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# Intelligent Data Mining and Analysis in Power and Energy Systems

Models and Applications for Smarter Efficient Power Systems

EDITED BY Zita Vale, Tiago Pinto, Michael Negnevitsky, Ganesh Kumar Venayagamoorthy







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# Edited by

# Zita Vale

GECAD Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) Polytechnic Institute of Porto (ISEP/IPP) Porto, Portugal

# Tiago Pinto

GECAD Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) Polytechnic Institute of Porto (ISEP/IPP) Porto, Portugal and University of Trás-os-Montes e Alto Douro Vila Real, Portugal

# Michael Negnevitsky

School of Engineering, University of Tasmania Hobart, Tasmania, Australia

# Ganesh Kumar Venayagamoorthy

Holcombe Department of Electrical and Computer Engineering, Real-Time Power and Intelligent Systems Laboratory Clemson University Clemson, SC, USA and School of Engineering University of KwaZulu-Natal Durban, South Africa



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"To our dear Parents and Children"

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# About the Editors

**Zita Vale**, IEEE Senior Member, graduated in electrical engineering in 1986, received the PhD degree in electrical and computer engineering in 1993, and the Agregação title (Habilitation) in 2003 from the University of Porto, Portugal. She is a full professor in the School of Engineering, Polytechnic of Porto. She leads the research activities on Intelligent Power and Energy Systems at GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development. She has been involved in more than 60 R&D projects and published more than 200 papers in international scientific journals. Her scientific research activities mainly focus on Power and Energy Systems Operation, Electricity Markets, Demand Response, Renewables, Electric Vehicles, and Distributed Generation and Storage. She has been developing artificial-intelligence-based models, methods, and applications for power and energy, using agents and multiagent systems, knowledge-based systems, semantics, machine learning, data mining, and evolutionary computation.

She actively participates in several technical working groups and committees. She is the chair of the IEEE PES Intelligent Data Analysis and Mining (IDMA) Working Group and of the Open Data Sets (ODS) Task Force. She is the chair of the board of directors of ISAP – Intelligent Systems Application to Power Systems. She is involved in editing activities for different journals and books and is a regular reviewer and evaluator for papers and for project proposals and monitoring from different funding agencies around the world.

**Tiago Pinto** is an assistant professor at the Universidade de Trás os Montes e Alto Douro (UTAD), Portugal, and researcher at INESC-TEC. He has concluded the BSc and MSc, both at the School of Engineering of the Polytechnic of Porto, where he has also developed his research work for more than 10 years, namely at GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development. He got the PhD from UTAD in 2016, after which he engaged in a postdoc at the University of Salamanca, in collaboration with the University of Oxford and ENGIE. His main research interests focus on artificial intelligence and its application in power and energy systems, particularly machine learning, multi-agent systems, decision support systems, and metaheuristic optimization. Through the involvement in more than 30 research projects in these fields, he has authored over 200 publications in international journals and conferences, and has co-edited several books and special issues in journals related to power and energy systems and artificial intelligence.

**Michael Negnevitsky** received the BE (Hons) in Electrical Engineering degree and PhD degree from Byelorussian University of Technology, Minsk, Belarus, in 1978 and 1983, respectively. From 1978 to 1980, he worked at the Electrical Maintenance, Construction and Commissioning Company, and from 1984 to 1991, he was Senior Research Fellow at the Department of Electrical Engineering, Byelorussian University of Technology, Minsk. After his arrival to Australia, he worked

# **xx** About the Editors

at Monash University, Melbourne, and then the University of Tasmania. Currently he is Professor and Chair in Power Engineering and Computational Intelligence, and Director of the Centre for Renewable Energy and Power Systems.

His research interests include power system analysis and control, micro-grids with distributed and renewable energy resources, smart grids, power quality and applications of artificial intelligence in power systems. He has published more than 450 papers in high-quality journals and refereed conference proceedings, authored 14 chapters in several books, and received 4 patents for inventions. His book *Artificial Intelligence* (Addison Wesley 2002, 2005, 2011) has been translated into Mandarin, Cantonese, Korean, Greek, and Vietnamese and adopted in many universities around the world.

He is Fellow of Engineers Australia, Fellow of the Japan Society for the Promotion of Science, Member of CIGRE AP C4 (System Technical Performance) and AP C6 (Distribution Systems and Dispersed Generation), Australian Technical Committee. Dr. Negnevitsky has served as Secretary and Deputy Chair of IEEE PES Energy Development and Power Generation Committee, Chair of IEEE PES International Practices Subcommittee, and Chair of the IEEE PES Working Group on High Renewable Energy Penetration in Remote and Isolated Power Systems. In 2018, he received the Joint Australasian Committee for Power Engineering and CIGRE Australia Award for "outstanding career-long contributions to research and teaching in electric power engineering as well as contribution to industry and CIGRE activities."

**Ganesh Kumar Venayagamoorthy** is the Duke Energy Distinguished Professor of Power Engineering and Professor of Electrical and Computer Engineering at Clemson University since January 2012. Prior to that, he was a Professor of Electrical and Computer Engineering at the Missouri University of Science and Technology (Missouri S&T), Rolla, USA, where he was from 2002 to 2011. Dr. Venayagamoorthy was a Senior Lecturer in Department of Electronic Engineering, Durban University of Technology, Durban, South Africa, where he was from 1996 to 2002. Dr. Venayagamoorthy is the Founder and Director of the Real-Time Power and Intelligent Systems Laboratory at Missouri S&T and Clemson University.

Dr. Venayagamoorthy received his PhD and MScEng degrees in Electrical Engineering from the University of Natal, Durban, South Africa, in April 2002 and April 1999, respectively. He received his BEng degree with a First-Class Honors in Electrical and Electronics Engineering from Abubakar Tafawa Balewa University, Bauchi, Nigeria, in March 1994. He holds an MBA degree in Entrepreneurship and Innovation from Clemson University, SC (August 2016).

Dr. Venayagamoorthy's interests are in research, development and innovation of power systems, smart grid, and artificial intelligence technologies. Dr. Venayagamoorthy is a Fellow of the IEEE, IET (UK), the South African Institute of Electrical Engineers (SAIEE) and Asia-Pacific Artificial Intelligence Association (AAIA), and a Senior Member of the International Neural Network Society.

# **List of Contributors**

#### A. Ahmed

Smart Grid Demonstration and Research Investigation Lab Washington State University Pullman, WA USA

#### Hirohisa Aki

Faculty of Engineering, Information and Systems University of Tsukuba Tsukuba, Ibaraki Japan

#### **Philipp Andelfinger**

Institute for Visual and Analytic Computing University of Rostock Rostock Germany

#### Victor Andrean

Department of Electrical Engineering National Taiwan University of Science and Technology Taipei Taiwan

#### Ramón Aranda

Tepic Technology Transfer Unit, Center for Scientific Research and Higher Education of Ensenada Tepic, Nayarit, Mexico

and

National Council of Science and Technology Mexico City, Mexico City Mexico

#### Nelson F. Avila

Independent Electricity System Operator Toronto, ON Canada

#### Wenlei Bai

Oracle Energy and Water Austin, TX USA

#### Rúben Barreto

Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) Institute of Engineering Polytechnic of Porto Porto Portugal

#### Miguel A. Carmona

Tepic Technology Transfer Unit, Center for Scientific Research and Higher Education of Ensenada Tepic Nayarit Mexico and

National Council of Science and Technology Mexico City Mexico City Mexico

```
xxii List of Contributors
```

Rajeev K. Chauhan

Department of Electrical Engineering, Faculty of Engineering Dayalbagh Educational Institute Agra, Uttar Pradesh India

# Chia-Chi Chu

Department of Electrical Engineering National Tsing Hua University HsinChu Taiwan, R.O.C.

# Juan M. Corchado

BISITE research group University of Salamanca Salamanca Spain

# Pavel Etingov

Pacific Northwest National Laboratory Richland, WA USA

# Pedro Faria

GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development Porto Portugal

# Gerardo Figueroa

Sentiance NV Antwerpen Belgium

# Zahra Forouzandeh

GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Polytechnic of Porto, School of Engineering (ISEP) Porto Portugal

# Reza Ghorbani

Renewable Energy Design Laboratory (REDLab), Department of Mechanical Engineering University of Hawaii at Manoa Honolulu, HI USA

# James Hamilton

School of Engineering, University of Tasmania Hobart Tasmania Australia

# Jens B. Holm-Nielsen

Department of Energy Technology Center for Bioenergy and Green Engineering Aalborg University Esbjerg Denmark

# Zhangshuan Hou

Pacific Northwest National Laboratory Richland, WA USA

# Qiuhua Huang

Pacific Northwest National Laboratory Richland, WA USA

# Xinda Ke

Pacific Northwest National Laboratory Richland, WA USA

# Irfan Khan

Supreme & Co. Pvt. Ltd. Kolkata, West Bengal India

# Rahmat Khezri

College of Science and Engineering Flinders University Adelaide, SA Australia

# Olivera Kotevska

Computer Science and Mathematics Oak Ridge National Laboratory Tennessee Oak Ridge USA

# Duehee Lee

Electrical Engineering Department Konkuk University Seoul Korea

# Kwang Y. Lee

Electrical and Computer Engineering Department Baylor University Waco, TX USA

# Fernando Lezama

Polytechnic of Porto (ISEP/IPP), Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) Porto Portugal

# Kuo-Lung Lian

Department of Electrical Engineering National Taiwan University of Science and Technology Taipei Taiwan

# Wen-Kai Lu

Department of Information Management National Taiwan University Taipei Taiwan, R.O.C.

# Amin Mahmoudi

College of Science and Engineering, Flinders University Adelaide, SA Australia

#### Achora P.O. Mamur

Faculty of Sociology, Environmental and Business Economics University of Southern Denmark Esbjerg Denmark

# Samson Masebinu

Department of Energy Technology, Center for Bioenergy and Green Engineering Aalborg University Esbjerg Denmark

# Hamed Moayyed

GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Polytechnic of Porto (P.PORTO) Porto Portugal

#### Behnam Mohammadi-Ivatloo

Faculty of Electrical and Computer Engineering University of Tabriz Tabriz Iran

# Arash Moradzadeh

Faculty of Electrical and Computer Engineering University of Tabriz Tabriz Iran

# Bruno Mota

GECAD Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) Polytechnic Institute of Porto (ISEP/IPP) Porto Portugal xxiv List of Contributors

# Sushri Mukherjee

Indian Institute of Technology Delhi Hauz Khas New Delhi India

# Michael Negnevitsky

School of Engineering, University of Tasmania Hobart Tasmania Australia

# Angel D. Pacheco

Tepic Technology Transfer Unit, Center for Scientific Research and Higher Education of Ensenada Tepic Nayarit Mexico

# S. Pandey

Smart Grid and Technology ComEd Oakbrook Terrace, IL USA

# Chirath Pathiravasam

Holcombe Department of Electrical and Computer Engineering, Real-Time Power and Intelligent Systems Laboratory Clemson University Clemson, SC USA

and

Department of Electrical Engineering University of Moratuwa Katubedda Sri Lanka

# Tiago Pinto

GECAD Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) Polytechnic Institute of Porto (ISEP/IPP) Porto Portugal

# and

University of Trás-os-Montes e Alto Douro Vila Real Portugal

#### Dharmbir Prasad

Asansol Engineering College Asansol, West Bengal India

#### **Carlos Ramos**

GECAD Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) Polytechnic Institute of Porto (ISEP/IPP) Porto Portugal

# Sérgio Ramos

GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Polytechnic of Porto, School of Engineering (ISEP) Porto Portugal

# Huiying Ren

Pacific Northwest National Laboratory Richland, WA USA

# Ansel Y. Rodríguez González

Tepic Technology Transfer Unit, Center for Scientific Research and Higher Education of Ensenada Tepic Nayarit Mexico and National Council of Science and Technology Mexico City

Mexico City Mexico

# Sajan K. Sadanandan

Smart Grid Integration R&D Center, Dubai Electricity & Water Authority (DEWA) Dubai UAE

# Evgenii Semshikov

School of Engineering, University of Tasmania Hobart, Tasmania Australia

# Mahendra P. Sharma

Department of Hydro and Renewable Energy Indian Institute of Technology Roorkee, Uttarakhand India

# Cátia Silva

GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development Porto Portugal

# Rudra P. Singh

Asansol Engineering College Asansol, West Bengal India

# João Soares

GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Polytechnic of Porto, School of Engineering (ISEP) Porto Portugal

# Anurag K. Srivastava

Smart Grid Resiliency and Analytics Lab West Virginia University Morgantown, WV USA

# Subho Upadhyay

Department of Electrical Engineering, Faculty of Engineering Dayalbagh Educational Institute Agra, Uttar Pradesh India

# Zita Vale

GECAD Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) Polytechnic Institute of Porto (ISEP/IPP) Porto Portugal

# Ganesh Kumar Venayagamoorthy

Holcombe Department of Electrical and Computer Engineering, Real-Time Power and Intelligent Systems Laboratory Clemson University Clemson, SC USA

and

School of Engineering University of KwaZulu-Natal Durban South Africa

# Xiaolin Wang

School of Engineering, University of Tasmania Hobart, Tasmania Australia

# Foreword

Recent machine learning and data analytics methods have proliferated into most areas of science, engineering, and commerce. There are excellent reasons for their increasing popularity and applications. Many real-world problems are too complex to come up with closed-form analytical solutions. However, such challenges did not make practitioners idle; instead, they have created working models, prototypes and even built systems with a careful understanding of critical components of the systems as a first step. The data generated from such systems are then analyzed by machine learning and data analytics methods to have a more comprehensive understanding of the systems.

This book titled *Intelligent Data Mining and Analysis in Power and Energy Systems* makes a huge leap in this direction in providing a better understanding of power and energy systems. Compiled by Zita Vale, Tiago Pinto, Michael Negnevitsky, and Ganesh Kumar Venayagamoorthy, the book begins with an introduction to machine learning and data analytics methods and then lays out state-of-the-art methods in addressing various topics in power and energy system design, clustering, classification, forecasting, and analysis with latest machine learning and data analytics methods.

The book is self-contained and written for both novice and experts on the topic. The topics are discussed in simple manner with adequate references and details, so that readers can understand the current state-of-the-art and also find relevant past studies in a single volume.

If you are working in power and energy systems either as a researcher or a practitioner, this is a must-have book to stay ahead in the game. Authors are experts in their own fields. The book will save your efforts in searching for materials on the topic, provide you with the latest methodologies, and direct you to other similar past studies.

Kudos to the editors for this compilation and authors for their contributions.

Kalyanmoy Deb University Distinguished Professor Withrow Senior Distinguished Research Scholar Koenig Endowed Chair Professor IEEE CIS Evolutionary Computation Pioneer IEEE Fellow

Department of Electrical and Computer Engineering Michigan State University, East Lansing, MI, USA