

Advanced AI Applications in Energy and Environmental Engineering Systems

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Artificial intelligence (AI) constitutes a kind of modelling method widely used in various fields of science including energy and environmental engineering [1].

Moreover, AI is considered a tool that can sometimes provide an alternative approach compared to programmed computing and laborious experiments [2,3]. Since they can describe an object or a process using data, strict knowledge of the process is not crucial [4,5]. For example, fuzzy-logic-based systems use expert knowledge to describe the complex behaviour of the systems [5].

This article constitutes an answer to the urgent need to briefly summarize published articles on advanced AI Applications in Energy and Environmental Engineering Systems.

Even though some AI methods are pretty old, they are still in use as they have the potential to extract new knowledge from the considered data domains. However, still new promising AI approaches emerge, which will also be briefly discussed here. Dellosa et al. [6] listed Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Genetic algorithms (GA) as the main techniques in power management maintenance and control of renewable energy systems. They underlined that ANNs were the best methods due to their short computing time, higher accuracy, and generalisation capabilities over other modelling methods [6].

Loads of publications confirm these observations as several ANN-based applications can be found in the literature, e.g., forecasting of the CO₂ emissions at the global level, low-cost prediction of soot emissions and NO_x emission from air-fired and oxy-fuel combustion of solid fuels in large-scale circulating fluidized bed boilers [7–9].

Another promising issue turned out to be a powerful combination of AI and the Internet of things (IoT) technologies since the IoT and sensors can harness large volumes of data, and AI can learn patterns in the data to automate tasks for various business benefits [1]. Multiple applications of IoT in the energy supply chain are classified in [10]. Numerous components of an IoT system are discussed in the paper, including those enabling communication and sensor technologies concerning their application in the energy sector, e.g., sensors of light, humidity, temperature, speed, passive infrared, and proximity. The authors underlined that managing heating, ventilation, and air conditioning (HVAC) systems is essential in reducing total electricity consumption, as the HVAC system's energy consumption typically accounts for half of the total residential energy consumption. An advanced approach for implementing industry 4.0 and ANN techniques in a 660 MW_e supercritical coal-fired plant using actual operational data is depicted in [11,12].

Other interesting ANN applications for sorption modelling via the deep learning (DL) approach were shown by Skrobek et al. [13]. The authors used Long Short-Term Memory (LSTM) network algorithm as a DL technique to predict the vapour mass adsorbed in the bed.

On the other hand, the ANFIS, as a governing data-driven and adaptive computational method having the fitness of plotting non-linear and multifaceted data, has been successfully used in several applications, including energy and exergy analyses and the prediction of thermodynamic parameters [14].



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Genetic algorithms (GA) are still interesting approaches to modelling and optimisation of energy and environmental engineering systems [15–17]. A promising direction of the model research seems to be Gene Expressions Programming (GEP). Like GA, GEP chooses populations of individuals based on their fitness and presents genetic variation using one or more operators. The main feature of GEP is the ability to formulate a mathematical expression between the dependent and independent variables that performs well for all fitness cases considered an adaptive algorithm. The GEP approach established an expert system to detect incipient faults within power transformers [18]. Another topical use case of the gene expression programming approach can be found in [19–21].

Finally, considering loads of approaches, automated machine learning (AutoML) seems to be a promising approach [22]. Exciting applications for the automated modelling of residential prosumer agents and worst-case energy consumption analysis can be found in [23,24]. Since AutoML makes machine learning accessible to everyone, it may be a promising alternative for other data handling approaches.

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