

Shu-Chuan Chu
Jerry Chun-Wei Lin
Jianpo Li
Jeng-Shyang Pan *Editors*

Genetic and Evolutionary Computing

Proceedings of the Fourteenth
International Conference on Genetic
and Evolutionary Computing,
October 21–23, 2021, Jilin, China

Lecture Notes in Electrical Engineering

Volume 833

Series Editors

Leopoldo Angrisani, Department of Electrical and Information Technologies Engineering, University of Napoli Federico II, Naples, Italy

Marco Arteaga, Departament de Control y Robótica, Universidad Nacional Autónoma de México, Coyoacán, Mexico

Bijaya Ketan Panigrahi, Electrical Engineering, Indian Institute of Technology Delhi, New Delhi, Delhi, India

Samarjit Chakraborty, Fakultät für Elektrotechnik und Informationstechnik, TU München, Munich, Germany

Jiming Chen, Zhejiang University, Hangzhou, Zhejiang, China

Shanben Chen, Materials Science and Engineering, Shanghai Jiao Tong University, Shanghai, China

Tan Kay Chen, Department of Electrical and Computer Engineering, National University of Singapore, Singapore, Singapore

Rüdiger Dillmann, Humanoids and Intelligent Systems Laboratory, Karlsruhe Institute for Technology, Karlsruhe, Germany

Haibin Duan, Beijing University of Aeronautics and Astronautics, Beijing, China

Gianluigi Ferrari, Università di Parma, Parma, Italy

Manuel Ferre, Centre for Automation and Robotics CAR (UPM-CSIC), Universidad Politécnica de Madrid, Madrid, Spain

Sandra Hirche, Department of Electrical Engineering and Information Science, Technische Universität München, Munich, Germany

Faryar Jabbari, Department of Mechanical and Aerospace Engineering, University of California, Irvine, CA, USA

Limin Jia, State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, China

Janusz Kacprzyk, Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland

Alaa Khamis, German University in Egypt El Tagamoa El Khames, New Cairo City, Egypt

Torsten Kroeger, Stanford University, Stanford, CA, USA

Yong Li, Hunan University, Changsha, Hunan, China

Qilian Liang, Department of Electrical Engineering, University of Texas at Arlington, Arlington, TX, USA

Ferran Martín, Departament d'Enginyeria Electrònica, Universitat Autònoma de Barcelona, Bellaterra, Barcelona, Spain

Tan Cher Ming, College of Engineering, Nanyang Technological University, Singapore, Singapore

Wolfgang Minker, Institute of Information Technology, University of Ulm, Ulm, Germany

Pradeep Misra, Department of Electrical Engineering, Wright State University, Dayton, OH, USA

Sebastian Möller, Quality and Usability Laboratory, TU Berlin, Berlin, Germany

Subhas Mukhopadhyay, School of Engineering & Advanced Technology, Massey University, Palmerston North, Manawatu-Wanganui, New Zealand

Cun-Zheng Ning, Electrical Engineering, Arizona State University, Tempe, AZ, USA

Toyoaki Nishida, Graduate School of Informatics, Kyoto University, Kyoto, Japan

Federica Pascucci, Dipartimento di Ingegneria, Università degli Studi "Roma Tre", Rome, Italy

Yong Qin, State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, China

Gan Woon Seng, School of Electrical & Electronic Engineering, Nanyang Technological University, Singapore, Singapore

Joachim Speidel, Institute of Telecommunications, Universität Stuttgart, Stuttgart, Germany

Germano Veiga, Campus da FEUP, INESC Porto, Porto, Portugal

Haitao Wu, Academy of Opto-electronics, Chinese Academy of Sciences, Beijing, China

Walter Zamboni, DIEM - Università degli studi di Salerno, Fisciano, Salerno, Italy

Junjie James Zhang, Charlotte, NC, USA

The book series *Lecture Notes in Electrical Engineering* (LNEE) publishes the latest developments in Electrical Engineering - quickly, informally and in high quality. While original research reported in proceedings and monographs has traditionally formed the core of LNEE, we also encourage authors to submit books devoted to supporting student education and professional training in the various fields and applications areas of electrical engineering. The series cover classical and emerging topics concerning:

- Communication Engineering, Information Theory and Networks
- Electronics Engineering and Microelectronics
- Signal, Image and Speech Processing
- Wireless and Mobile Communication
- Circuits and Systems
- Energy Systems, Power Electronics and Electrical Machines
- Electro-optical Engineering
- Instrumentation Engineering
- Avionics Engineering
- Control Systems
- Internet-of-Things and Cybersecurity
- Biomedical Devices, MEMS and NEMS

For general information about this book series, comments or suggestions, please contact leontina.dicecco@springer.com.

To submit a proposal or request further information, please contact the Publishing Editor in your country:

China

Jasmine Dou, Editor (jasmine.dou@springer.com)

India, Japan, Rest of Asia

Swati Meherishi, Editorial Director (Swati.Meherishi@springer.com)

Southeast Asia, Australia, New Zealand

Ramesh Nath Premnath, Editor (ramesh.premnath@springernature.com)

USA, Canada:

Michael Luby, Senior Editor (michael.luby@springer.com)

All other Countries:

Leontina Di Cecco, Senior Editor (leontina.dicecco@springer.com)

**** This series is indexed by EI Compendex and Scopus databases. ****

More information about this series at <https://link.springer.com/bookseries/7818>


Shu-Chuan Chu · Jerry Chun-Wei Lin ·
Jianpo Li · Jeng-Shyang Pan
Editors

Genetic and Evolutionary Computing

Proceedings of the Fourteenth International
Conference on Genetic and Evolutionary
Computing, October 21–23, 2021, Jilin, China

Editors

Shu-Chuan Chu
College of Computer Science
and Engineering
Shandong University of Science
and Technology
Qingdao, Shandong, China

Jianpo Li 
Northeast Electric Power University
Jilin City, Jilin, China

Jerry Chun-Wei Lin
Western Norway University
of Applied Sciences
Bergen, Norway

Jeng-Shyang Pan
College of Computer Science
and Engineering
Shandong University of Science
and Technology
Qingdao, Shandong, China

ISSN 1876-1100

ISSN 1876-1119 (electronic)

Lecture Notes in Electrical Engineering

ISBN 978-981-16-8429-6

ISBN 978-981-16-8430-2 (eBook)

<https://doi.org/10.1007/978-981-16-8430-2>

© The Editor(s) (if applicable) and The Author(s), under exclusive license
to Springer Nature Singapore Pte Ltd. 2022

This work is subject to copyright. All rights are solely and exclusively licensed 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 Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721,
Singapore

Preface

This volume composes the proceedings of the Fourteenth International Conference on Genetic and Evolutionary Computing (ICGEC 2021), which was hosted by Northeast Electric Power University and was held in Jilin City, Jilin Province, China, on October 21–23, 2021. ICGEC 2021 was technically co-sponsored by Fujian University of Technology (China), Shandong University of Science and Technology (China), Western Norway University of Applied Sciences (Norway), and Springer. It aimed to bring together researchers, engineers, and policymakers to discuss the related techniques, to exchange research ideas, and to make friends. More than sixty excellent papers were accepted for the final proceeding. We would like to thank the authors for their tremendous contributions. Furthermore, we would also express our sincere appreciation to the reviewers, program committee members, and local committee members for making this conference successful.

October 2021

Jerry Chun-Wei Lin
General Chair

Conference Organization

Conference Founder

Jeng-Shyang Pan Shandong University of Science and Technology,
China

Honorary Chairs

Jeng-Shyang Pan Shandong University of Science and Technology,
China

Leon S. L. Wang National University of Kaohsiung, Taiwan
Yao Qingguo Fujian University of Technology, China

Advisory Committee Chairs

Tzung-Pei Hong National University of Kaohsiung, Taiwan
Josh Han-Chieh Chao National Dong Hwa University, Taiwan

General Chairs

Jerry Chun-Wei Lin Western Norway University of Applied Sciences,
Norway

Shu-Chuan Chu Flinders University, Australia
Liang Yonquan Shandong University of Science and Technology,
China

Program Chairs

I-Hsin Ting National University of Kaohsiung, Taiwan
Philippe Fournier-Viger Harbin Institute of Technology (Shenzhen),
China

Jimmy Ming-Tai Wu Shandong University of Science and Technology,
China
Hong-Bo Liu Dalian Maritime University, China

Local Organization Chairs

Weimin Zhang Shandong University of Science and Technology,
China
Chien-Ming Chen Shandong University of Science and Technology,
China

Electronic Media Chairs

Tsu-Yang Wu Shandong University of Science and Technology,
China
Thi-Thi Zin University of Miyazaki, Japan
Matin Pirouz Nia California State University, Fresno, USA

Invited Session Chairs

Peng Yanjun Shandong University of Science and Technology,
China
Voznak Miroslav VSB-Technical University of Ostrava,
Czech Republic

Publication Chair

Zhongying Zhao Shandong University of Science and Technology,
China

Finance Chair

Jui-Fang Chang National Kaohsiung University of Sciences
and Technology, Taiwan

Program Committee Members

Yongtang Bao Shandong University of Science and Technology,
China
Binge Cui Shandong University of Science and Technology,
China
Hsing-Chung Chen Asia University, Taiwan
Chun-Hao Chen National Taipei University of Technology,
Taiwan

Chien-Ming Chen	Shandong University of Science and Technology, China
Youcef Djenouri	SINTEF Digital, Norway
Hamido Fujita	Iwate Prefectural University, Japan
Vicente Garcia Diaz	University of Oviedo, Spain
Philippe Fournier-Viger	Shenzhen University, China
Tzung-Pei Hong	National University of Kaohsiung, Taiwan
Jean Lai	Hong Kong Baptist University, Hong Kong
Jerry Chun-Wei Lin	Western Norway University of Applied Sciences, Norway
Wei-Cheng Lin	National Kaohsiung University of Science and Technology, Taiwan
Irfan Mehmood	Bradford university, UK
Weijian Ni	Shandong University of Science and Technology, China
Matin Pirouz Nia	California State University, USA
Seungmin Rho	Sejong University, South Korea
Ja-Hwung Su	National University of Kaohsiung, Taiwan
Wei Song	North China University of Technology, China
I-Hsing Ting	National University of Kaohsiung, Taiwan
Pei-Wei Tsai	Swinburne University of Technology, Australia
Cun-Wei Tsai	National Sun-Yat Sen University, Taiwan
Raylin Tso	National Chengchi University, Taiwan
Bay Vo	Ho Chi Minh City University of Technology, Vietnam
Miroslav Voznák	VSB-Technical University of Ostrava, Czech Republic
Chen-Shu Wang	National Taipei University of Technology, Taiwan
Mu-En Wu	National Taipei University of Technology, Taiwan
Wei-min Chen	Yili Vocational and Technical College, China
Wen-quan Zeng	Guangdong University of Science & Technology, China
Tsu-Yang Wu	Shandong University of Science and Technology, China
Jimmy Ming-Tai Wu	Shandong University of Science and Technology, China
Cheng-Wei Wu	National Ilan University, Taiwan
Chen Xin	Shandong University of Science and Technology, China
Lu Yan	Shandong University of Science and Technology, China
Ji Zhang	University of Southern Queensland, Australia
Thi-Thi Zin	University of Miyazaki, Japan

Zhongying Zhao

Shandong University of Science and Technology,
China

Jianli Zhao

Shandong University of Science and Technology,
China

Weimin Zheng

Shandong University of Science and Technology,
China

Contents

Nature Inspired Constrained Optimization

Adaptive Droop Control Strategy for Island Microgrid Based on Improved Particle Swarm Optimization Algorithm	3
Xiangbiao Leng, Hao Zheng, Taiping Yuan, Yubin Lai, Fei Peng, Haixiang Yu, and Jingfeng Ou	
Coordinated Optimization Control Technology of Clean Energy Consumption Based on Spatiotemporal Characteristics of Controllable Load	14
Weichun Ge, Shunjiang Wang, Qingbo Yin, Feng Sun, Peng Jin, and Shengbin Chi	
A Beta Distribution Based Optimization Algorithm and Its Application in Power Load Forecasting	25
Jiao Wang, Shu-Chuan Chu, Shi-Jian Liu, and Jeng-Shyang Pan	
Optimization of Li-ion Battery Charge and Discharge Model Based on Genetic Algorithm	36
Xiang Li, Wen Yang, Huan Wang, Xiaopeng Chang, Rongxin Dang, and Dejun Wang	
An Enhanced Harmony Search Based on Quantum Mechanism	47
Maomao Liang, Ying Deng, Wen Xiao, Lijin Wang, and Yiwen Zhong	
Performance Evaluation of Three Intelligent Optimization Algorithms for Obstacle Avoidance Path Planning	60
Shumeng Chen, Chia-Hung Wang, Zhenyu Dong, Qigen Zhao, Qipeng Yang, Yi Wei, and Guoshu Huang	

Software Development and Reliability Systems

Experimental Data Acquisition and Processing System Based on the Internet of Things 73
Hang Liu, Jun Wang, Mingtai Liu, Xiukai Jian, Yuhong Zhang, and Yuli Li

A Mill Control System Based on GA-BP Network for Output Prediction 82
Hongwei Ren, Sheng Zheng, and Xinyu Li

State Evaluation and Attack Signal Reconstruction of Power Cyber-Physics System Based on Intermediate Variable Observer 92
Lin Lin, Zhipeng Cong, Qigui Nie, Xin Liu, Weiting Wang, Jian Li, and Defu Yang

Risk Assessment Method of Power Monitoring System Vulnerability Based on Attack Graph 102
Hongbo Ye, Kexiang Qian, Minghui Jin, Xiao Han, and Fei Xiao

Dynamic Multiple Indicators Matching Processing for Power Load Forecasting System 114
Tiehua Zhou, Jiayu Hao, Futao Ma, and Ling Wang

Design of Cyber Security Monitoring System for Smart Substation 125
Qiang Ma, Zhipeng Cong, Zhenyu Shi, Fen Chen, and Jianpo Li

Bioinformatics and Biomedical Analysis

Multi-attention and Multi-layer Hashing for Cross-Modal Retrieval 139
Zhiyou Wang, Meijing Li, and Tianjie Chen

Quantitative Analysis Indicators and Risk Factor Assessment of HR-HPV 150
Ling Gong, Hua Xie, Ling Wang, Lu Zhang, Site Li, and Beibei Miao

Prediction of Drug-Gene Interaction by Using Biomedical Subgraph Patterns 159
Guangjin Zhao, Meijing Li, and Yingying Jiang

Medical Phrase Mining Method for Biomedical Text Processing 169
Ling Wang, Minglei Shan, Tong Li, Yingxuan Tang, and Tiehua Zhou

BioBERT Based Efficient Clustering Framework for Biomedical Document Analysis 179
Khishigsuren Davagdorj, Kwang Ho Park, Tsatsral Amarbaysgalan, Lkhagvadorj Munkhdalai, Ling Wang, Meijing Li, and Keun Ho Ryu

Distantly Supervised Relation Extraction Based on Multi-head Self-attention and Gate Mechanism 189
Fengzhu Xu, Meijing Li, and Keun Ho Ryu

Image and Video Processing

Research on Small Target Pedestrian Detection Algorithm Based on Improved YOLOv3 203
 Shuaishi Liu, Yining Geng, Yihu Song, Wenyang Yan, and Yufeng Lian

Zhuang Characteristic Culture Detection Based on Improved YOLOV3-SPP Network 215
 Shu Guo, Baohua Qiang, Wu Xie, Yijie Zhai, Ruidong Chen, and Hong Zheng

A Method for Detecting Safety Helmet in Substation Operation Scene Based on Yolov3. 227
 Xiaoyu Chen, Jianyou Yu, Dezhi Zhao, Jian Sun, Xianghong Chen, Mingli Yi, and Lin Xia

Gray-Scale Image Color Migration Algorithm Based on Dual-Stream Convolutional Neural Network 239
 Xiwen Zhang and Jin Duan

FM-Mnet Real-Time Object Detection Model for Video Feature Fusion Processing. 249
 Tiehua Zhou, Yifan Zhang, Yuan Li, and Ling Wang

Modeling and Trajectory Tracking Control Simulation of 3-DOF Hoisting Manipulator 259
 Mujun Xie, Shaoshi Qin, Changhong Jiang, and Aoshuang Li

Intelligent Multimedia Tools and Applications

Virtual Display and Interaction System Design of Bingxi Scroll Painting Based on Augmented Reality Technique 273
 Yihang Du, Yan Pei, Lijun Wang, Chenzong Bai, and Ke Niu

GPU Implementation of Staggered Period Estimation Algorithm Acceleration 284
 Zhuojun Xu, Hangwei Hu, Long Wang, Chengzhi Yang, and Yantao Tian

BioAR: Bio-Laboratory Automation Meets Augmented Reality 294
 Zheng Zou and Shi-Jian Liu

3D Voxel Reconstruction Based on Shape Layer 306
 Linlin Tang, Shuaijie Shi, Shiyu Qin, Xin Huang, and Yijie Fan

Research on Weld Recognition and NURBS Curve Fitting Method Based on Improved OTSU Double Threshold Segmentation 316
 Liu Shuaishi, Zhou Siyu, Bai Rong, and Zhu Jiaqi

Modeling and Simulation of Non-common Field Position and Pose Measurement of Dual Cameras 328
 Mujun Xie, Aoshuang Li, Changhong Jiang, and Shaoshi Qin

Neural Network and Deep Learning

Transformer Combination Weighting Evaluation Model Based on BP Neural Network 341
Xiaohuan Wu, Pengcheng Wang, Liquan Wang, Yinfei Xu, and Zhongwei Zhao

Research on Target Recognition Algorithm Based on Improved Faster-RCNN 350
Fangxiao Cheng, Borui Yin, and Ming Chu

Identification Method of Dust Accumulation of Air Cooled Condenser Based on Convolution Neural Learning 360
Bo Zhao, Hongda Lin, Zhihui Wang, and Jiayue Xu

A Pedestrian Intrusion Detection Method Based on Improved Mask R-CNN Model 370
Xiaoyu Chen, Jianyou Yu, Dezhi Zhao, Jian Sun, Xianghong Chen, Mingli Yi, and Lin Xia

A Flight Simulation Model Architecture for Reinforcement Learning 381
KaiXuan Wang, YuTing Shen, FuQuan Zhang, Nan Zhao, and Lijie Yang

NLP and Clustering

HDMacBERT-FGM-CRF Model-Based Chinese Event Element Extraction 395
Peng Chen, Baohua Qiang, Yufeng Wang, Chen Wang, Ruidong Chen, Baolian Li, Bo Peng, and Xiangyu Zhou

Abstractive Sentences Summarization Model Combining Entity Information and Bidirectional Decoding 407
Chen Wang, Baohua Qiang, Bo Peng, Peng Chen, Ruidong Chen, Hong Zheng, and Yufeng Wang

Multi-group Discrete Symbiotic Organisms Search Algorithm Based Clustering Method for Large-Scale Traveling Salesman Problem 419
Shu-Chuan Chu, Zhi-Gang Du, and Jeng-Shyang Pan

Cluster Analysis of Smart Meter Load Based on Electricity Behavior Characteristics 429
Dachi Zhang, Xuanyuan Zhao, Yunfeng Guo, Jingying Yang, Peng Liu, and Yu Lu

Improved Affinity Propagation Clustering Based on K-Nearest Neighbors and Canopy Algorithm 438
Zhihe Wang, Gang Zhang, Hui Du, and Yiyang Ni

Research on Multi-dimensional Load Characteristics Based on Vertical and Horizontal Hybrid Clustering 449
 Xiaotong Zhang, Zhijun Yuan, Yicheng Jin, Shunjiang Wang, Feng Sun, Bing Xie, and Xingtong Ma

Big Data Analysis and Ontology System

An Improved Fireworks Algorithm for Ontology Matching 461
 Huanting Shi and Jinyuan Shi

Revealing Top-*k* Dominant Individuals in Incomplete Data Based on Spark Environment 471
 Ke Wang, Jimmy Ming-Tai Wu, Bingjie Cui, and Jerry Chun-Wei Lin

Optimizing Task Processing in Big Data with Federated Learning 481
 Chunyi Wu and Ya Li

Privacy of Web Browsers: A Challenge in Digital Forensics 493
 Adnan Ahmed, Abdul Rehman Javed, Zunera Jalil, Gautam Srivastava, and Thippa Reddy Gadekallu

Mining High Utility-probability Sequential Patterns in Bigdata Environments 505
 Jimmy Ming-Tai Wu, Shuo Liu, Mu-En Wu, and Jerry Chun-Wei Lin

The Timeliness Position Recommendation Based on Geographical Impacts and Social Impacts 515
 Baolian Li, Jianghua Zhu, Yufeng Wang, and Haiyao Xie

Smart Grid and Energy Internet

Division of Power Grid Dispatching Domain and Analysis of Operation Characteristics 529
 Shunjiang Wang, Yifan Wang, Tianhang Wang, Jiancheng Hao, Weichun Ge, and Aihua Wang

Distribution Network Load Forecasting Based on Smart Meter User Behavior Clustering 538
 Shunjiang Wang, Qianbin Dai, Guiping Zhou, Yangyang Ge, Peng Jin, and Yifan Wang

Regulation Strategy of Electric Vehicle Charging Station Taking into Account New Energy Consumption 548
 Yuxing Li, Dongyuan Liu, Jingying Yang, Qunying Li, Lei Song, and Xuefeng Gao

Evaluation Model of Power Staff Skill State Based on Improved Analytic Hierarchy Process_Fuzzy Comprehensive Evaluation 560
 Xiuming Wang, Zhaoyang Qu, Lichao Wang, Miao Li, Chunhui Liu, Yaowei Liu, Zhongfeng Kan, and Huashun Li

Information Recommendation Method of Network Blended Skill Learning Based on Personalized Adaptive of Electric Power Staff 573
 Yan Gao, Lei Wang, Miao Li, Chunhui Liu, and Lichao Wang

A Differential Evolution Algorithm for Wind Farm Layout Optimization Using a New Bilevel Programming Model 584
 Lijuan Chen, Hecheng Li, and Yu Shen

Genetic Algorithm and Machine Learning

Test Paper Automatic Generating Method Based on Hybrid Genetic Algorithm 599
 Yan Wang and Xinhua Wang

Improved Multi-objective Genetic Algorithm for Unit Economic Operating Load Distribution 610
 Minghao Guo, Wei Wang, and Renhui Chen

An Improved GA-Based Recommendation System for Soil Fertilization 619
 Usman Ahmed, Jerry Chun-Wei Lin, Gautam Srivastava, and Jimmy Ming-Tai Wu

Survey on Initialization Methods of Cuckoo Search Algorithm 629
 Wen Xiao, Maomao Liang, Lijin Wang, and Yiwen Zhong

Tumbleweed Algorithm and Its Application for Solving Location Problem of Logistics Distribution Center 641
 Qing-yong Yang, Shu-Chuan Chu, Anhui Liang, and Jeng-Shyang Pan

Research on Evasion Strategy of Aircraft Based on Deep Reinforcement Learning 653
 Ye Li, Lin Zhang, Kaixuan Wang, Fuquan Zhang, and Yi Fan

Wireless Sensor Networks and Internet of Things

Research on NPE Algorithm of Ring Main Unit Fault Detection Based on Internet of Things Technology 669
 Liu Baojun

Mechanical Fault Diagnosis of Circuit Breaker Based on Improved Grey Relational Analysis 679
 Xiaohuan Wu, Pengcheng Wang, Liqun Wang, Yinfei Xu, and Zhongwei Zhao

A Matrix-Analytic Solution to Three-Level Multi-Server Queueing Model with a Shared Finite Buffer 690
 Qigen Zhao, Chia-Hung Wang, Zhenyu Dong, Shumeng Chen, Qipeng Yang, and Yi Wei

A Novel Learning-Based Approach for Large Outdoor Power Transmission Equipment Detection 700
Fatana Jafari, Rui Xu, Gilbert Shyirambere, Jean Bosco Ndungutse, and Shi-Jian Liu

Fusion Structure-based Fault State Prediction of Wind Turbine Spindle 712
Baohua Qiang, Wenqiang Yin, Xiaoling Tao, Longge Li, Baolian Li, Bo Peng, and YuFeng Wang

TDOA Location Based on Pigeon-Inspired Optimization Algorithm in WSNs 724
Jeng-Shyang Pan, Ai-Qing Tian, Shu-Chuan Chu, Tsu-Yang Wu, and Jin Wang

Author Index 735

Nature Inspired Constrained Optimization



Adaptive Droop Control Strategy for Island Microgrid Based on Improved Particle Swarm Optimization Algorithm

Xiangbiao Leng¹(✉), Hao Zheng², Taiping Yuan¹, Yubin Lai¹, Fei Peng¹,
Haixiang Yu¹, and Jingfeng Ou³

¹ China Southern Power Grid Energy Development Research Institute CSG,
Guangzhou 510700, China

² Jining Power Supply Company, State Grid Shandong Electric Power Company, Jining
272000, China

³ Guangdong Chengyu Engineer Consultation and Supervision Co., Ltd., Foshan 528200, China

Abstract. The isolated island microgrid with multiple distributed power sources operating in parallel cannot ensure that the voltage information is equal everywhere due to the difference in line impedance. As a result, its droop control may cause some problems such as unbalanced power distribution and bus voltage fluctuation. For this, a method to improve particle swarm optimization (IPSO) using fuzzy rule system to optimize droop control is proposed. Firstly, the principle and shortcomings of traditional droop control are analyzed. Then, in order to reach optimization of droop factor, a particle swarm (PSO) algorithm with fuzzy rule system is proposed, which can dynamically adjust the learning factor and inertia weight of the particle swarm algorithm, and effectively improve the convergence ability and search speed of the algorithm. The experiment results show that the proposed IPSO algorithm can maintain the real-time stability of bus voltage and microgrid frequency under complex operating conditions, efficaciously improve the accuracy of power balance distribution, and enhance the dynamic performance and stability of islanded microgrid.

Keywords: Microgrid · PSO algorithm · Fuzzy rule-based systems · Droop control · Power distribution

1 Introduction

As a small power system, the microgrid integrates distributed generations, energy storing equipment, energy transformers, protection devices and loads, and has two operating modes: islanding and grid-connected [1]. The control mode of microgrid is classified as master-slave control and equivalence control [2]. Compared with the master-slave control, the equivalence control mode simulates the external characteristics of the grid-connected operation of the synchronous motor. Under this control mode, the droop control of the distributed generations (DG) can automatically participate in the distribution of the output power, which is convenience for realizing the plug-and-play of the distributed generations [3, 4].

The droop controller of the alternating current (AC) microgrid mainly includes two parts: the inner loop that uses the droop curve to generate the voltage reference quantity, and the outer voltage-current loop that tracks the reference value generated by the inner loop [5]. Whereas, the existence of line impedance and local load makes the voltage and frequency information of each DG not equal everywhere, which will lead to insufficient power allocation accuracy and bus voltage drop [6]. At present, artificial intelligence control algorithm plays an increasingly significant role in solving complex problems in power grid. Artificial intelligence control algorithm has incomparable advantages. Artificial intelligence control algorithms have been the primary way to study and settle electrical power system problems in control, modeling, operation and analysis [7].

Therefore, this paper proposed the IPSO algorithm by using the fuzzy rule-based system to optimize the droop control. The function of introducing fuzzy rule system is to dynamically adjust the learning factor and inertia weight of particle swarm algorithm, and improve the global search ability and local search ability of the algorithm. The simulation experiment results show that the proposed IPSO algorithm can sustain real-time voltage and frequency stability under different operating conditions, effectively improve the power allocation accuracy and the dynamic performance and stability of the microgrid.

2 Traditional Droop Control

The topology of the AC microgrid droop controller is similar to equivalent circuit of synchronous generator. The topology of the simplified multi-distributed power microgrid in Fig. 1 is obtained [8].

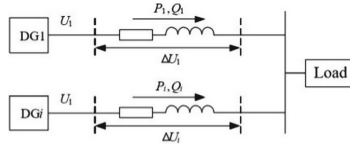


Fig. 1. Simplified structure of microgrid.

As illustrated in the picture above, the DG is connected to the microgrid through inverter and LC filter respectively and is connected to the AC bus through line impedance to supply power to the load [9]. Since $R \ll X$, the resistance part of the line impedance does not need to be calculated. The power output P_i and Q_i of the i -th DG are:

$$P_i = \frac{U_i U_{PCC} \sin \delta_i}{X_i} \quad (1)$$

$$Q_i = \frac{U_i U_{PCC} \cos \delta_i - U_{PCC}^2}{X_i} \quad (2)$$

In the formulas, U_i is the amplitude of the i -th DG output voltage, U_{PCC} is the amplitude of the AC microgrid bus voltage, X_i is the line reactance from the i -th DG to the AC bus, and δ_i is the phase of the i -th DG output voltage Phase difference with PCC voltage.

According to formula (1) and (2), the variation factors of active power P and reactive power Q of the DGs are voltage phase difference δ and voltage magnitude U . Thus the droop characteristics of microgrid are illustrated in the picture blow.

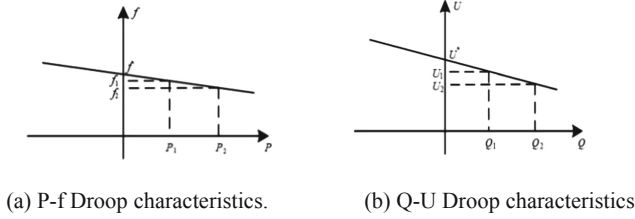


Fig. 2. Droop characteristics.

From Fig. 2, we can get that the droop characteristic equation of the DG_i are

$$f_i = f^* - k_p P_i \quad (3)$$

$$U_i = U^* - k_q Q_i, \quad (4)$$

Where k_p is the frequency droop factor in the microgrid droop control, and k_q is the voltage droop factor in the microgrid droop control, f^* is the reference frequency value of the microgrid system, U^* is the reference voltage value of the microgrid system.

Therefore, the traditional droop control principle is illustrated in Fig. 3 [10].

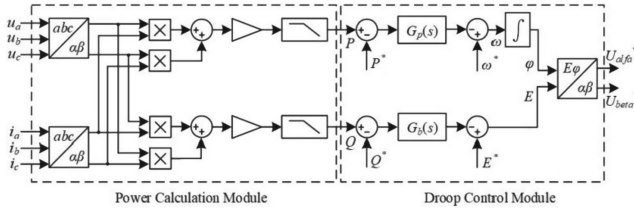


Fig. 3. Traditional droop control schematic

In the microgrid, the reactive power of the DG can't be accurately distributed by droop control according to the local variable output voltage. Hereby, we should need to optimize the distribution of the DG reactive power output [8].

In the simplified microgrid topology diagram, the following formulas can be obtained:

$$U_i = U_{PCC} + \Delta U_i \quad (5)$$

$$\Delta U_i = \frac{X_i Q_i + R_i P_i}{U^*} \quad (6)$$

Among them, ΔU is the voltage drop of the i -th DG line impedance. As mentioned earlier, because of $R \ll X$, the above formula can be simplified to:

$$\Delta U_i = \frac{X_i}{U^*} Q_i \quad (7)$$

According to the simplified microgrid topology diagram in Fig. 1 and Eqs. (5) to (7), the reactive power transmission characteristic curves of each DG is shown as follows:

$$U_1 = U_{PCC} + \frac{X_1}{U^*} Q_1 = U_{PCC} + k_1 Q_1 \quad (8)$$

$$U_2 = U_{PCC} + \frac{X_2}{U^*} Q_2 = U_{PCC} + k_2 Q_2 \quad (9)$$

Among them, k_1 and k_2 are the impedance factors of the DG1 and DG2 exit line. Combined with the droop characteristic diagram shown in formula (4), the reactive power distribution relationship of double parallel distributed power sources is illustrated in the picture blow.

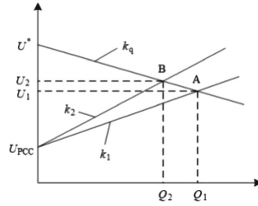


Fig. 4. Reactive power distribution relationship

When $X_1 \neq X_2$, the stable operation points of the systems are situated at A and B in Fig. 4. Assuming that there is $\Delta Q_1 = \Delta Q_2$, when $X_1 < X_2$, there is $Q_1 > Q_2$, and the reactive power output of double parallel distributed power sources cannot be accurately distributed.

3 Improved Particle Swarm Algorithm

3.1 Basic Particle Swarm Algorithm

The PSO algorithm has the characters of structure simplification and good optimization effect, and can search for appropriate parameters without establishing an accurate mathematical model [12]. The initial parameters of PSO are quantitative random particles. In the PSO running process, the particles update the parameters of individual extremum and global extremum through each iteration in order to find the optimum result [13].

In PSO algorithm, the particle velocity and position update formula are as follows:

$$v_{id} = \omega \times v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \quad (10)$$

$$x_{id} = x_{id} + v_{id} \quad (11)$$

Among them, c_1 and c_2 are study rates of the PSO algorithm; r_1 and r_2 are symmetrical random numbers in $[0,1]$; ω is the adaptive weight value.

3.2 Introduction of Fuzzy Rule System

Despite of simple structure of the basic PSO algorithm, when optimizing complex non-linear microgrids based on droop control strategy, the basic PSO algorithm has the shortcomings of insufficient global search and detection ability. Therefore, a series of improvements to the basic PSO are required.

This thesis introduces a fuzzy rule-based system on the basis of the proposed method in the reference [14] to enhance the performance of the PSO algorithm, and dynamically adjusts the learning factor c_1 and c_2 of the particle swarm algorithm through fuzzy inference and the inertia weight ω . Among them, the iteration coefficient λ of each particle is the ratio of the current iteration number to the maximum iteration number, and the iteration coefficient λ of each particle is between 0 and 1. The calculation formula is:

$$\lambda = \frac{t}{t_{max}} \quad (12)$$

Among them, t is the particle current iteration number, and t_{max} is the maximum iteration number of the particle. During the initial operation of the algorithm, λ approaches 0. With the change of the iteration number, λ gradually increases and approximates 1.

The particle similarity γ is the reciprocal of the square root of the average value of the optimum result of all particle distances in the whole world, and its value is between 0 and 1. The calculation formula is:

$$r = \frac{1}{\sqrt{\frac{1}{m} \sum_{i=1}^m \sqrt{\sum_{j=1}^d (x_{ij}(t-1) - gbest_i(t-1))^2 + 1}}} \quad (13)$$

Among them, m is the total particle number, d is the search space dimension, x_{ij} is the position of the i -th particle in the j -th dimension during the previous iteration, and $gbest_j$ is the j -th dimension of the optimum result found in the previous iteration. When the distance between the particle and the optimum result in the algorithm is larger, the average value is also larger, and the particle similarity is smaller, until it is 0; otherwise, the particle similarity is larger, until it is 1.

The fitness error ε of a particle is the difference between the average of the ratio of the fitness value of the global optimal particle to the fitness value of all particles and 1, and its value is between 0 and 1. The calculation formula is:

$$\varepsilon = 1 - \frac{1}{m} \sum_{i=1}^m \frac{f_{gbest}}{fit(i)} \quad (14)$$

Among them, f_{gbest} is the fitness value of the algorithm's global optimal particle, and $fit(i)$ is the adaptation degree of the i -th particle in the IPSO algorithm. When the algorithm has a good convergence effect, the particles approach the global optimum result, the ratio of f_{gbest} and $fit(i)$ becomes larger, approaching 1, and the fitness error approaches 0. Conversely, the difference between f_{gbest} and $fit(i)$ The ratio becomes smaller and approaches 0, and the fitness error approaches 1.

In the fuzzy rule-based system, the inputs are the iteration coefficient λ , the particle similarity γ and the particle fitness error ε , and the output is the learning factor c_1 , c_2

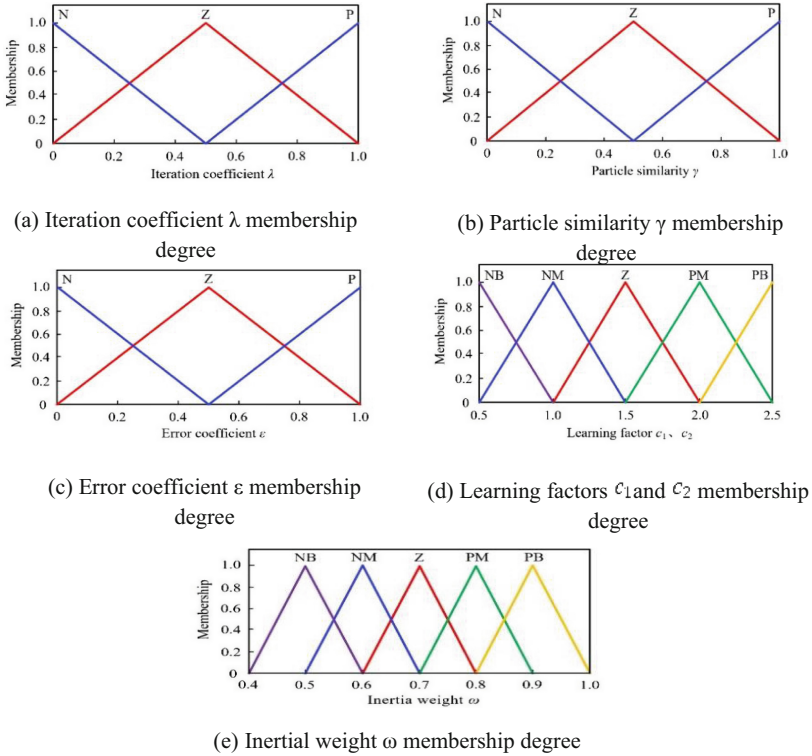


Fig. 5. Fuzzy rule system membership degree

and the inertia weight ω of the PSO algorithm, and there are 27 rules. For one thing, this article sets the delimited region of iteration coefficient λ , particle similarity γ and particle fitness error ε to $[0,1]$, the delimited region of ω to $[0.4,1]$, and the delimited region of c_1 and c_2 to $[0.5,2.5]$. Afterwards, this article set the number of input fuzzy divisions to 3. The number of output fuzzy divisions is 5. The fuzzy inference system adopts the Mamdani type system and the centroid method of gravity for the defuzzification [10]. Otherwise, because of the excellent performance and good application result, the triangular membership function is applied to the IPSO algorithm proposed in the thesis.

The application of fuzzy rule-based system must meet two requirements as follow. In the early stage of the IPSO operation, the large distance between the particle and the optimum result and the small value of the particle iteration coefficient λ , the particle similarity γ , and the particle fitness error ε can make the IPSO algorithm obtain the better exploration ability. In the late stage of the IPSO operation, the small distance between the particles and the optimum result, and the large value of the particle iteration coefficient λ , the particle similarity γ and the particle fitness error ε can make the IPSO algorithm obtain the local searching capability.

3.3 Fitness Function

In this paper, an island microgrid with double parallel distributed power sources is the research object, considering the power balanced distribution, bus voltage fluctuations and frequency oscillations, a control method using an IPSO algorithm to find the optimal droop factor is proposed.

The fitness function optimized for the IPSO algorithm is:

$$F = \Delta P + \Delta Q + \Delta U + \Delta f \quad (15)$$

In the above formula, ΔP can be expressed as:

$$\Delta P = |P_1 - P_2| \quad (16)$$

$$\Delta Q = |Q_1 - Q_2| \quad (17)$$

Among them, P_1 and P_2 are the active power output, and Q_1 and Q_2 are the reactive power output.

Similarly, ΔU can be expressed as:

$$\Delta U = \Delta U_1 - \Delta U_2 = |U_1 - U_0| + |U_2 - U_0| \quad (18)$$

Among them, ΔU and ΔU_2 are the output voltage deviations, U_1 and U_2 are the output voltages, and U_0 is the system rated voltage.

Similarly, Δf can be expressed as

$$\Delta f = \Delta f_1 - \Delta f_2 = |f_1 - f_0| + |f_2 - f_0| \quad (19)$$

Among them, Δf_1 and Δf_2 are the frequency deviations, f_1 and f_2 are the frequencies and f_0 is the power frequency of 50 Hz.

4 Simulation Analysis

4.1 System Control Structure and Parameter Design

There is the IPSO algorithm present in the second section of this article in application to the droop control of the island microgrid as demonstrated in Fig. 6. Among them, DG i is the i -th distributed power supply put into operation in the system, and droop control gives control signals for inverter i . The IPSO optimization module and the droop control part achieve the intercommunication of the microgrid system: when the microgrid is running, the measured system deviation information is input into the IPSO part, and the IPSO part receives the input signal to optimize the particles, and at the same time fuzzy rules the system. Through the calculated particle information, the parameters of IPSO can be dynamically adjusted to speed up the convergence speed of the algorithm, and then update its own speed and position. After completing the final optimization to get the optimum result of the particle, the obtained two values d_p and d_q will be used as the input of the droop control strategy to get the new droop factor, and then the reference voltage and reference current are obtained to generate inverter control signal through the voltage and current loop.

The frequency band of the current and voltage loop are set to 200 Hz and 26.6 Hz, and their parameters are set to: $k_{pc} = 0.3$, $k_{ic} = 6$ and $k_{pv} = 4$ and $k_{iv} = 82.8$.

The parameter settings of the microgrid system are demonstrated in the table blow.

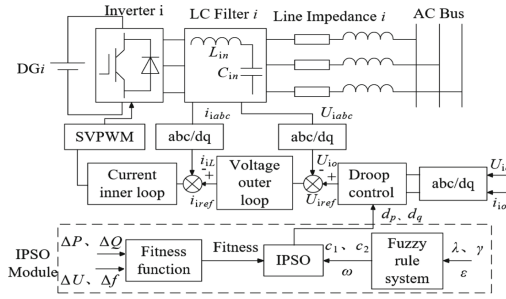


Fig. 6. Microgrid droop control structure diagram based on IPSO

Table 1. Parameter setup of simulation experiment

Parameter	Value
DC voltage source/V	700
Initial active power droop factor	2×10^{-4}
Initial reactive power droop factor	1×10^{-5}
Inverter resistance/ Ω	0.3
System frequency/Hz	50
Filter inductance/mH	3
Simulation time/s	3
Initial load power/VA	$2000 + j2000$
Filter capacitor/ μF	15
Effective value of bus voltage/V	220
DG1 line impedance/ Ω	$0.642 + j2.64 \times 10^{-4}$
DG2 line impedance/ Ω	$0.321 + j1.32 \times 10^{-4}$

4.2 Simulation Results

In the thesis, an island microgrid with double parallel distributed power source is used as the experimental subject. In the simulation experiment, DG1 and DG2 have the same capacity, the power distribution ratio of DG1 and DG2 is set to 3:2 [15]. The other parameters are illustrated in the above table. The initial active and reactive power are set to 2000W and 2000var. The load active and reactive power are 1000W and 1000var in 1s, but the reactive power become 500var in 2s. The simulation result under original droop control is demonstrated in the pictures.

In accordance with the first section of this article, the active power corresponding to the DG output can be accurately allocated according to the droop curve, as shown in Fig. 7(a), the overall distribution accuracy of the distributed power source active power output is high, and its fluctuation is small, but due to the inherent inflexibility of the droop factor, the active power output by DG1 and DG2 still has a small amplitude difference,

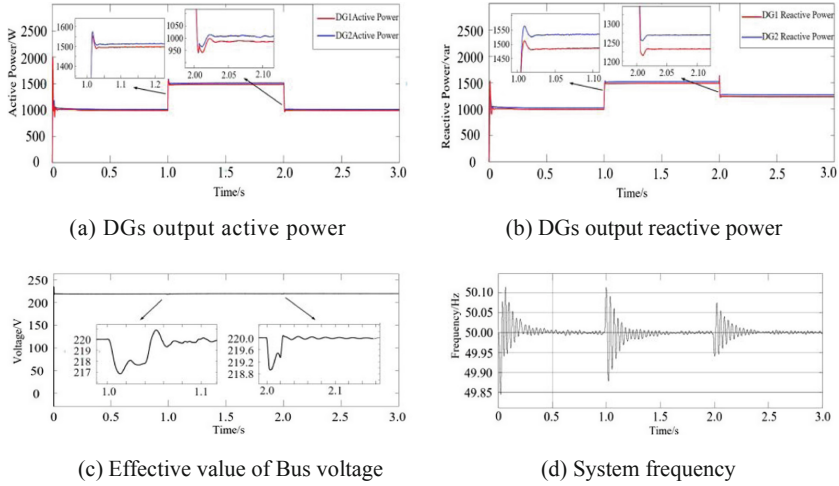


Fig. 7. Simulation results of original droop control

with a power difference of 20 W. On the contrary, the reactive power cannot be accurately distributed through the original control strategy. As shown in Fig. 7(b), because of the different line impedance, the reactive power output by the two power supplies has a large difference, which is 50W, and the fluctuation range is large, and the reactive output of the two sources is unstable. Therefore, the reactive distribution under the traditional control needs to be optimized urgently. In addition, as shown in Fig. 7(c) and (d), as the load varies in the traditional control, the system frequency and bus voltage will have large fluctuation in value, and the duration will be longer, and the bus voltage fluctuation time will continue 0.1s, the fluctuation size reaches 3V, the system frequency fluctuation time lasts 0.5 s, and the fluctuation range is 0.1 Hz.

Figure 8 gives the experiment results of the IPSO optimized droop control present in this thesis. We could learn that the active and reactive output by DG1 and DG2 can be distributed in a high-precision and balanced manner in the above picture, and the output power is relatively stable with little fluctuation, realizing the coordinated output between the two power sources. In Fig. 8(c) and (d), under the improvement of the algorithm present in the thesis, when the load changes, the bus voltage and frequency are significantly improved in comparison with the traditional control strategy. The voltage fluctuation is controlled within 1V, and the frequency fluctuation is within 0.05 Hz, the bus voltage recovery time is also shortened from 0.1 s to 0.05 s, and the system frequency fluctuation time is shortened from 0.5 s to 0.2 s, which meets the requirements of system operation.

To sum up, the improved control strategy present in the thesis has great advantages in power allocation, voltage and frequency stability, and can enhance the performance of system operation.

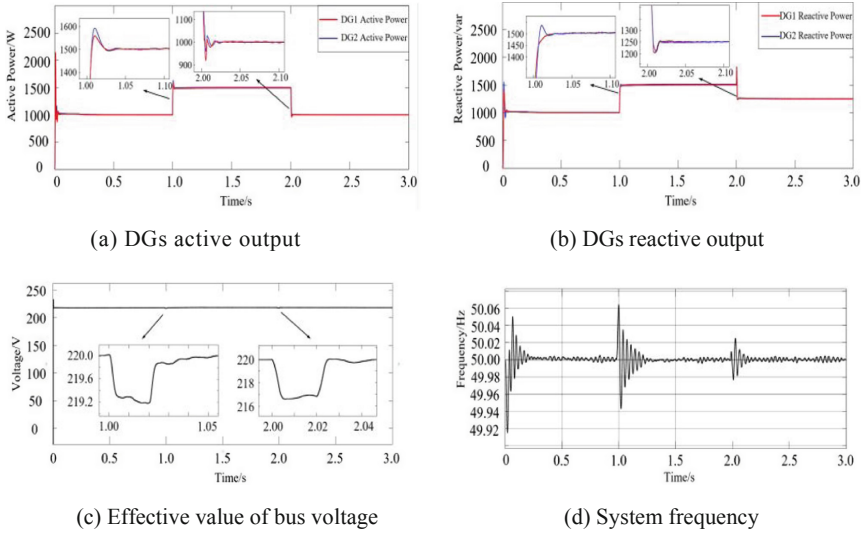


Fig. 8. Adaptive droop control simulation results based on IPSO

5 Conclusion

This thesis presents a power distribution control strategy for parallel multi-distributed power source microgrid based on an IPSO algorithm. The introduction of fuzzy rule system can make the PSO algorithm obtain better droop factor and enhance the convergence and optimization ability of the original algorithm. Then the IPSO algorithm is used to find the optimum droop factor. The simulation effects demonstrate that the present strategy realizes the intercommunication between the PSO part and the control part, and the optimization and allocation of power under the condition of unequal impedance, and achieves the non-difference power control, and effectively enhances the performance and stability in all aspects of the microgrid.

References

1. Liu, Z., Wang, X., Zhuo, R., et al.: Flexible network planning of autonomy microgrid. *IET Renew. Power Gener.* **12**(16), 1931–1940 (2018)
2. Shahparasti, M., Mohamadian, M., Baboli, P.T., et al.: Toward power quality management in hybrid AC-DC microgrid using LTC-L utility interactive inverter: load voltage-grid current tradeoff. *IEEE Trans. Smart Grid* **8**(2), 857–867 (2017)
3. Wang, C.S., Li, W., Wang, Y.F., Meng, Z., Yang, L.: DC Bus voltage fluctuation classification and restraint methods review for DC microgrid. *Proc. CSEE* **37**(1), 84–97 (2017)
4. Yan, L.F., Liu, J., Shi, M.X., Chen, X., Wen, J.Y.: Adaptive power allocation strategy based on fuzzy logic algorithm for hybrid energy storage system in DC microgrid. *Proc. CSEE* **39**(9), 2658–2670 (2019)
5. Yong, J., Xu, X., Zeng, L.Q., Li, L.L.: A review of low voltage DC power distribution system. *Proc. CSEE* **33**(7), 42–52 (2013)

6. Mi, Y., Wu, Y.W., Zhu, Y.Z., Fu, Y., Wang, C.S.: Coordinated control for autonomous DC microgrid with dynamic load power sharing. *Power Syst. Technol.* **41**(2), 440–447 (2017)
7. Xu, Q.W., Hu, X.L., Wang, P., et al.: A decentralized dynamic power sharing strategy for hybrid energy storage system in autonomous DC microgrid. *IEEE Trans. Ind. Electron.* **64**(7), 5930–5941 (2017)
8. Zhu, S.S., Wang, F., Guo, H., Wang, Q.F., Gao, Y.X.: Overview of droop control in DC microgrid. *Proc. CSEE* **38**(1), 72–84 (2018)
9. Zhang, L., Zheng, H., Hu, Q.G., Su, B., Lyu, L.: An adaptive droop control strategy for Islanded microgrid based on improved particle swarm optimization. *IEEE Access* **8**, 3579–3593 (2020)
10. Xia, Y.H., Wei, W., Peng, Y.G., et al.: Decentralized coordination control for parallel bidirectional power converters in a grid-connected DC microgrid. *IEEE Trans. Smart Grid* **9**(6), 6850–6861 (2018)
11. Cai, C.C., Cheng, S.S., Deng, Z.X., Jiang, B., He, W.G., Ma, J.X.: DC Microgrid equivalent modeling based on fuzzy-RBF artificial neural network. *Power Syst. Technol.* **40**(11), 3446–3452 (2016)
12. Khorsandi, A., Ashourloo, M., Mokhtari, H.: A decentralized control method for a low-voltage DC microgrid. *IEEE Trans. Energy Conversion* **29**(4), 793–801 (2014)
13. Huang, Z.H., Dang, D.S., Gao, C.C., Wang, L.: Grey verhulst power load forecasting method based on background value optimization. *IOP Conf. Ser. Earth Environ. Sci.* **218**(1) (2019)
14. Yang, J., Jin, X.M., Wu, X.Z., Jiang, C.: An improved load current sharing control method in DC microgrids. *Proc. CSEE* **36**(01), 59–67 (2016)
15. Zhang, L., Zheng, H., Wan, T., Shi, D.H., Lyu, L., Cai, G.W.: An integrated control algorithm of power distribution for islanded microgrid based on improved virtual synchronous generator. *IET Renew. Power Gener.* **15**(12), 2674–2685 (2021)



Coordinated Optimization Control Technology of Clean Energy Consumption Based on Spatiotemporal Characteristics of Controllable Load

Weichun Ge¹, Shunjiang Wang¹, Qingbo Yin^{2(✉)}, Feng Sun¹, Peng Jin¹,
and Shengbin Chi³

¹ State Grid Liao Ning Electric Power Co. Ltd., Shenyang, China

² College of Electrical Engineering, Northeast Electric Power University, Ji Lin, China

³ State Grid Shandong Electric Power Company Zibo Power Supply Company, Zibo, China

Abstract. As controllable load, electric vehicles (EVs) have great adjustable ability. This paper mainly analyzes how to charge EVs orderly according to the obtained state information, in order to shrink the power fluctuation and peak-to-valley gap of power grid. This paper analyzes the spacio-temporal characteristics of the travel of EV owners, and sets up the spacio-temporal model of the travel of EV owners based on the travel chain. The state information of the EV in the spacio-temporal model is obtained through the PLC communication system between the EV and the charging pile. Firstly, this paper analyzes the spacio-temporal characteristics of EV travel on the basis of the travel chain; Secondly, the Monte Carlo technique is applied to count the charging power of a certain number of EVs during disorderly charging; Finally, considering the basic load of residential area, genetic algorithm is introduced to shorten the charging time of EVs, the simulation experiment is carried out with the peak valley difference as the optimization objective.

Keywords: Electric vehicle · Space-time characteristics · Genetic algorithm · Orderly charging

1 Introduction

By 2020, there will be more than 5 million EVs in China. It can be predicted that with the popularity of EVs in next years, large-scale EVs connected to the power grid charging will have great influence on power system planning and operation. Among them, one of the important impacts is that large-scale EV charging will bring a new round of load growth, especially in the peak period of EV charging, which will farther increase the peak-valley gap of power grid load. Accordingly, there is an urgent need to study and lead the charging behavior of EVs to enhance the economy and reliability of power grid operation.

In [1], a space-time forecasting model of EV charging load for user travel simulation on the condition of the traffic network restrictions is proposed. Reference [2] present