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Editorial

The Recent Development of Artificial Intelligence for Smart and Sustainable Energy Systems and Applications

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Abstract: Human beings share the same community in which the usage of energy by fossil fuels leads to deterioration in the environment, typically global warming. When the temperature rises to the critical point and triggers the continual melting of permafrost, it can wreak havoc on the life of animals and humans. Solutions could include optimizing existing devices, systems, and platforms, as well as utilizing green energy as a replacement of non-renewable energy. In this special issue "Artificial Intelligence for Smart and Sustainable Energy Systems and Applications", eleven (11) papers, including one review article, have been published as examples of recent developments. Guest editors also highlight other hot topics beyond the coverage of the published articles.

Keywords: artificial intelligence; computational intelligence; energy management; machine learning; optimization algorithms; sensor network; smart city; smart grid; sustainable development

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1. Introduction

The world mission is not only improving energy systems to become smart but also progressing sustainable development. It can be further divided into environmental [1], economic [2], and socio-cultural [3] perspectives. However, there does not exist a perfect energy source as the solution for sustainable energy. It requires multidisciplinary techniques and systems to achieve the targets.

The rapid advanced development of computer science and engineering enables the implementation and adoption of artificial intelligence (AI) into various energy systems and applications. This special issue aims at consolidating recent developments of AI for smart and sustainable energy systems and applications. Pilot studies are especially welcome. Topics of interest for the special issue include (but are not limited to):

- New theories and applications of machine learning algorithms in smart grid;
- Design, development, and application of deep learning in smart grid;
- Artificial intelligence in advanced metering infrastructure;
- Multiobjective optimization algorithms in smart grid;
- Disaggregation techniques in non-intrusive load monitoring;
- Modelling and simulation (or co-simulation) in smart grid;
- Internet of Things and smart grid;
- Data driven analytics (descriptive, diagnostic, predictive, and prescriptive) in smart grid;
- Artificial intelligence techniques for security;

- Fraud detection and predictive maintenance;
- Demand response in smart grid;
- Peak load management approach in smart grid;
- Interoperability in smart grid;
- Cloud computing based smart grid;
- Vehicle-to-grid design, development, and application.

This Editorial is organized as follows. Section 2 summarizes the published articles in this special issue. In addition, editors discuss several hot topics beyond the coverage of the special issue articles in Section 3. Finally, the conclusion is drawn in Section 4.

2. Special Issue Articles

This section not only discusses each of the published articles in the main text but also summarizes these in the form of a table (Table 1) as a quick review. It is worth mentioning that the topic of non-intrusive load monitoring (NILM) has contributed five published papers.

Table 1. Summary of the application and methodology of the special issue articles.

Work	Application	Methodology
[4] #	Home energy management and ambient assisted living	Non-intrusive load monitoring techniques
[5]	Non-intrusive load monitoring for energy disaggregation	Genetic algorithm; support vector machine; multiple kernel learning
[6]	Optimizing residential energy consumption	Bacterial foraging optimization; flower pollination
[7]	Non-intrusive load monitoring for energy disaggregation	Long short-time memory and decision tree
[8]	Energy efficient coverage in wireless sensor network	Distributed genetic algorithm
[9]	Estimation of load and price of electric grid	Enhanced logistic regression; enhanced recurrent extreme learning machine; classification and regression tree; relief-F and recursive feature elimination
[10]	Detection of the insulators in power transmission and transformation inspection images	Improved faster region-convolutional neural network
[11]	Non-intrusive load monitoring for energy disaggregation	Concatenate convolutional neural network
[12]	Non-intrusive load monitoring for energy disaggregation	Linear-chain conditional random fields
[13]	Prediction of the rheological properties of calcium chloride brine-based mud	Artificial neural network
[14]	Estimation of Static Young's Modulus for sandstone formation	Artificial neural network; self-adaptive differential evolution

Review article.

The review article "NILM techniques for intelligent home energy management and ambient assisted living: A review" authored by A. Ruano, A. Hernandez, J. Ureña, M. Ruano, and J. Garcia provided a constructive review on home energy management and ambient assisted living [4]. The focus was on NILM, which aimed at producing a breakdown of the energy profile in equipment level based on the total energy profile of the apartment. Here, the energy profile could be information related to current, voltage, power, energy, power factor, harmonic distortion, etc. This review article divided NILM techniques into four parts: data collection, event detection, feature extraction, and load identification. The authors highlighted that NILM was a highly scalable but less accurate homecare monitoring system for ambient assisted living, compared to direct and indirect methods via biosensors and sensors for activity monitoring.

There are ten technical papers that proposed various AI techniques for energy systems and applications, towards the goal of smart and sustainable development. The first article "Energy sustainability in smart cities: artificial intelligence, smart monitoring, and optimization of energy consumption" [5] written by K. T. Chui, M. D. Lytras, and A. Visvizi formulated the NILM algorithm as a multiobjective optimization problem. Multiple kernel learning was introduced to the support vector machine classifier to enhance the classification accuracy by integrating valuable characteristics of kernels. Weighting factors between kernels were added and solved by a genetic algorithm to optimize the performance.

M. Awais, N. Javaid, K. Aurangzeb, S. Haider, Z. Khan, and D. Mahmood published an extended article "Towards effective and efficient energy management of single home and a smart community exploiting heuristic optimization algorithms with critical peak and real-time pricing tariffs in smart grids" [6] from the conference paper in the 2018 IEEE 32nd International Conference on Advanced Information Networking and Applications (AINA) [15]. The residential energy consumption problem was considered as a heuristic multiobjective optimization problem. The bacterial foraging optimization algorithm and flower pollination algorithm were utilized to minimize the electricity cost and peak-to-average ratio while maximizing the user comfort. The trade-off solution was recommended attributable to conflicting objectives.

In [7], T. T. H. Le and H. Kim presented an article "Non-intrusive load monitoring based on novel transient signal in household appliances with low sampling rate". Differing from [4], the authors divided the NILM framework into three parts: data acquisition, feature extraction, and classification model. The feature vector was constructed by transient signal. Long short-term memory and decision tree models were applied for the energy disaggregation problem. The performance evaluation of the proposed method was tested through five appliances: Samsung monitor, LG monitor, hairdryer, fan, and air purifier, where the accuracy was up to 97%.

Z. J. Wang, Z. H. Zhan, and J. Zhang in their article "Solving the energy efficient coverage problem in wireless sensor networks: A distributed genetic algorithm approach with hierarchical fitness evaluation" [8] proposed a distributed genetic algorithm to address the issue of energy efficient coverage (EEC) in wireless sensor networks. The authors evaluated the fitness using a hierarchical approach and constructed a two-level fitness function to determine the number of disjoint sets and its coverage performance. It was demonstrated to be effective in the maximization of the number of disjoint sets.

Predicting the load and price of the electric grid have been important tasks for utility in lowering the electricity cost and improving the service quality for end customers. A. Naz, M. U. Javed, N. Javaid, T. Saba, M. Alhussein, and K. Aurangzeb have addressed these topics via an article "Short-term electric load and price forecasting using enhanced extreme learning machine optimization in smart grids" [9]. Two-feature extraction approaches were adopted, namely classification and regression tree, relief-F, and recursive feature elimination. The extracted features were passed to enhanced logistic regression and enhanced recurrent extreme learning machines for load and price estimation. Results showed that the proposed two algorithms outperformed existing methods by 5%.

Z. Zhao, Z. Zhen, L. Zhang, Y. Qi, Y. Kong, and K. Zhang have published an article "Insulator detection method in inspection image based on improved faster R-CNN" [10]. This paper proposed an improved faster region-convolutional neural network to detect the insulators in power transmission and transformation inspection images. It yielded a precision of 81.8% with an enhancement of 28%. It was noted by the authors that the proposed method was customized to the specific type of insulator. For other insulators, it required further fine-tuning to achieve an optimal performance.

The article "Concatenate convolutional neural networks for non-intrusive load monitoring across complex background" was presented by Q. Wu and F. Wang [11]. The concatenate convolutional neural network was newly proposed as the NILM technique, which was evaluated based on key performance indicators: accuracy, robustness, and generalization of load recognition. A key observation was concluded regarding the background load, which is almost stationary in a given short period of time. This method improved the F1-score, precision, and recall by 12%, 19%, and 4% respectively.

In [12], H. He, Z. Liu, R. Jiao, and G. Yan proposed a novel algorithm named linear-chain conditional random fields for energy disaggregation in the article "A novel nonintrusive load monitoring approach based on linear-chain conditional random fields". This approach has eliminated some obstacles for performance improvement: (i) they relax the independent assumption of the hidden Markov model, and (ii) current and real power are included as representative features. As a result, it achieved an outstanding accuracy of 96–100%.

A. Gowida, S. Elkatatny, E. Ramadan, and A. Abdulraheem wrote an article "Data-driven framework to predict the rheological properties of CaCl2 brine-based drill-in fluid using artificial neural network" [13]. Artificial neural network was adopted to forecast the rheological properties of brine-based drill-in fluid so that it could avoid the loss of circulation, pipe sticking, and hole cleaning. The correlation coefficient and average absolute percentage error were 0.97 and <6.1%, respectively.

Finally, A. A. Mahmoud, S. Elkatatny, A. Ali, and T. Moussa contributed an article "Estimation of static Young's modulus for sandstone formation using artificial neural networks" [14]. The authors introduced self-adaptive differential evolution on top of artificial neural network to further enhance the performance of the estimation of static Young's modulus for sandstone formation. This approach reduced the average absolute percentage error significantly from 36% to 1%, as well as the perfect correlation coefficient.

3. Trends and Future Development

Besides the applications in Table 1, there are numerous applications that apply AI for smart and sustainable energy systems. The guest editors would like to summarize the key topics—renewable energy, cloud platform, edge computing, fog computing, as well as electric and plug-in hybrid electric vehicles—in this section. Also, we have attached a few related works as recommended readings in each field.

Renewable energy (specifically energy harvesting), acting as an alternative of fossil fuels, is one of the directions to fight against global warming. Typical sources are solar [16,17] and wind [18,19]. Focuses are basically on the reliability and efficiency of energy harvesting. Other emergent topics include vibration energy [20], water wave energy [21], acoustic energy [22], and waste-to-energy [23].

The cloud platform is not unfamiliar in today's era, as many smartphone users have linked their personal information to it. A more advanced technique of the cloud platform possesses not only big data storage but also massive computation power, which allows complex data analytics for smart grid data streaming, processing, analyzing, and storage. Readers are encouraged to read the following articles [24–27].

Edge computing and fog computing are alternatives to cloud computing that offer relatively local (lower latency) computation. In other words, data processing and loading can be distributed to edge, fog, and cloud services. For edge computing, it is recommended for readers to read [28,29], and the readings for fog computing are [30,31].

There is an increasing portion of new buyers purchasing electric or plug-in hybrid electric vehicles, which can reduce the usage of fuel. Various AI techniques have been applied to plug-in hybrid electric vehicles, for instance, artificial neural network [32] and integrated model predictive controller [33]. When it comes to electric vehicles, biased coupling, torque estimation, and cognitive heuristic techniques were adopted in [34] and deep neural networks in [35].

4. Conclusions

This special issue is composed of eleven papers (one review article) with various topics and methodologies in AI for smart and sustainable energy systems and applications. Contributors have shared many valuable insights on recent developments and beyond. The guest editors have briefly summarized the details of each work, as well as highlighted four groups of emergent topics in the energy industry. The guest editors would like to thank the contributions of all colleagues and reviewers. We hope to witness a lot of real implementation and adoption of AI techniques in the energy industry in the near future.

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