applied sciences

MDPI

Editorial

# Computational Intelligence in Photovoltaic Systems

**Sonia Leva * and Emanuele Ogliari ***

Department of Energy, Politecnico di Milano, 20156 Milano, Italy
* Correspondence: sonia.leva@polimi.it (S.L.); emanuelegiovanni.ogliari@polimi.it (E.O.); Tel.: +39-2399-8524 (E.O.)

Received: 26 April 2019; Accepted: 29 April 2019; Published: 2 May 2019

check for updates

**Keywords:** computational intelligence; day-ahead forecast; photovoltaics

---

Photovoltaics, among renewable energy sources (RES), has become more popular. However, in recent years, many research topics have arisen, mainly due to problems that are constantly faced in smart-grid and microgrid operations, such as output power plants production forecast, storage sizing, modeling, and control optimization of photovoltaic systems.

Computational intelligence algorithms (evolutionary optimization, neural networks, fuzzy logic, etc.) have become more and more popular as alternative approaches to conventional techniques in solving problems such as modeling, identification, optimization, availability prediction, forecasting, sizing and control of stand-alone, grid-connected, and hybrid photovoltaic systems. In this Special Issue, the most recent developments and research for solar power systems are investigated. There are ten papers selected to focus on computational intelligence methods employed in solar energy systems.

Jeong et al. [1] designed and developed prototype models of smart photovoltaic system blind (SPSB) by evaluating PV panel, tracking system, and monitoring system. This study shows that a-Si PV panel are linked in parallel, by applying four tracker types and the direct tracking method based on electricity generation with the monitoring system that can establish a time-series database on the electricity generation, the environmental conditions, and optimal tilted and azimuth angles has the best configuration.

Hammami et al. [2] conducted thermal analysis to evaluate cell temperature and battery temperature in different environmental conditions to determine the thermal limits in the 1D thermal model using the thermal library of Simulink-Matlab, with or without a set of lithium-iron-phosphate (LiFePO4) flat batteries back side of PV module. The model validation has been carried out considering the PV module to be at Normalized Operational Cell Temperature (NOCT) given by the manufacturer, and by specific experimental measurements on the real PV module, including thermographic camera images, with and without the proposed Battery energy storage systems (BESS).

Hong and Yo [3] propose an enhanced genetic algorithm (GA) to deal with unit commitment (UC) and demand response (DR) considering uncertain amounts of generated power from renewable sources in the factory power system. The uncertainty of PV power is modeled using stochastic distributions and the problem is solved by a two-level method: the master level using a novel genetic algorithm, the slave level using the point estimate method, incorporating the interior point algorithm.

In order to forecast day-ahead power from PV, Grimaccia et al. [4] proposed a general procedure to set up the main characteristics of the network contains number of neurons, layout, and number of trials using a physical hybrid method (PHANN) provided by forecasted meteorological parameters, historical measurements of power production and estimation of clear sky radiation data to perform the day-ahead PV power forecast. The minimum absolute mean error (normalized or weighted) index has been studied to create the most effective configuration for a feed-forward neural network (FFNN). The Levenberg–Marquardt (LM) algorithm is chosen as the training method, together with slow convergence setting.

Harmony search (HS) meta-heuristic algorithm is proposed by Guo et al. [5] after the optimization problem is specified to discover optimum tilt and azimuth angle to maximize extraterrestrial radiation on a collector in China. The results are compared with a reference group which is obtained by the ergodic method conducted in different cities to understand the performance of HS. Additionally, particle swarm optimization (PSO) is used to compare the solution quality with the HS algorithm.

Petrone et al. [6] proposed a genetic algorithm(GA) to obtain the exact solution for SDM parameter identification requiring only some measured points close to a maximum power point (MPP).

Xiong et al. [7] use a symbiotic organisms search algorithm (SOS) to extract parameters from solar cell models. The effectiveness of this model validated by the single diode model, double diode model, and PV module model. In addition, to verify the effectiveness of SOS, five state-of-the-art algorithms including an across neighborhood search (ANS) biogeography-based learning particle swarm optimization (BLPSO), competitive swarm optimizer (CSO), chaotic teaching-learning algorithm (CTLA), and levy flight trajectory-based whale optimization algorithm (LWOA) are used for performance comparison. Comparison on a statistical level is done by the Wilcoxon's rank sum test at a 0.05 confidence level to identify the significance difference between SOS and other compared methods on the same case.

Dolara et al. [8] simulated different dynamic and partial shading conditions based on the PSO evolutionary approach maximum power point tracking (MPPT) algorithm and compared it with classical MPPT methods to investigate conversion efficiency in the conducted scenarios.

Dolara et al. [9] analyzed different approaches in training data set composition for ANN to be used in the physical hybrid method. For ANN, the training algorithm is chosen as Levenberg–Marquardt while the activation function is sigmoid and the number of trials in the ensemble forecast is 40. An additional performance index (envelope-weighted mean absolute error) is proposed to compare results between different approaches.

Mohamed Louzazni et al. [10] perform a comparison among bioinspired algorithms by taking three cases: single diode model, double diode model, and photovoltaic module to predict solar cell and PV module parameters. The Firefly algorithm is chosen for the optimization problem. The results are compared with recent techniques such as the biogeography-based optimization algorithm with mutation strategies (BBO-M), the Levenberg–Marquardt algorithm combined with simulated annealing (LMSA), artificial bee swarm optimization algorithm, artificial bee colony optimization (ABC), hybrid Nelder–Mead and modified particle swarm optimization (NMMPSO), repaired adaptive differential evolution (RADE), chaotic asexual reproduction optimization (CARO) for solar cell single and double diodes; quasi-Newton (Q-N) method and self-organizing migrating algorithm (SOMA) for a-Si:H solar cell and the optimal parameters of Photowatt-PWP 201 are compared with the Newton–Raphson pattern search(PS), genetic algorithm (GA) and simulated annealing algorithm(SA). In conclusion, this Special Issue contains a series of up-to-date research work covering a wide area of application-oriented computational intelligence. This collection of ten papers is highly recommended and will benefit readers in various aspects dealing with solar power systems.

**Acknowledgments:** We would like to thank all authors, the many dedicated referees, the editor team of *Applied Sciences*, and especially Xiaoyan Chen (Assistant Managing Editor), for their valuable contributions, making this special issue a success.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Jeong, K.; Hong, T.; Koo, C.; Oh, J.; Lee, M.; Kim, J. A Prototype Design and Development of the Smart Photovoltaic System Blind Considering the Photovoltaic Panel, Tracking System, and Monitoring System. *Appl. Sci.* **2017**, *7*, 1077. [CrossRef]
2. Hammami, M.; Torretti, S.; Grimaccia, F.; Grandi, G. Thermal and Performance Analysis of a Photovoltaic Module with an Integrated Energy Storage System. *Appl. Sci.* **2017**, *7*, 1107. [CrossRef]

3. Hong, Y.-Y.; Yo, P.-S. Novel Genetic Algorithm-Based Energy Management in a Factory Power System Considering Uncertain Photovoltaic Energies. *Appl. Sci.* **2017**, *7*, 438. [CrossRef]
4. Grimaccia, F.; Leva, S.; Mussetta, M.; Ogliari, E. ANN Sizing Procedure for the Day-Ahead Output Power Forecast of a PV Plant. *Appl. Sci.* **2017**, *7*, 622. [CrossRef]
5. Guo, M.; Zang, H.; Gao, S.; Chen, T.; Xiao, J.; Cheng, L.; Wei, Z.; Sun, G. Optimal Tilt Angle and Orientation of Photovoltaic Modules Using HS Algorithm in Different Climates of China. *Appl. Sci.* **2017**, *7*, 1028. [CrossRef]
6. Petrone, G.; Luna, M.; la Tona, G.; di Piazza, M.; Spagnuolo, G. Online Identification of Photovoltaic Source Parameters by Using a Genetic Algorithm. *Appl. Sci.* **2018**, *8*, 9. [CrossRef]
7. Xiong, G.; Zhang, J.; Yuan, X.; Shi, D.; He, Y. Application of Symbiotic Organisms Search Algorithm for Parameter Extraction of Solar Cell Models. *Appl. Sci.* **2018**, *8*, 2155. [CrossRef]
8. Dolara, A.; Grimaccia, F.; Mussetta, M.; Ogliari, E.; Leva, S. An evolutionary-based MPPT algorithm for photovoltaic systems under dynamic partial shading. *Appl. Sci.* **2018**, *8*, 558. [CrossRef]
9. Dolara, A.; Grimaccia, F.; Leva, S.; Mussetta, M.; Ogliari, E. Comparison of Training Approaches for Photovoltaic Forecasts by Means of Machine Learning. *Appl. Sci.* **2018**, *8*, 228. [CrossRef]
10. Louzazni, M.; Khouya, A.; Amechnoue, K.; Gandelli, A.; Mussetta, M.; Crăciunescu, A. Metaheuristic Algorithm for Photovoltaic Parameters: Comparative Study and Prediction with a Firefly Algorithm. *Appl. Sci.* **2018**, *8*, 339. [CrossRef]