


Ana I. Pereira · Armando Mendes ·
Florbela P. Fernandes · Maria F. Pacheco ·
João P. Coelho · José Lima
Editors


Optimization, Learning Algorithms and Applications

Third International Conference, OL2A 2023
Ponta Delgada, Portugal, September 27–29, 2023
Revised Selected Papers, Part II

Editors

Ana I. Pereira 
Instituto Politécnico de Bragança
Bragança, Portugal

Armando Mendes 
University of Azores
Ponta Delgada, Portugal

Florbela P. Fernandes 
Instituto Politécnico de Bragança
Bragança, Portugal

Maria F. Pacheco 
Instituto Politécnico de Bragança
Bragança, Portugal

João P. Coelho 
Instituto Politécnico de Bragança
Bragança, Portugal

José Lima 
Instituto Politécnico de Bragança
Bragança, Portugal

ISSN 1865-0929 ISSN 1865-0937 (electronic)
Communications in Computer and Information Science
ISBN 978-3-031-53035-7 ISBN 978-3-031-53036-4 (eBook)
<https://doi.org/10.1007/978-3-031-53036-4>

© The Editor(s) (if applicable) and The Author(s), under exclusive license
to Springer Nature Switzerland AG 2024
Chapters 13 and 23 are licensed under the terms of the Creative Commons Attribution 4.0 International License
(<http://creativecommons.org/licenses/by/4.0/>). For further details see license information in the chapters.

This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of
the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation,
broadcasting, reproduction on microfilms or in any other physical way, and transmission or information
storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now
known or hereafter developed.

The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication
does not imply, even in the absence of a specific statement, that such names are exempt from the relevant
protective laws and regulations and therefore free for general use.

The publisher, the authors, and the editors are safe to assume that the advice and information in this book
are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the
editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors
or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in
published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Paper in this product is recyclable.

Preface

The volumes CCIS 1981 and 1982 contains the refereed proceedings of the III International Conference on Optimization, Learning Algorithms and Applications (OL2A 2023), a hybrid event held on September 27–29.

OL2A provided a space for the research community in optimization and learning to get together and share the latest developments, trends and techniques as well as develop new paths and collaborations. OL2A had the participation of more than four hundred participants in an online and face-to-face environment throughout three days, discussing topics associated with areas such as optimization and learning and state-of-the-art applications related to multi-objective optimization, optimization for machine learning, robotics, health informatics, data analysis, optimization and learning under uncertainty and 4th industrial revolution.

Six special sessions were organized under the topics Learning Algorithms in Engineering Education, Optimization in the SDG context, Optimization in Control Systems Design, Computer Vision Based on Learning Algorithms, Machine Learning and AI in Robotics and Machine Learning and Data Analysis in Internet of Things. The event had 66 accepted papers. All papers were carefully reviewed and selected from 172 submissions. All the reviews were carefully carried out by a scientific committee of 115 PhD researchers from 23 countries.

The OL2A 2023 volume editors,

September 2023

Ana I. Pereira
Armando Mendes
Florabela P. Fernandes
Maria F. Pacheco
João P. Coelho
José Lima

Organization

General Chairs

Ana I. Pereira	Polytechnic Institute of Bragança, Portugal
Armando Mendes	University of the Azores, Portugal

Program Committee Chairs

Florbela P. Fernandes	Polytechnic Institute of Bragança, Portugal
M. Fátima Pacheco	Polytechnic Institute of Bragança, Portugal
João P. Coelho	Polytechnic Institute of Bragança, Portugal
José Lima	Polytechnic Institute of Bragança, Portugal

Special Session Chairs

João P. Teixeira	Polytechnic Institute of Bragança, Portugal
José Cascalho	University of the Azores, Portugal

Technology Chairs

Paulo Medeiros	University of the Azores, Portugal
Rui Pedro Lopes	Polytechnic Institute of Bragança, Portugal

Program Committee

Ana Isabel Pereira	Polytechnic Institute of Bragança, Portugal
Abeer Alsadoon	Charles Sturt University, Australia
Ala' Khalifeh	German Jordanian University, Jordan
Alberto Nakano	Federal University of Technology – Paraná, Brazil
Alexandre Douplik	Ryerson University, Canada
Ana Maria A. C. Rocha	University of Minho, Portugal
Ana Paula Teixeira	University of Trás-os-Montes and Alto Douro, Portugal
André Pinz Borges	Federal University of Technology – Paraná, Brazil

André Rodrigues da Cruz	Federal Center for Technological Education of Minas Gerais, Brazil
Andrej Košir	University of Ljubljana, Slovenia
António José Sánchez-Salmerón	Universitat Politècnica de València, Spain
António Valente	University of Trás-os-Montes and Alto Douro, Portugal
Armando Mendes	University of the Azores, Portugal
Arnaldo Cândido Júnior	Federal Technological University – Paraná, Brazil
B. Rajesh Kanna	Vellore Institute of Technology, India
Bilal Ahmad	University of Warwick, UK
Bruno Bispo	Federal University of Santa Catarina, Brazil
C. Sweetlin Hemalatha	Vellore Institute of Technology, India
Carlos Henrique Alves	CEFET - Rio de Janeiro, Brazil
Carmen Galé	University of Zaragoza, Spain
Carolina Gil Marcelino	Federal University of Rio de Janeiro, Brazil
Christopher Expósito Izquierdo	University of Laguna, Spain
Clara Vaz	Polytechnic Institute of Bragança, Portugal
Damir Vrančić	Jožef Stefan Institute, Slovenia
Dhiah Abou-Tair	German Jordanian University, Jordan
Diamantino Silva Freitas	University of Porto, Portugal
Diego Brandão	CEFET - Rio de Janeiro, Brazil
Dimitris Glotsos	University of West Attica, Greece
Eduardo Vinicius Kuhn	Federal Technological University – Paraná, Brazil
Elaine Mosconi	Université de Sherbrooke, Canada
Eligius M. T. Hendrix	Malaga University, Spain
Elizabeth Fialho Wanner	Federal Center for Technological Education of Minas Gerais, Brazil
Felipe Nascimento Martins	Hanze University of Applied Sciences, The Netherlands
Florbela P. Fernandes	Polytechnic Institute of Bragança, Portugal
Florentino Fernández Riverola	University of Vigo, Spain
Francisco Sedano	University of León, Spain
Fredrik Danielsson	University West, Sweden
Gaukhar Muratova	Dulaty University, Kazakhstan
Gediminas Daukšys	Kauno Technikos Kolegija, Lithuania
Gianluigi Ferrari	University of Parma, Italy
Glaucia Maria Bressan	Federal University of Technology – Paraná, Brazil
Glotsos Dimitris	University of West Attica, Greece
Humberto Rocha	University of Coimbra, Portugal
João Paulo Carmo	University of São Paulo, Brazil
João Paulo Coelho	Polytechnic Institute of Bragança, Portugal
João Paulo Teixeira	Polytechnic Institute of Bragança, Portugal

Jorge Igual	Universitat Politècnica de Valencia, Spain
Jorge Ribeiro	Polytechnic Institute of Viana do Castelo, Portugal
José Boaventura-Cunha	University of Trás-os-Montes and Alto Douro, Portugal
José Cascalho	University of the Azores, Portugal
José Lima	Polytechnic Institute of Bragança, Portugal
José Ramos	Nova University Lisbon, Portugal
Joseane Pontes	Federal University of Technology – Ponta Grossa, Brazil
Josip Musić	University of Split, Croatia
Juan A. Méndez Pérez	University of Laguna, Spain
Juan Alberto García Esteban	University de Salamanca, Spain
Júlio Cesar Nievola	Pontifícia Universidade Católica do Paraná, Brazil
Kristina Sutiene	Kaunas University of Technology, Lithuania
Laura Belli	University of Parma, Italy
Lidia Sánchez	University of León, Spain
Lino Costa	University of Minho, Portugal
Luca Davoli	University of Parma, Italy
Luca Oneto	University of Genoa, Italy
Luca Spalazzi	Marche Polytechnical University, Italy
Luis Antonio De Santa-Eulalia	Université de Sherbrooke, Canada
Luís Coelho	Polytechnic Institute of Porto, Portugal
M. Fátima Pacheco	Polytechnic Institute of Bragança, Portugal
Mahmood Reza Khabbazi	University West, Sweden
Manuel Castejón Limas	University of León, Spain
Marc Jungers	Université de Lorraine, France
Marco Aurélio Wehrmeister	Federal University of Technology – Paraná, Brazil
Marek Nowakowski	Military Institute of Armoured and Automotive Technology in Sulejowek, Poland
Maria do Rosário de Pinho	University of Porto, Portugal
Martin Hering-Bertram	Hochschule Bremen, Germany
Matthias Funk	University of the Azores, Portugal
Mattias Bennulf	University West, Sweden
Michał Podpora	Opole University of Technology, Poland
Miguel Ángel Prada	University of León, Spain
Mikulas Huba	Slovak University of Technology in Bratislava, Slovakia
Milena Pinto	Federal Center of Technological Education Celso Suckow da Fonseca, Brazil
Miroslav Kulich	Czech Technical University Prague, Czech Republic
Nicolae Cleju	Technical University of Iasi, Romania

Paulo Alves	Polytechnic Institute of Bragança, Portugal
Paulo Leitão	Polytechnic Institute of Bragança, Portugal
Paulo Lopes dos Santos	University of Porto, Portugal
Paulo Medeiros	University of the Azores, Portugal
Paulo Moura Oliveira	University of Trás-os-Montes and Alto Douro, Portugal
Pavel Pakshin	Nizhny Novgorod State Tech University, Russia
Pedro Luiz de Paula Filho	Federal Technological University – Paraná, Brazil
Pedro Miguel Rodrigues	Catholic University of Portugal, Portugal
Pedro Morais	Polytechnic Institute of Cávado e Ave, Portugal
Pedro Pinto	Polytechnic Institute of Viana do Castelo, Portugal
Roberto Molina de Souza	Federal University of Technology – Paraná, Brazil
Rui Pedro Lopes	Polytechnic Institute of Bragança, Portugal
Sabrina Šuman	Polytechnic of Rijeka, Croatia
Sancho Salcedo Sanz	Alcalá University, Spain
Sandro Dias	Federal Center for Technological Education of Minas Gerais, Brazil
Sani Rutz da Silva	Federal Technological University – Paraná, Brazil
Santiago Torres Álvarez	University of Laguna, Spain
Sara Paiva	Polytechnic Institute of Viana do Castelo, Portugal
Shridhar Devamane	Global Academy of Technology, India
Sławomir Stępień	Poznań University of Technology, Poland
Sofia Rodrigues	Polytechnic Institute of Viana do Castelo, Portugal
Sudha Ramasamy	University West, Sweden
Teresa Paula Perdicoulis	University of Trás-os-Montes and Alto Douro, Portugal
Toma Rancevic	University of Split, Croatia
Uta Bohnebeck	Hochschule Bremen, Germany
Virginia Castillo	University of León, Spain
Vítor Duarte dos Santos	Nova University Lisbon, Portugal
Vitor Pinto	University of Porto, Portugal
Vivian Cremer Kalempa	State University of Santa Catarina, Brazil
Wojciech Giernacki	Poznań University of Technology, Poland
Wojciech Paszke	University of Zielona Gora, Poland
Wynand Alkema	Hanze University of Applied Sciences, The Netherlands
Zahia Guessoum	University of Reims Champagne-Ardenne, France

Contents – Part II

Computer Vision Based on Learning Algorithms

Assessing the Reliability of AI-Based Angle Detection for Shoulder and Elbow Rehabilitation	3
<i>Luan C. Klein, Arezki Abderrahim Chellal, Vinicius Grilo, José Gonçalves, Maria F. Pacheco, Florbela P. Fernandes, Fernando C. Monteiro, and José Lima</i>	
Movement Pattern Recognition in Boxing Using Raw Inertial Measurements	19
<i>Radosław Puchalski and Wojciech Giernacki</i>	
An Evaluation of Image Preprocessing in Skin Lesions Detection	35
<i>Giuliana M. Silva, André E. Lazzaretti, and Fernando C. Monteiro</i>	
Pest Detection in Olive Groves Using YOLOv7 and YOLOv8 Models	50
<i>Adília Alves, José Pereira, Salik Khanal, A. Jorge Morais, and Vitor Filipe</i>	
An Artificial Intelligence-Based Method to Identify the Stage of Maturation in Olive Oil Mills	63
<i>João Mendes, José Lima, Lino A. Costa, Nuno Rodrigues, Paulo Leitão, and Ana I. Pereira</i>	
Enhancing Forest Fire Detection and Monitoring Through Satellite Image Recognition: A Comparative Analysis of Classification Algorithms Using Sentinel-2 Data	78
<i>Thadeu Brito, Ana I. Pereira, Paulo Costa, and José Lima</i>	
Assessing the 3D Position of a Car with a Single 2D Camera Using Siamese Networks	93
<i>Youssef Bel Haj Yahia, Júlio Castro Lopes, Eduardo Bezerra, Pedro João Rodrigues, and Rui Pedro Lopes</i>	
Deep Learning-Based Hip Detection in Pelvic Radiographs	108
<i>Cátia Loureiro, Vítor Filipe, Pedro Franco-Gonçalo, Ana Inês Pereira, Bruno Colaço, Sofia Alves-Pimenta, Mário Ginja, and Lio Gonçalves</i>	

Using LiDAR Data as Image for AI to Recognize Objects in the Mobile Robot Operational Environment	118
<i>Marek Nowakowski, Jakub Kurylo, João Braun, Guido S. Berger, João Mendes, and José Lima</i>	
Adaptive Convolutional Neural Network for Predicting Steering Angle and Acceleration on Autonomous Driving Scenario	132
<i>Ive Vasiljević, Josip Musić, João Mendes, and José Lima</i>	
Deep Learning-Based Classification and Quantification of Emulsion Droplets: A YOLOv7 Approach	148
<i>João Mendes, Adriano S. Silva, Fernanda F. Roman, Jose L. Diaz de Tuesta, José Lima, Helder T. Gomes, and Ana I. Pereira</i>	
Identification of Late Blight in Potato Leaves Using Image Processing and Machine Learning	164
<i>Renan Lemes Leepkahn, Angelita Maria de Ré, and Kelly Lais Wiggers</i>	
Machine Learning and AI in Robotics	
Deep Learning-Based Localization Approach for Autonomous Robots in the RobotAtFactory 4.0 Competition	181
<i>Luan C. Klein, João Mendes, João Braun, Felipe N. Martins, Andre Schneider de Oliveira, Paulo Costa, Heinrich Wörtche, and José Lima</i>	
Deep Learning and Machine Learning Techniques Applied to Speaker Identification on Small Datasets	195
<i>Enrico Manfron, João Paulo Teixeira, and Rodrigo Minetto</i>	
Impact of EMG Signal Filters on Machine Learning Model Training: A Comparison with Clustering on Raw Signal	211
<i>Ana Barbosa, Edilson Ferreira, Vinicius Grilo, Laercio Mattos, and José Lima</i>	
Fault Classification of Wind Turbine: A Comparison of Hyperparameter Optimization Methods	229
<i>Danielle Pinna, Rodrigo Toso, Gustavo Semaan, Fernando de Sá, Ana I. Pereira, Ângela Ferreira, Jorge Soares, and Diego Brandão</i>	
Realistic Model Parameter Optimization: Shadow Robot Dexterous Hand Use-Case	244
<i>Tiago Correia, Francisco M. Ribeiro, and Vítor H. Pinto</i>	

<p>Performance of Heuristics for Classifying Leftovers from Cutting Stock Problem</p> <p style="padding-left: 2em;"><i>Glauca Maria Bressan, Esdras Battosti da Silva, Matheus Henrique Pimenta-Zanon, Elisângela Aparecida da Silva Lizzi, and Fabio Sakuray</i></p>	<p>256</p>
Optimization in Control Systems Design	
<p>On Strong Anti-learning of Parity</p> <p style="padding-left: 2em;"><i>Alexei Lisitsa and Alexei Vernitski</i></p>	<p>271</p>
<p>Sub-system Integration and Health Dashboard for Autonomous Mobile Robots</p> <p style="padding-left: 2em;"><i>André França, Eduardo Loures, Luísa Jorge, and André Mendes</i></p>	<p>280</p>
<p>Optimization Models for Hydrokinetic Energy Generated Downstream of Hydropower Plants</p> <p style="padding-left: 2em;"><i>Nelio Moura de Figueiredo, Maisa Sales GamaTobias, Lucio Carlos Pinheiro Campos Filho, and Paulo Afonso</i></p>	<p>294</p>
<p>Vehicle Industry Big Data Analysis Using Clustering Approaches</p> <p style="padding-left: 2em;"><i>Lenon Diniz Seixas, Fernanda Cristina Corrêa, Hugo Valadares Siqueira, Flavio Trojan, and Paulo Afonso</i></p>	<p>312</p>
<p>Multi-objective Optimal Sizing of an AC/DC Grid Connected Microgrid System</p> <p style="padding-left: 2em;"><i>Yahia Amoura, André Pedroso, Ângela Ferreira, José Lima, Santiago Torres, and Ana I. Pereira</i></p>	<p>326</p>
<p>Deep Conditional Measure Quantization</p> <p style="padding-left: 2em;"><i>Gabriel Turinici</i></p>	<p>343</p>
<p>ECG and sEMG Conditioning and Wireless Transmission with a Biosignal Acquisition Board</p> <p style="padding-left: 2em;"><i>Luiz E. Luiz, Fábio R. Coutinho, and João P. Teixeira</i></p>	<p>355</p>
<p>An Efficient GPU Parallelization of the Jaya Optimization Algorithm and Its Application for Solving Large Systems of Nonlinear Equations</p> <p style="padding-left: 2em;"><i>Bruno Silva and Luiz Guerreiro Lopes</i></p>	<p>368</p>
<p>Author Index</p>	<p>383</p>

Contents – Part I

Machine Learning

A YOLO-Based Insect Detection: Potential Use of Small Multirotor Unmanned Aerial Vehicles (UAVs) Monitoring	3
<i>Guido S. Berger, João Mendes, Arezki Abderrahim Chellal, Luciano Bonzatto Junior, Yago M. R. da Silva, Matheus Zorawski, Ana I. Pereira, Milena F. Pinto, João Castro, António Valente, and José Lima</i>	
A Comparison of Fiducial Markers Pose Estimation for UAVs Indoor Precision Landing	18
<i>Luciano Bonzatto Junior, Guido S. Berger, Alexandre O. Júnior, João Braun, Marco A. Wehrmeister, Milena F. Pinto, and José Lima</i>	
Effect of Weather Conditions and Transactions Records on Work Accidents in the Retail Sector – A Case Study	34
<i>Lucas D. Borges, Inês Sena, Vitor Marcelino, Felipe G. Silva, Florbela P. Fernandes, Maria F. Pacheco, Clara B. Vaz, José Lima, and Ana I. Pereira</i>	
Exploring Features to Classify Occupational Accidents in the Retail Sector	49
<i>Inês Sena, Ana Cristina Braga, Paulo Novais, Florbela P. Fernandes, Maria F. Pacheco, Clara B. Vaz, José Lima, and Ana I. Pereira</i>	
Resource Dispatch Optimization for Firefighting Using a Differential Evolution Algorithm	63
<i>Marina A. Matos, Rui Gonçalves, Ana Maria A. C. Rocha, Lino A. Costa, and Filipe Alvelos</i>	
A Pattern Mining Heuristic for the Extension of Multi-trip Vehicle Routing	78
<i>Leila Karimi, Connor Little, and Salimur Choudhury</i>	
Time-Dependency of Guided Local Search to Solve the Capacitated Vehicle Routing Problem with Time Windows	93
<i>Adriano S. Silva, José Lima, Adrián M. T. Silva, Helder T. Gomes, and Ana I. Pereira</i>	
Federated Learning for Credit Scoring Model Using Blockchain	109
<i>Daniel Djolev, Milena Lazarova, and Ognyan Nakov</i>	

PhishVision: A Deep Learning Based Visual Brand Impersonation Detector for Identifying Phishing Attacks	123
<i>Giovanni Graziano, Daniele Ucci, Federica Bisio, and Luca Oneto</i>	
Call Centre Optimization Based on Personalized Requests Distribution	135
<i>Elizaveta Tarasova and Dmitry Ivanov</i>	
AquaVitae: Innovating Personalized Meal Recommendations for Enhanced Nutritional Health	148
<i>Henrique S. Marcuzzo, Maria J. V. Pereira, Paulo Alves, and Juliano H. Foleis</i>	
Barriers to Organizations to Adopt Digital Transformation for Driving Eco-Innovation and Sustainable Performance	162
<i>Zornitsa Yordanova</i>	
Interpretable Structural Analysis for Evolutionary Generative Design of Coastal Breakwaters	172
<i>Denis O. Sidorenko, Nikita O. Starodubcev, Maiia Pinchuk, and Nikolay O. Nikitin</i>	
An Example of Ontology in Medical Diagnosis: A Case Study	186
<i>Antonela Prnjak, Marko Rosić, Goran Zaharija, Divna Krpan, and Monika Mladenović</i>	
Text Chunking to Improve Website Classification	197
<i>Mohamed Zohir Koufi, Zahia Guessoum, Amor Keziou, Itheri Yahiaoui, Chloé Martineau, and Wandrille Domin</i>	
Automatic Speech Recognition for Portuguese: A Comparative Study	217
<i>Pedro Henrique Borghi, João Paulo Teixeira, and Diamantino Rui Freitas</i>	
Comparative Analysis of Windows for Speech Emotion Recognition Using CNN	233
<i>Felipe L. Teixeira, Salviano Pinto Soares, J.L. Pio Abreu, Paulo M. Oliveira, and João P. Teixeira</i>	
Exploring the Role of OR/MS in Cancer Research	249
<i>A. Teixeira and R. Almeida</i>	
On the Use of VGs for Feature Selection in Supervised Machine Learning - A Use Case to Detect Distributed DoS Attacks	269
<i>João Lopes, Alberto Partida, Pedro Pinto, and António Pinto</i>	

Learning Algorithms in Engineering Education

Accuracy Optimization in Speech Pathology Diagnosis with Data Preprocessing Techniques	287
<i>Joana Filipa Teixeira Fernandes, Diamantino Rui Freitas, and João Paulo Teixeira</i>	

Application of Pattern Recognition Techniques for MathE Questions Difficulty Level Definition	300
<i>Beatriz Flávia Azevedo, Roberto Molina de Souza, Maria F. Pacheco, Florbela P. Fernandes, and Ana I. Pereira</i>	

Machine Learning and Data Analysis in Internet of Things

Predicting Flood Events with Streaming Data: A Preliminary Approach with GRU and ARIMA	319
<i>Rodrigo Moura, Armando Mendes, José Cascalho, Sandra Mendes, Rodolfo Melo, and Emanuel Barcelos</i>	

Digital Twin for Regional Water Consumption Simulation and Forecasting	333
<i>Matheus Galvão, Pedro Rici, and Rui Pedro Lopes</i>	

Automatic Fall Detection with Thermal Camera	347
<i>Rebeca B. Kalbermatter, Tiago Franco, Ana I. Pereira, António Valente, Salviano Pinto Soares, and José Lima</i>	

Image Transfer over MQTT in IoT: Message Segmentation and Encryption for Remote Indicator Panels	360
<i>David Valente, Thadeu Brito, Márcio Correia, José A. Carvalho, and José Lima</i>	

Optimization

An Extension of a Dynamic Heuristic Solution for Solving a Multi-Objective Optimization Problem in the Defense Industry	377
<i>Khwansiri Ninpan, Kirill Kondratenko, Shuzhang Huang, Alexandra Plancon, Arthur Aumont, Lucas Artaud, Mouna Baker, Emir Roumili, Francesco Vitillo, Lies Benmiloud Bechet, and Robert Plana</i>	

BHO-MA: Bayesian Hyperparameter Optimization with Multi-objective Acquisition	391
<i>Vedat Dogan and Steven Prestwich</i>	

Prediction of Health of Corals <i>Mussismilia hispida</i> Based on the Microorganisms Present in their Microbiome	409
<i>Barry Malick Barque, Pedro João Soares Rodrigues, Pedro Luiz de Paula Filho, Raquel Silva Peixoto, and Deborah Catharine de Assis Leite</i>	
The Consistent Vehicle Routing Problem: An Application to the Pharmaceutical Supply Chain	424
<i>Manuel Eusébio, Telmo Pinto, and Miguel Vieira</i>	
Using OR-Tools When Solving the Nurse Scheduling Problem	438
<i>Márcia Oliveira, Ana Maria A. C. Rocha, and Filipe Alves</i>	
Predicting the Solution Time for Optimization Problems Using Machine Learning: Case of Job Shop Scheduling Problem	450
<i>Shaheen Pouya, Oguz Toragay, and Mehrdad Mohammadi</i>	
Optimization in the SDG Context	
Schedule Modeling in a Fire Station: A Linear Approach to Optimize Service and Human Resources	469
<i>Ana Rita Silva, Helena Sofia Rodrigues, and Ângela Silva</i>	
Help us to Help: Improving Non-urgent Transport on a Portuguese Fire Station	482
<i>Emanuel Lopes, Eliana Costa e Silva, Óscar Oliveira, and Wellington Alves</i>	
Location of an Electric Vehicle Charging Station: Demographic Factor as Decision Making	498
<i>Catarina Gonçalves, Ângela Silva, and Helena Sofia Rodrigues</i>	
Speeding up the Oscillation-Free Modified Heavy Ball Algorithm	516
<i>Koba Gelashvili and Paata Gogishvili</i>	
Performance Comparison of NSGA-II and NSGA-III on Bi-objective Job Shop Scheduling Problems	531
<i>Francisco dos Santos, Lino A. Costa, and Leonilde Varela</i>	
A Multiobjective Tuning of a Procedural Content Generator for Game Level Design via Evolutionary Algorithms	544
<i>Vitor Gomes Soares Lins Peixoto, Elizabeth Fialho Wanner, and André Rodrigues da Cruz</i>	

<p>Optimal Location of Electric Vehicle Charging Stations in Distribution Grids Using Genetic Algorithms</p> <p style="padding-left: 2em;"><i>Eduardo Gomes, Adelaide Cerveira, and José Baptista</i></p>	<p>560</p>
<p>Nonlinear Regression on Growth Curves for Placental Parameters in R</p> <p style="padding-left: 2em;"><i>Daniela Lemos, Ana Cristina Braga, and Rosete Nogueira</i></p>	<p>575</p>
<p>GLM's in Data Science as a Tool in the Prediction of <i>Delirium</i></p> <p style="padding-left: 2em;"><i>Alexandra Coelho, Ana Cristina Braga, and José Mariz</i></p>	<p>591</p>
<p>Author Index</p>	<p>607</p>



Multi-objective Optimal Sizing of an AC/DC Grid Connected Microgrid System

Yahia Amoura^{1,3}, André Pedroso^{1,4}, Ângela Ferreira¹, José Lima^{1,2},
Santiago Torres³, and Ana I. Pereira¹ (✉)

¹ Research Centre in Digitalization and Intelligent Robotics (CeDRI),
Instituto Politécnico de Bragança, Bragança, Portugal
{yahia, andre.pedroso, apf, jllima, apereira}@ipb.pt

² INESC TEC - INESC Technology and Science, Porto, Portugal

³ University of Laguna, San Cristbal de La Laguna, Spain
storres@ull.es

⁴ Federal University of Technology - Paraná, Curitiba, Brazil

Abstract. Considering the rising energy needs and the depletion of conventional energy sources, microgrid systems combining wind energy and solar photovoltaic power with diesel generators are promising and considered economically viable for usage. To evaluate system cost and dependability, optimizing the size of microgrid system elements, including energy storage systems connected with the principal network, is crucial. In this line, a study has already been performed using a uni-objective optimization approach for the techno-economic sizing of a microgrid. It was noted that, despite the economic criterion, the environmental criterion can have a considerable impact on the elements constructing the microgrid system. In this paper, two multi-objective optimization approaches are proposed, including a non-dominated sorting genetic algorithm (NSGA-II) and the Pareto Search algorithm (PS) for the eco-environmental design of a microgrid system. The k-means clustering of the non-dominated point on the Pareto front has delivered three categories of scenarios: best economic, best environmental, and trade-off. Energy management, considering the three cases, has been applied to the microgrid over a period of 24 h to evaluate the impact of system design on the energy production system's behavior.

Keywords: Microgrid · Renewable energy · Optimization · Clustering · Sizing

1 Introduction

Renewable energies are the main substitute for fossil fuels responsible for greenhouse gas (GHG) emissions [1], with investments totaling 350 billion euros in 2021. Solar and wind energy supply more than 10% of the world's electricity, predicted to have a 15-18% share by 2050 [2]. The need for a sustainable energy system is increasing due to overpopulation, industrialization, and urbanization.

© The Author(s) 2024

A. I. Pereira et al. (Eds.): OL2A 2023, CCIS 1982, pp. 326–342, 2024.

https://doi.org/10.1007/978-3-031-53036-4_23

Renewable energy sources must be pursued due to rising costs and energy security issues [3,4]. Microgrid systems powered by renewable energy are the best option for remote communities [5]. The worldwide microgrid market exceeded 14.3 billion dollars in 2021 and is expected to reach 43.9 billion US dollars in 2028 [6]. Microgrid systems provide electricity in a reliable, secure, flexible, cost-effective, and sustainable manner, but must be well-sized and monitored to maintain reliability and keep costs low [7].

The use of optimization to design a microgrid system has been widely explained by researchers. Recently, meta-heuristic approaches have been frequently used as a single and a multi-objective approach for the optimal design of a microgrid hybrid renewable power plant in a clean energy production system, including several types of distributed generators arranged in Direct Current (DC bus), Alternative Current (AC bus), or hybrid DC/AC busses configurations, considering the whole system as a standalone or grid-connected system. However, in terms of constraints consideration, the economic and environmental implications are the main criterion, despite other technical considerations such as power losses. On [8,9], several single-objective approaches have been studied. Nevertheless, some multi-objective techniques have been employed in the literature in accordance with this work. For instance, a Multiobjective Particle Swarm Optimization (MOPSO) has been applied to minimize cost, carbon emissions, energy use, and power use in [10]. The same approach has been used by Sellami et al. [11], to reduce network losses and increase efficiency. Non-dominated Sorting Genetic Algorithm II (NSGA-II) [18], has been used on [12,13] to optimize both cost of operation and the rate of consumption of renewable energy, and the same optimization method has been used on [14] to increase the rate of oxygen production, short payback time and lower overall cost inside a microgrid system. An enhanced Differential Evolution (DE) have been used in [15] for the multi-objective optimal sizing of a hybrid micro-grid system considering technical-economic and social factors. In a Stand-Alone Marine Context, a microgrid has been sized by Zhu et al. [16] using an improved multi-objective grey wolf optimizer based on the Halton Sequence and Social Motivation Strategy (HSMGWO).

The study described in this paper is a continuation of [8], in which uni-evolutionary optimization methods, including the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), were used to achieve the optimal size of a hybrid energy system based on renewable energy. In addition to the technical-economic objective function, the environmental criterion describing the carbon emissions during the manufacture of microgrid components has been taken into account in this work. As a result, a multi-objective optimization problem emerges from the situation. The case study has been applied to the campus de Santa Apolónia, located in Bragança, Portugal.

The main contributions of this paper are organized as the following:

1. Optimal allocation of micro-grid elements subject to technical-economic and environmental consideration.

2. Application of two Multi-optimization approaches including, the non-dominated sorting genetic algorithm (NSGA-II) and the Pareto Search algorithm (PS).
3. Identification of configurations scenario as best economic, best environmental, and trade-off by using the k-means clustering approach.
4. Identification of the microgrid power flow behavior considering all identified scenarios.

The rest of the paper is organized as follows: Sect. 2 describes the adopted configuration of the microgrid system. In Sect. 3, the meteorological and consumption data of microgrid users are presented. The generators used to constitute the microgrid system are defined in Sect. 4. The optimal sizing of the microgrid is formulated as result of multi-objective functions in Sect. 5. The adopted sizing methodology is explained in Sect. 6. The results of the simulation and their discussion are presented in Sect. 7. Section 8 summarises the findings of the paper and proposes guidelines for future work.

2 Microgrid Arrangement

The microgrid configuration proposed in this study is the AC/DC architecture shown in Fig. 1.

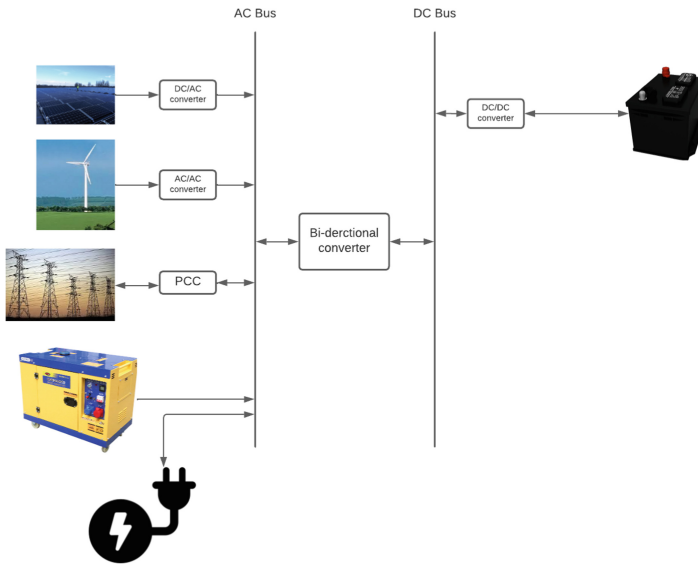


Fig. 1. Microgrid configuration.

The microgrid configuration includes two renewable resources: photovoltaic and wind turbines. Through a common coupling point, the microgrid is connected to the main grid, which acts as a buffer. In the event of a blackout,

the diesel group connected to the AC bus is employed as a last-resort solution. The battery system connects to the DC bus in a bidirectional manner, and a bi-directional converter allows energy to flow between the two buses in both directions. Control and energy management technologies are used to ensure the flow of energy and supervision of the microgrid power quality. Microgrids that combine AC and DC power provide harmonic control, economic viability, and voltage transformation, but have drawbacks such as safety and unit coordination [9].

3 Study Data Description

Weather data is essential for sizing a microgrid, as weather mistakes can lead to errors in real operations and larger initial investments. In this study, the Polytechnic Institute of Bragança (IPB), located in the north region of Portugal (Latitude: 41.8072, Longitude: -6.75919 41° $48'$ $26''$ North, 6° $45'$ $33''$ West, with an elevation of 690 m), was the location of the study case. A sequence of measurement series, including average solar irradiation, wind speed, and temperature data for one year (from January 1, 2019, to December 31, 2019), as well as the average load data, have been gathered. Figure 2 represents the profile of data mentioned above. Table 1 describes the critical values of the weather data set, including the minimal value, maximal value, average value, and standard deviation.

Table 1. Data summary.

Parameters	Measurement tool	Max	Min	Mean	Std
Temperature	Thermocouple K-Type	20.06	8	13.42	0.7620
Wind speed (m/s)	Anemometer	5.78	3.19	4.46	4.26
Solar irradiation	Pyranometer	830.73	54.44	279	328.71
Load	Energy meter	9.50	5.50	6.49	1.28

4 System Modeling

The work [8] is the main inspiration of this study that describes the rationale behind the concepts and technology selected. For this reason, the equipment modeling of photovoltaic systems, wind turbines, battery systems, and diesel generators is assumed the same as in [8]. The new contribution of this work is the connection of the microgrid to the main grid which is presented in the following sections.

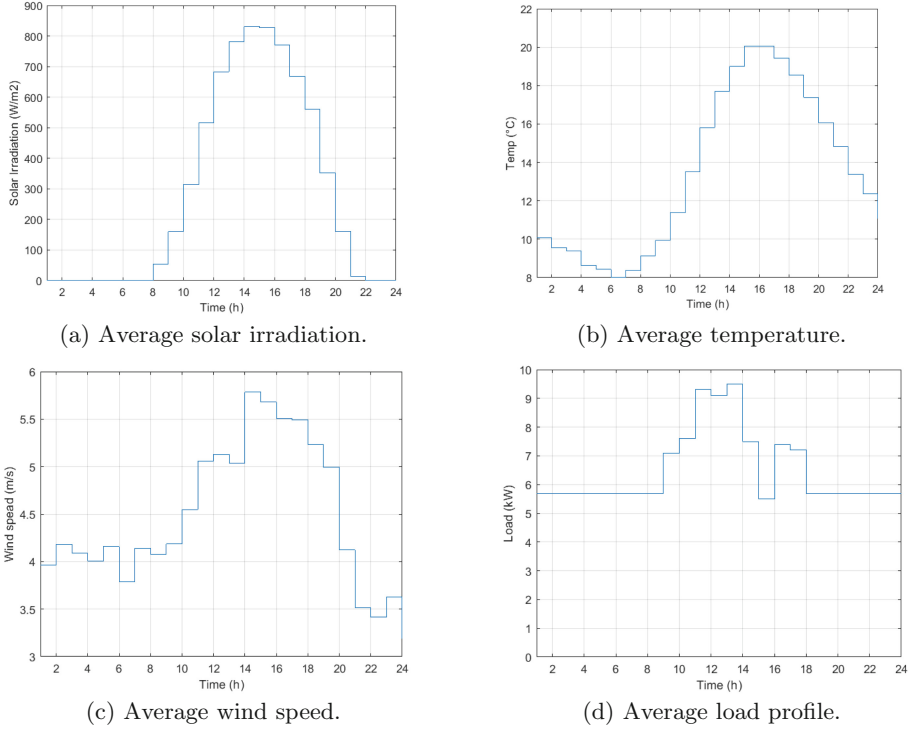


Fig. 2. Study data.

4.1 Main Grid

The main grid with microgrid can operate bi-directionally according to three scenarios as follow, where P_{pv}^t , P_{wt}^t are the total active power output of photovoltaic panels, and wind turbines. $E(t)$, is the energy delivered from/to the energy storage system in an hour t and P_{load} is the total load power, Δ_t is the step time between two periods in this case it is considered 1 h. All defined parameters are widely explained on [15].

- The first scenario occurs when the power verifies the following relation:

$$P_{pv}^t(t) + P_{wt}^t(t) + \frac{E(t)}{\Delta_t} = P_{load}(t) \tag{1}$$

In this case, the main grid has no interaction with the microgrid in terms of reception or feeding.

- The second scenario occurs when the following relationship is verified:

$$P_{pv}^t(t) + P_{wt}^t(t) + \frac{E(t)}{\Delta_t} < P_{load}(t) \tag{2}$$

$$P_{grid}(t) = P_{load}(t) - \left(P_{pv}^t(t) + P_{wt}^t(t) + \frac{E(t)}{\Delta t} \right) \quad (3)$$

In this case, the main grid will inject the required power noted $P_{grid}(t)$ to balance the energy inside the microgrid by covering all the needed power.

- The third scenario occurs when the following relationship is verified:

$$P_{pv}^t(t) + P_{wt}^t(t) + \frac{E(t)}{\Delta t} > P_{load}(t) \quad (4)$$

In this case, the microgrid will inject extra power into the main grid.

In this study, the power converters are considered to work in ideal conditions, which means that it will not take into account the losses provided; however, the converters are presented by their theoretical efficiency in the technical study, and they are not subject to optimization. The characteristics of the components for the microgrid presented in this study are described in Table 2.

Table 2. Components technical specifications.

Equipment	Rated power (W)	Rated voltage (V)	Efficiency (%)	Life time (years)
PV Panel	340	44.52	17.12	20
Wind Turbine	3000	240	59	20
Diesel Group	10000	230	5 h in max capacity	20
Battery	2.5 kWh (Capacity)	48	90	5
DC/AC inverter	4000	48DC/220AC	95	4
DC/DC converter	310	48 VDC	80	4

5 Problem Formulation

The problem of optimal sizing the microgrid system is formulated as a multi-objective optimization approach, taking into account two cost functions characterizing the economical and environmental criteria, respectively, subjected to constraints that are defined to satisfy the correct microgrid operation.

5.1 Objective Functions

Objective 1: Installation Cost Minimization. The economic criteria, including the system's component purchase price, maintenance expenses, and component replacement prices, are taken into account by the economic objective function. The objective function aims to satisfy the necessary technical constraints while getting the ideal number of microgrid components. For a system lifespan of T equal to 20 years, the microgrid system cost, in euros, is provided by [8]:

$$C_t(N_{pv}, N_{wt}, N_b) = N_{pv}(C_{pv} + C_{pv}K_{pv} + TM_{pv}) + N_{wt}(C_{wt} + C_{wt}K_{wt} + TM_{wt}) + N_b(C_b + C_bK_b + (T - K_b - 1)M_b) + C_{die} + C_{conv}$$

where, N_{pv} , N_{wt} , N_b are, respectively, the number of units of photovoltaic modules, wind turbines and batteries, C_{pv} , C_{wt} , C_b , C_{die} , C_{conv} are respectively the purchase costs of renewable units (photovoltaic and wind), battery unit, diesel group and overall converters, M_{pv} , M_{wt} , M_b are the maintenance costs for the renewable energy systems (photovoltaic and wind systems) and also battery bank. Finally, K_{pv} , K_{wt} , K_b are, respectively, the number of equipment replacements during the system lifetime.

The optimization model for microgrid installation cost can be written as follow:

$$\min f_1 = \min (C_t(N_{pv}, N_{wt}, N_b)) \tag{5}$$

The optimization model will lead to finding N_{pv} , N_{wt} , and N_b , i.e., the optimum set points that define the optimal number of microgrid components: wind turbines, photovoltaics, and batteries, at the lowest price while respecting the constraint that will be defined in the rest of the paper.

Objective 2: Environmental Function. Nitrous oxide (N_2O), carbon dioxide (CO_2), and methane (CH_4) are the main components of GHG emissions. In most cases, carbon dioxide (CO_2), or its equivalent (CO_2eq), is used as the measurement unit for GHG emissions. The overall carbon footprint estimation for the microgrid system set-up represents the emissions released during its manufacturing process [17]. However, the total (CO_2eq) emission function is given as follows:

$$E_t(N_{pv}, N_{wt}, N_b) = GHG_{PV}^{CO_2eq} + GHG_{WT}^{CO_2eq} + GHG_b^{CO_2eq}$$

where, $GHG_{PV}^{CO_2eq}$, $GHG_{WT}^{CO_2eq}$, $GHG_b^{CO_2eq}$ are, respectively, the GHG emissions of the photovoltaic, wind turbine, and battery released during the manufacturing process of the units represented on carbon dioxide (CO_2) and expressed on (CO_2eq).

$$E_t(N_{pv}, N_{wt}, N_b) = N_{pv}(138.3 \times S_{pv} - 2.54) + N_{wt}(156 \times S_{WT}) + N_b(1.99 \times C^m + 27.2)$$

where, S_{pv} is the photovoltaic surface panel, S_{WT} is the swept area by the blades of the wind turbine, and C^m is battery nominal capacity [17].

The optimization model for the microgrid environmental model can be written as follows:

$$\min f_2 = \min (E_t(N_{pv}, N_{wt}, N_b)) \tag{6}$$

5.2 Constraints

Power Balance Constraint. The total amount of power generated must be sufficient to meet the overall demand (including storage) and transmission losses. In terms of frequency stability, the active power balance is a requirement for steady operation. Since the transmission losses are thought to be numerically insignificant, they are neglected in this work. The power balance's state takes on the following form:

$$P_{pv}(t)N_{pv} + P_{wt}(t)N_{WT} + P_b(t)N_b \geq P_{load}(t) \quad (7)$$

being $P_{load}(t)$, the total electrical load demand at hour t . Moreover, the power of the energy storage system $P_b(t)$ can be positive in the case of discharging or negative in the case of charging, and $P_{pv}(t)$ and $P_{wt}(t)$ are the power delivered by the photovoltaic and wind turbine generators at hour t .

Limit Generators Number Constraint. The limited number of generators in terms of setup surface must be considered during the optimization procedure as follows:

$$0 \leq N_{pv} \leq N_{pv}^{max} \quad (8)$$

$$0 \leq N_{wt} \leq N_{wt}^{max} \quad (9)$$

$$0 \leq N_b \leq N_b^{max} \quad (10)$$

where, N_{pv}^{max} , N_{wt}^{max} and N_b^{max} is the maximal permitted numbers of photovoltaic, wind turbines, and batteries, respectively, to be installed.

6 Methodology

In this paper, two multiobjective optimization methods are used to define the optimal configuration of the microgrid: the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Pareto Search algorithm. The results will be presented on a set of Pareto fronts, including the non-dominated points that reflect the scenarios proposed by the optimization process according to the constraints defined above, to ensure technical satisfaction for the secure and reliable operation of the microgrid system. Given the clustering of the non-dominated points using the k-means approach, an informed choice of scenarios will be determined. On the reverse side, the effectiveness of scenarios will be investigated through the microgrid operating system's behavior. However, the proposed microgrid system can operate both in isolated mode and/or grid-connected mode. The power distribution approach is simplified into the following situations:

1. The power generated by renewable sources must meet the load demand in order for the system to operate safely. Additionally, excessive amounts of power produced by renewable resources require that batteries be charged first before any extra power is put onto the main grid.

2. Renewable energy sources cannot produce enough power to fulfill demand; an energy storage system will satisfy the shortage. In the event that this latter is insufficient, the main network compensates for the energy imbalance.
3. The electricity produced by the diesel group is regarded as the last resort and a highly polluting source that will only be used in the event of a complete blackout within the main grid.

7 Results and Discussions

This section presents the results of the optimization strategies. After the optimal number of units is reached, a technical study is done to evaluate the installation’s dependability given the number of microgrid units. Additionally, a lifetime cost estimate of the system is given, taking into account every scenario that has been suggested. The optimization problem and microgrid operation were programmed and simulated using the MATLAB programming language.

7.1 Optimization Results and Scenarios Identification

The study’s microgrid sizing problem has been solved using two multi-objective optimization techniques, NSGA-II and Pareto search algorithms. The Pareto front of non-dominated points is displayed in Fig. 3.

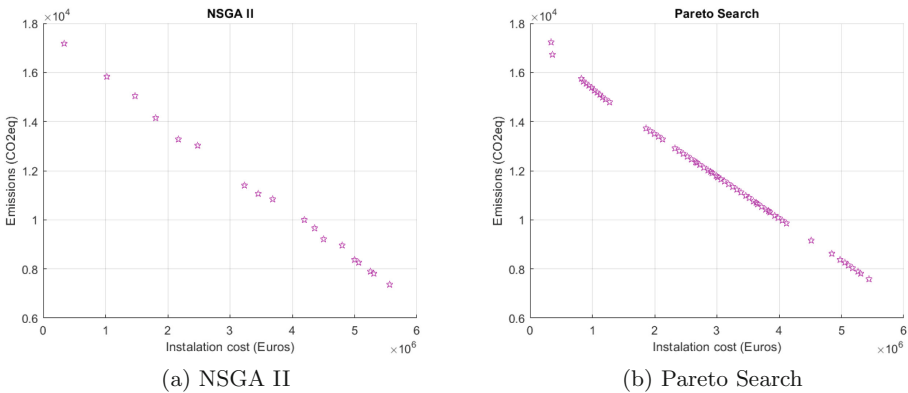


Fig. 3. Pareto front of microgrid optimization sizing scenarios.

A cluster evaluation using the “silhouette” approach has been carried out in order to determine scenarios that exist in accordance with the optimization results achieved. The silhouette plot reveals that the data are separated into three clusters. Each of the three clusters has a substantial silhouette value determined by the Euclidean distance metric, as illustrated in Fig. 4.

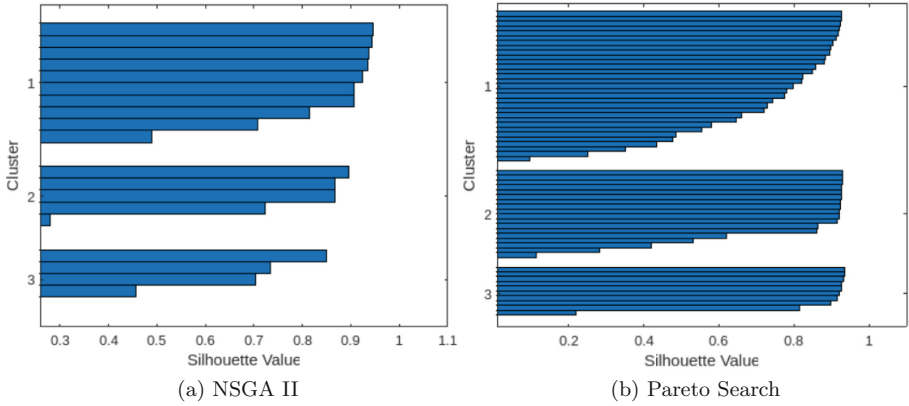


Fig. 4. Silhouette values.

The clustering has been performed using the k-means approach with ($k = 3$), the results are presented in Fig. 5.

According to the clusters, three sets of scenarios can be identified, including the best economic scenarios (**Cluster 03**), best environmental scenarios (**Cluster 02**), and traded-off scenarios (**Cluster 01**). The distinct scenario that represents each cluster has been chosen from the extreme of each recognized set of situations, except for the trade-off case, in which the centroid has been selected as a cluster-representative scenario. Table 3 displays the microgrid sizing scenarios that were selected based on the previously addressed device characteristics.

Table 3. Microgrid sizing scenarios.

Scenario	N_{PV}	N_{WT}	N_{Batt}	Installation Cost (€)	Total Emissions ($KgCO_{2eq}$)
Best Economical	50	3	13	157755.87	17071,00
Trade-off	55	2	7	2351703.20	17302
Best environmental	46	1	44	5623707.70	7468,52

The optimal configurations illustrate three microgrids from different perspectives. However, the first scenario takes into consideration adopting a combination of elements that gives an optimal installation cost; the outcomes of this case were similar compared to the results obtained in [8], in which installation cost minimization was the objective of the study. The second scenario represents a balance between the two criteria, economic and environmental, respectively. The third scenario gives priority to installing sources that emit less CO_2 during their

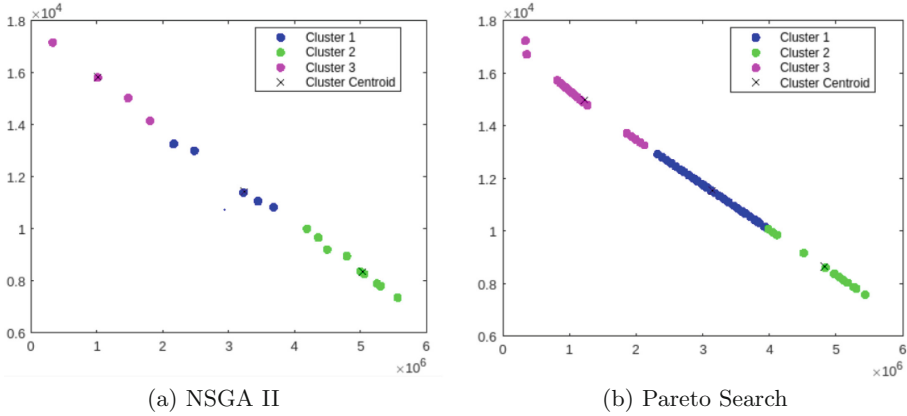


Fig. 5. Results obtained by k-means ($k = 3$) with the Pareto front solutions.

manufacturing process. According to Sect. 5.1, it can be noted that the batteries are the least emissive, which justifies the high number of these devices employed in this scenario.

7.2 Scenarios Technical Evaluation

The effectiveness of the scenario has been evaluated using a 24-hour operation analysis of each microgrid configuration.

Best Economical Scenario. In this case, the microgrid was established via 50 photovoltaic panels, 3 wind turbines, and an energy storage system consisting of 13 batteries, along with the diesel group and connection to the main grid. As shown in Fig. 6b by a 24-hour operation taking into account the presence of all RE sources, it can be seen that under these circumstances, the microgrid is capable of operating in a stable condition in which the load is continuously fed and the excess energy has been used to charge the energy storage system during peak production, when the set of batteries reached nearly the SOC_{max} as Fig. 6a illustrate.

Furthermore, the microgrid was able to feed the user continuously for 24h in the absence of all RES, reaching SOC_{min} in the last hours of the day, as illustrated in Fig. 7a.

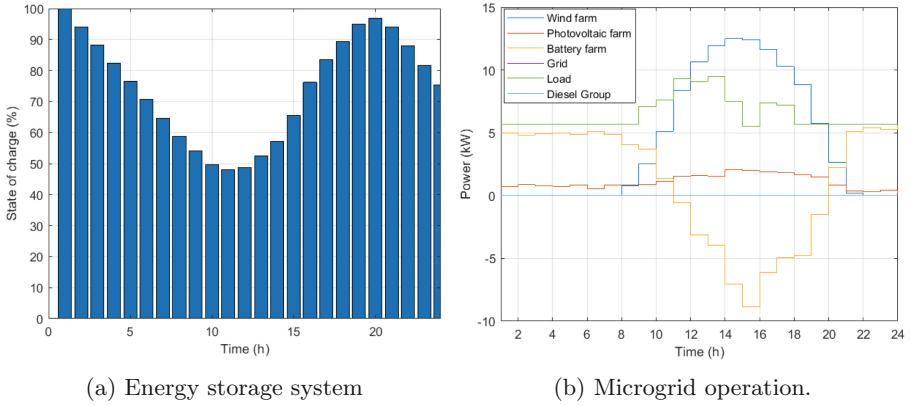


Fig. 6. Scenario 1: Presence of all RES.

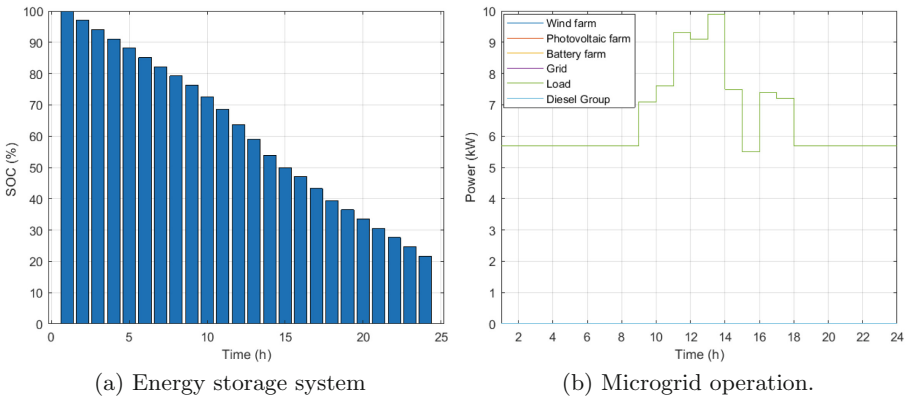


Fig. 7. Scenario 1: Absence of RES

Trade-Off Scenario. This setup consists of 55 photovoltaic panels, 2 wind turbines, 7 batteries, and a diesel generator that serves as a backup system in the event of a microgrid failure or a main grid blackout. As seen in Fig. 8a the batteries were able to feed the microgrid at night in normal operation. The microgrid users were able to meet their energy needs during the day owing to the photovoltaic park and the wind turbine. In addition, the battery was fully charged at 16 o'clock, when both the wind and the sun's potential were still present, and the excess energy was injected into the main grid between 17 o'clock and 20 o'clock, as shown in Fig. 8b. Practically, the microgrid was producing more energy than was required to supply the load while simultaneously charging the energy storage system to its fullest capacity.

In the absence of all renewable energy sources, the batteries fed the microgrid up to the point of minimal charge before feeding the consumer directly from the

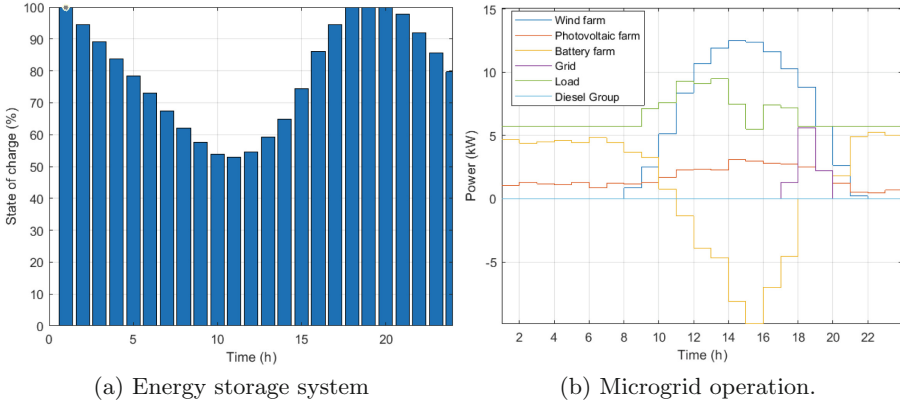


Fig. 8. Scenario 2: Presence of all RES.

main network, ensuring that the system’s dependability is maintained and the user’s comfort is unaffected by the microgrid’s power shortage, as illustrated in Fig. 9.

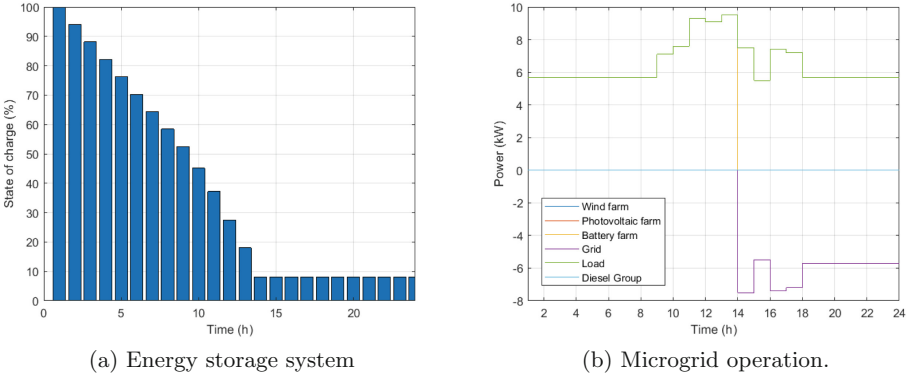


Fig. 9. Scenario 2: Absence of RES

Best Environmental Scenario. In this instance, the diesel group and the main grid were connected to the microgrid, which included 46 photovoltaic panels, 1 wind turbine, and a system of 44 batteries for energy storage. An abusive number of batteries made the microgrid able to work permanently even in the absence of all renewable features As presented in Fig. 11a. This case brings a very high cost of installation that will not ensure the gain on the investment

during the lifetime of the installation ($T = 20$ years) mainly because the batteries have to be changed every 4 years as required to ensure their reliability inside the microgrid system. This set of changes will undoubtedly bring a huge cost of replacement.

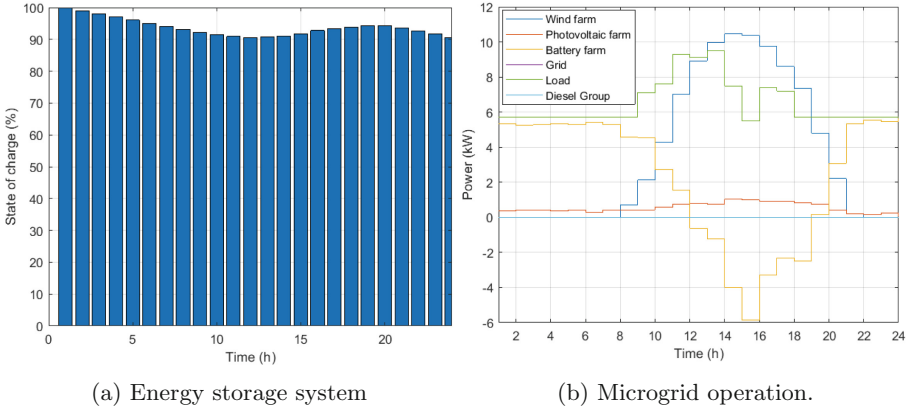


Fig. 10. Scenario 3: Presence of all RES.

Without ignoring the duration of charging and the high energy flow that must be fully supplied for reaching the SOC_{max} of the energy storage system, the microgrid's local energy sources are insufficient, necessitating an assortment of energy compensations from the main grid.

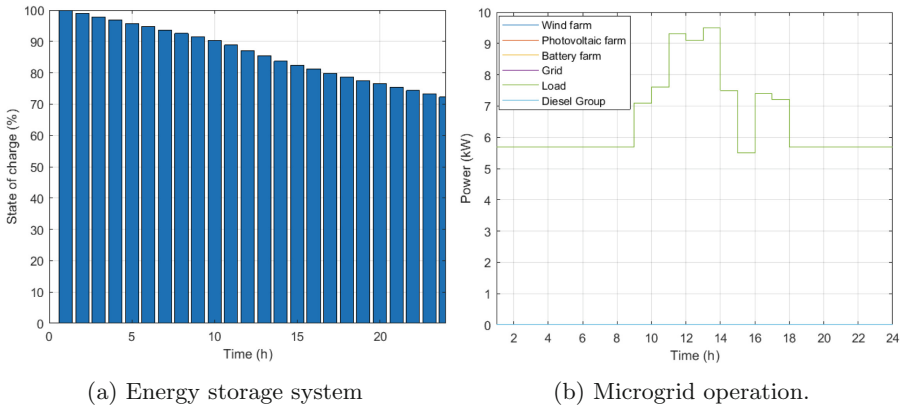


Fig. 11. Scenario 3: Absence of all RES.

8 Conclusions and Future Work

This study is a continuation of [8] and focuses on the sizing and optimization of an AC/DC microgrid composed of a set of distributed generators, including a park of photovoltaic panels, a wind turbine farm, and a set of electrochemical batteries. The microgrid is connected to the main grid through a common coupling point (PCC). A diesel generator has been used as a backup system in the event of a microgrid failure or main grid blackout. A data set of solar potential, wind speed, and temperature has been analyzed. Two multi-objective optimization algorithms have been used to solve the problem, including the Non-dominated Sorting Genetic Algorithm (NSGA II) and the Pareto Search (PS) algorithm. The results delivered a Pareto front of non-dominated points consisting of two objectives: total installation cost, and total GHG emissions. Three groups of scenarios have been identified by clustering the points of the Pareto front using the k-means method: economic, environmental, and traded-off. The best scenarios for each cluster are analyzed in 24-hour microgrid operation to identify its reliability.

In the future, the authors will extend this paper by including a third objective function representing embodied energy (EE), which represents the quantity of non-renewable energy consumed during the life cycle of different elements of the microgrid with an economic analysis of the microgrid investment costs taking into account all potential outcomes. Additionally, the authors are studying the sizing of the system in a DC configuration.

Acknowledgements. This work has been supported by FCT - Fundação para a Ciência e Tecnologia within the R&D Units Project Scope: UIDB/05757/2020, UIDP/05757/2020.

References

1. Amoura, Y., Torres, S., Lima, J., Pereira, A.I.: Hybrid optimisation and machine learning models for wind and solar data prediction. *Int. J. Hybrid Intell. Syst.* **19**(7875), 1–16 (2023). <https://doi.org/10.3233/his-230004>
2. Christopher, S.: Renewable energy potential towards attainment of net-zero energy buildings status - a critical review. *J. Clean. Prod.* **405**, 136942 (2023). <https://doi.org/10.1016/j.jclepro.2023.136942>
3. Tvaronavičienė, M.: Towards renewable energy: opportunities and challenges. *Energies* **16**(5), 2269 (2023). <https://doi.org/10.3390/en16052269>
4. Li, C., Umair, M.: Does green finance development goals affects renewable energy in China. *Renewable Energy* **203**, 898–905 (2023). <https://doi.org/10.1016/j.renene.2022.12.066>
5. Hossain, J., et al.: A review on optimal energy management in commercial buildings. *Energies* **16**(4), 1609 (2023). <https://doi.org/10.3390/en16041609>
6. Statista Research Department. Global Microgrid Market Value 2017–2028. Statista (2023). <https://www.statista.com/statistics/1313998/global-microgrid-market-size/>. Accessed 29 Apr 2023

7. Mustafa Kamal, M., Ashraf, I.: Evaluation of a hybrid power system based on renewable and energy storage for reliable rural electrification. *Renewable Energy Focus* **45**, 179–191 (2023). <https://doi.org/10.1016/j.ref.2023.04.002>
8. Amoura, Y., Ferreira, Á.P., Lima, J., Pereira, A.I.: Optimal sizing of a hybrid energy system based on renewable energy using evolutionary optimization algorithms. In: Pereira, A.I., et al. (eds.) *OL2A 2021. CCIS*, vol. 1488, pp. 153–168. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-91885-9_12
9. Amoura, Y., Pereira, A.I., Lima, J.: Optimization methods for energy management in a microgrid system considering wind uncertainty data. In: Kumar, S., Purohit, S.D., Hiranwal, S., Prasad, M. (eds.) *Proceedings of International Conference on Communication and Computational Technologies. AIS*, pp. 117–141. Springer, Singapore (2021). https://doi.org/10.1007/978-981-16-3246-4_10
10. Zhang, J., Cho, H., Mago, P.J., Zhang, H., Yang, F.: Multi-objective particle swarm optimization (MOPSO) for a distributed energy system integrated with energy storage. *J. Therm. Sci.* **28**(6), 1221–1235 (2019). <https://doi.org/10.1007/s11630-019-1133-5>
11. Sellami, R., Sher, F., Neji, R.: An improved MOPSO algorithm for optimal sizing and placement of distributed generation: a case study of the Tunisian offshore distribution network (ASHTART). *Energy Rep.* **8**, 6960–6975 (2022). <https://doi.org/10.1016/j.egy.2022.05.049>
12. Yusuf, A., Bayhan, N., Tiryaki, H., Hamawandi, B., Toprak, M.S., Ballikaya, S.: Multi-objective optimization of concentrated photovoltaic-thermoelectric hybrid system via non-dominated sorting genetic algorithm (NSGA II). *Energy Convers. Manage.* **236**, 114065 (2021). <https://doi.org/10.1016/j.enconman.2021.114065>
13. Bora, T.C., Mariani, V.C., dos Santos Coelho, L.: Multi-objective optimization of the environmental-economic dispatch with reinforcement learning based on non-dominated sorting genetic algorithm. *Appl. Therm. Eng.* **146**, 688–700 (2019). <https://doi.org/10.1016/j.applthermaleng.2018.10.020>
14. Fathima, A.H., Palanisamy, K.: Optimization in microgrids with hybrid energy systems - a review. *Renew. Sustain. Energy Rev.* **45**, 431–446 (2015). <https://doi.org/10.1016/j.rser.2015.01.059>
15. Singh, P., Pandit, M., Srivastava, L.: Multi-objective optimal sizing of hybrid micro-grid system using an integrated intelligent technique. *Energy* **269**, 126756 (2023). <https://doi.org/10.1016/j.energy.2023.126756>
16. Zhu, W., Guo, J., Zhao, G.: Multi-objective sizing optimization of hybrid renewable energy microgrid in a stand-alone marine context. *Electronics* **10**(2), 174 (2021). <https://doi.org/10.3390/electronics10020174>
17. Khelifi, F., Cherif, H., Belhadj, J.: Environmental and economic optimization and sizing of a micro-grid with battery storage for an industrial application. *Energies* **14**(18), 5913 (2021). <https://doi.org/10.3390/en14185913>
18. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* **6**(2), 182–197 (2002). <https://doi.org/10.1109/4235.996017>

Open Access This chapter is licensed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

