respectively. All of these figures show the evolution of the model parameters as functions of time although the changes are relatively very small. The largest changes that can be seen from the figures above is in the ambient temperature.

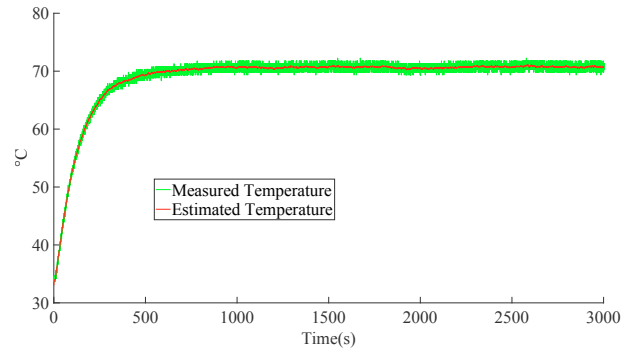


Fig. 3. Measured temperature ( $y(k)$ ) compared to the estimated temperature ( $\hat{z}_1(k)$ ).

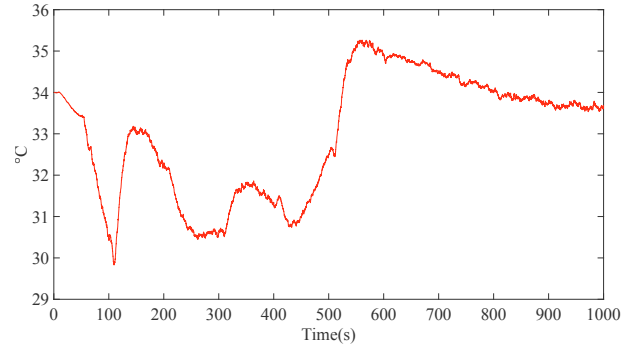


Fig. 4. Estimated ambient temperature ( $z_2(k)$  or  $T_\infty(k)$ ).

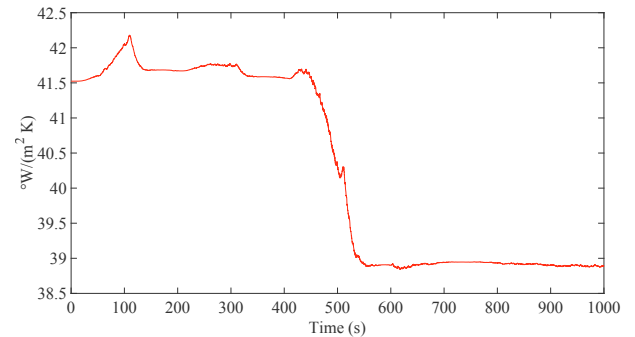


Fig. 5. Estimated normal convective heat transfer coefficient ( $z_3(k)$  or  $h_1(k)$ ).

However, there is no guarantee that we can ignore such slight variations in the model parameters. We will investigate this issue in the next section. Moreover, due to the nature of the deployed model, we must be aware that the selected initial values may significantly affect the parameter estimation results, although the state estimation may not be affected. Therefore, the preliminary optimization procedure is a crucial part of this EKF procedure.

## 5. EVALUATION WITH A CONSTANT INPUT EXPERIMENT

In Section 3, the data-set used for the optimization procedure was collected from the device transient phase only. On the contrary, we evaluated the developed model by using a different data-set collected during the device steady-state phase to create a more significant discrepancy between the model and the experiment. Therefore, we collected the data by applying 50% of PWM input to the heater and the

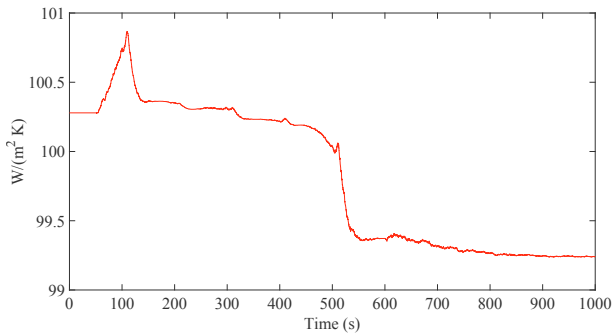


Fig. 6. Estimated forced convective heat transfer coefficient ( $z_4(k)$  or  $h_2(k)$ ).

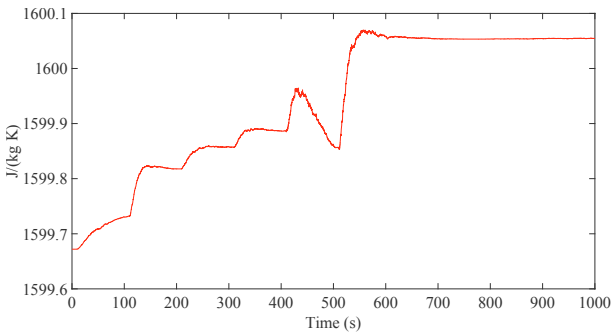


Fig. 7. Estimated power resistor's heat capacity ( $z_5(k)$  or  $c_r(k)$ ).

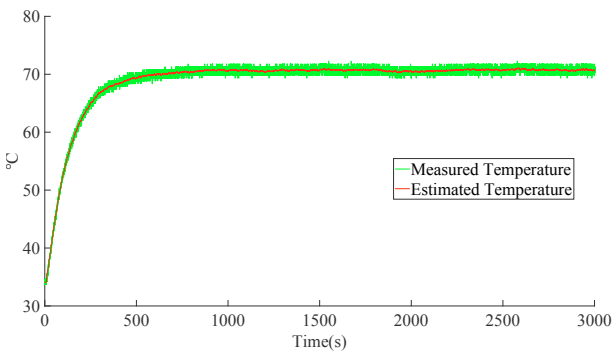


Fig. 8. Measured temperature ( $y(k)$ ) compared to the estimated temperature ( $\hat{z}_1(k)$ ) for constant inputs.

fan for a more extended period, which was 3000 seconds. As a result, the power resistor's temperature rose to about 70 degrees of centigrade (see Figure 8), and mostly, it was seated in its steady-state condition. At the same time, the EKF procedure was running, performing estimations to the state and the model parameters.

The EKF was initialized with the optimal parameter values as in Table 1. The estimated state, in this case, the power resistor's temperature, is also shown in Figure 8. While for the estimated model parameters, they are shown in Figure 9, Figure 10, 11, and Figure 12. Similar to the earlier experiments, changes in those model parameters are also relatively very small.

Nonetheless, those small changes may still contribute to performance differences. To test this idea, we implemented a test scenario with two models. One model receives parameter updates from the EKF, while another model

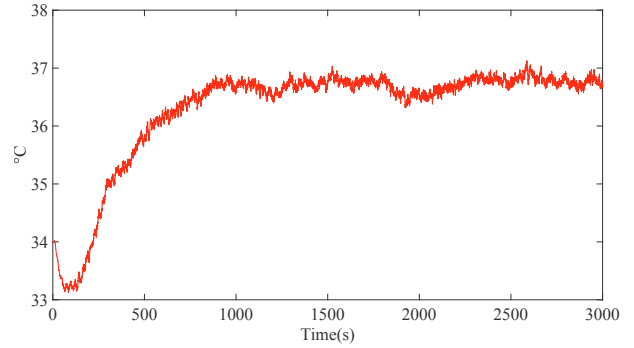


Fig. 9. Estimated ambient temperature ( $z_2(k)$  or  $T_\infty(k)$ ) for constant inputs.

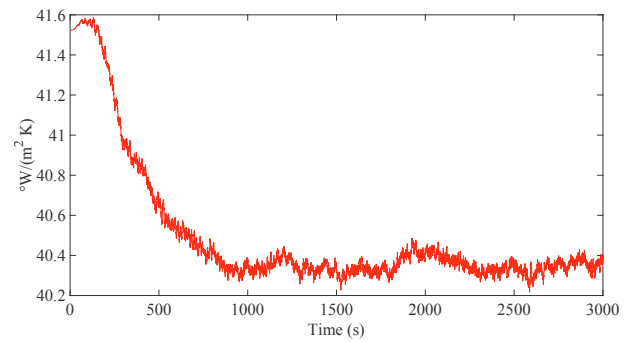


Fig. 10. Estimated normal convective heat transfer coefficient ( $z_3(k)$  or  $h_1(k)$ ) for constant inputs.

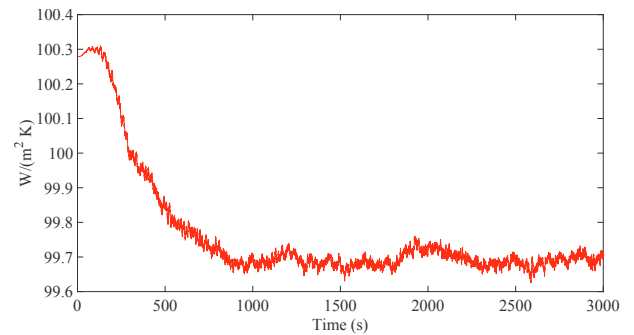


Fig. 11. Estimated forced convective heat transfer coefficient ( $z_4(k)$  or  $h_2(k)$ ) for constant inputs.

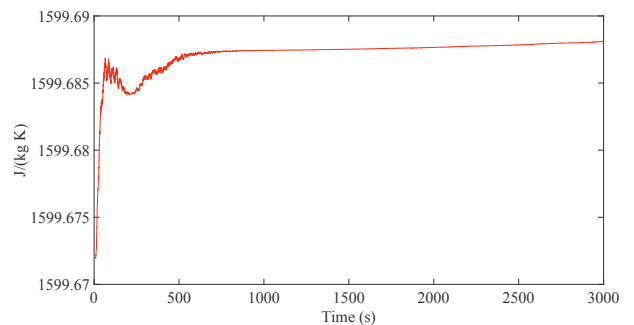


Fig. 12. Estimated power resistor's heat capacity ( $z_5(k)$  or  $c_r(k)$ ) for constant inputs.

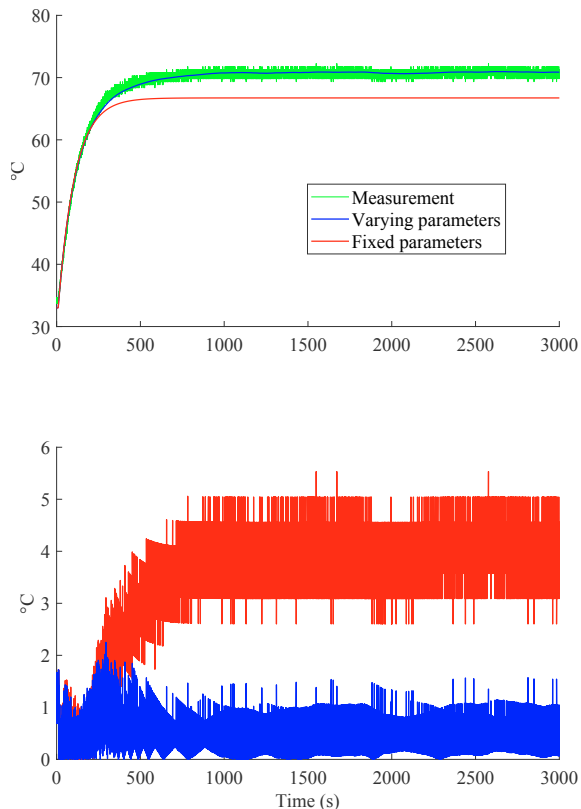


Fig. 13. The model with sn online parameter update provides better estimations.

has its parameters set to fixed optimal values from Table 1. For each model, we compare its output to the measured temperature from the actual device. As shown in Figure 13, the model that receives parameter updates from an EKF does provide better estimation to the actual power resistor's temperature (top figure). The model with fixed parameter gives a maximum estimation error of about five degrees centigrade. As for the model with adaptive parameters, the maximum estimation error is smaller, which is about two degrees centigrade (bottom figure).

## 6. CONCLUSION AND FUTURE WORK

This paper has performed modeling of a thermal system and implemented an EKF to estimate its state and model parameters. Using an EKF for parameter estimation allows us to improve the modeling performance. An accurate model is often necessary for control applications, especially model-based controls. However, this method might only be applicable for a process system with low noise sensor readings and a sufficiently good initial model and parameter guesses. Such limitations are caused by the nature of the model we selected, where the implemented EKF can pick many local optimal values. Finding a more robust function template becomes another topic that needs more in-depth studies.

On the other hand, the model that we deployed can be considered as simple. It is a zero-order energy balance model with two input variables, one state variable, and one output variable. However, there are five model parameters for the implemented EKF to estimate, which causes the solutions to the model parameters to become mathemat-

ically non-unique. In a more complex system, such as in a higher-order energy balance model, in which there are more state and output variables, the improvement offered by the implemented EKF to the modeling is expected to be higher since the system has fewer local optimum solutions. Thus, in the future, we plan to implement this method into a more complex system.

## REFERENCES

- Barbosa, R.S. (2020). Educational platform for modeling and control. *IEEE International Conference on Technologies Applied to Electronics Teaching Conference*, 1–9.
- Blanchard, E.D., Sandu, A., and Sandu, C. (2007). Parameter Estimation for Mechanical Systems Using an Extended Kalman Filter. *Proceedings of the Joint North America, Asia-Pacific ISTVS Conference and Annual Meeting of Japanese Society for Terramechanics*, 1–14.
- Chui, C.K. and Chen, G. (2017). *Kalman Filtering with Real-Time Applications*. Springer International Publishing AG, Cham, Switzerland, 5 edition.
- Cui, W., Tan, W., Li, D., and Wang, Y. (2020). Tuning of Linear Active Disturbance Rejection Controllers Based On Step Response Curves. *IEEE Access*, 8.
- Jonsson, G. and Palsson, O.P. (1994). An application of extended kalman filtering to heat exchanger models. *Journal of Dynamic Systems, Measurement and Control, Transactions of the ASME*, 116(2), 257–264.
- Kim, J., Cho, K., and Choi, S. (2016). Lumped disturbance compensation using extended Kalman filter for permanent magnet linear motor system. *International Journal of Control, Automation and Systems*, 14(5), 1244–1253.
- Kristiana, L. and Manurung, A. (2021). An Energy Balance Model for a Small Educational Thermal Device. *ELKOMIKA*, 9(2), 333–343.
- Mutambara, A.G. and Al-Haik, M.S. (1999). EKF based parameter estimation for a heat exchanger. *Proceedings of the American Control Conference*, 6, 3918–3922.
- Park, J., Martin, R.A., Kelly, J.D., and Hedengren, J.D. (2020). Benchmark temperature microcontroller for process dynamics and control. *Computers and Chemical Engineering*, 135, 106736.
- Roques, L., Chekroun, M.D., Cristofol, M., Soubeyrand, S., and Ghil, M. (2014). Parameter estimation for energy balance models with memory. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 470.
- Song, D., Yang, J., Dong, M., and Joo, Y.H. (2017). Kalman filter-based wind speed estimation for wind turbine control. *International Journal of Control, Automation and Systems*, 15(3), 1089–1096.
- Tran, L.Q., Radcliffe, P., and Wang, L. (2019). A low budget take-home control engineering laboratory for undergraduate. *International Journal of Electrical Engineering and Education*, Online First.
- Walker, D.M. (2006). Parameter estimation using kalman filters with constraints. *International Journal of Bifurcation and Chaos*, 16(4), 1067–1078.
- Yanou, A., Hosoya, N., Wada, K., Minami, M., and Matsuno, T. (2016). Estimation of thermal conductivity for model with radiative heat transfer by extended Kalman filter. *IEEE International Conference on Emerging Technologies and Factory Automation*, 1–4.