Journal of Physics:
Conference Series

PURPOSE-LED
PUBLISHING™

PAPER • OPEN ACCESS

Artificial intelligence for hydrogen-based hybrid renewable energy systems: A review with case study

To cite this article: Shenglin Su *et al* 2022 *J. Phys.: Conf. Ser.* **2208** 012013

Artificial intelligence for hydrogen-based hybrid renewable energy systems: A review with case study

Shenglin Su[1], Xianglin Yan[1], Kodjo Agbossou[2,*], Richard Chahine[2] and Yi Zong[3,*]

[1] Hubei Research Center for New Energy & Intelligent Connected Vehicle, School of Automotive Engineering, Wuhan University of Technology, Hubei 430070, China
[2] Hydrogen Research Institute, Université du Québec à Trois-Rivières, QC G8Z 4M3, Canada
[3] Center for Electric Power and Energy, Technical University of Denmark, Roskilde, 4000, Denmark

* Corresponding authors: Kodjo.Agbossou@uqtr.ca (Kodjo Agbossou), yizo@elektro.dtu.dk (Yi Zong)

Abstract. In recent years, with the progress of computer technology, artificial intelligence has been rapidly developed and begun to be applied in industry, economy and other aspects. Besides, with the pursuit of green hydrogen, hydrogen-based hybrid renewable energy systems have become the focus of the development of the hydrogen industry. This paper compares different artificial intelligence applications in hydrogen-based hybrid renewable energy systems and carries out a case study in a typical area. Firstly, this paper summarizes important works in literature, which use artificial intelligence methods to predict the supply chain of the renewable energy system, including the prediction of renewable energy system resources, output power, load demand and terminal electricity price. Secondly, main articles about artificial intelligence optimization algorithms used in renewable energy systems are also summarized, including swarm and non-swarm biological heuristics, physical or chemical heuristics and hybrid optimization algorithms. Finally, a case study is carried out in Tikanlik, Xinjiang, China. Tikanlik's weather and load data train the artificial neural network to predict system output power. It shows that 99.32% of the relative error of the test set is less than 3%, which proves that this model can achieve good prediction results.

1. Introduction

Hydrogen can be acted as an energy vector for renewable energy and has a high calorific value compared to traditional fossil fuels. Nowadays, the application scenarios of hydrogen energy are gradually increasing, which have obtained extensive attention. However, the industry chain of hydrogen energy develops a bit slowly, and the sources of hydrogen production are not clean enough. Therefore, the hydrogen produced by renewable energy such as solar and wind, which names green hydrogen, has become a hot topic of current research.

The most common system configurations for renewable energy systems (RESs) include photovoltaic (PV) and wind turbine (WT) power generation with batteries or hydrogen storage tanks to store energy [1]. However, due to the location of the RES, wind and solar energy may not be enough to satisfy the load demand, so the traditional energy sources such as diesel engines are often used to build them [2]. In addition, because of the particular location of some regions, other forms of renewable energy, including fuel cells (FC), hydro generators, biomass, biogas, have also got a wide range of applications [3]. On the other hand, thanks to the continuous development of computer technology, artificial intelligence (AI) has been widely used in modern industry, such as hydrogen purification and filling, which can significantly improve the performance and economy of production [4, 5]. However, the kinds of AI optimization algorithms are too many to classify. This problem is well solved by dividing the optimization algorithms into swarm biological, non-swarm biological and physical or chemical heuristic algorithms. Recently, artificial intelligence has been used to predict, plan, and control RES [6]. The artificial neural network is the most popular technique among machine learning algorithms because of its generalization ability [7].

In summary, this paper takes the RES with different configurations as the research object and focuses on the hydrogen-based ones. According to the various functions of the AI methods in the RES, the content of this paper is mainly divided into two parts: prediction and optimization. As for the prediction part, the papers with the artificial neural network (ANN) model are classified and summarized according to the variables at different stages in the supply chain of the RES, mainly including the RES's resources, output power, load demand and electricity price. In the optimization part, related articles are classified and summarized according to the different optimization algorithms, including swarm biological, non-swarm biological, physical or chemical heuristic algorithms and hybrid optimization algorithms. Finally, as a case study, an ANN model is established to predict the output power of RES in Tikanlik, Xinjiang, China.

2. Artificial intelligence methods in renewable energy systems for prediction

The artificial intelligence methods are mainly used to forecast the variables generated in different supply chain stages: renewable resources (wind speed, solar radiation, and ambient temperature), system output power, user load, and terminal electricity price.

2.1. Characteristics prediction of renewable resources

The prediction of RES's resources such as wind velocity, solar radiation and ambient temperature was carried out in the literature [8-11]. Zhang et al. [8] used weather forecast and ANN model to predict solar radiation, ambient temperature and wind velocity. Mert [9] took the observed and forecasted solar radiation values as the core dataset to train the ANN and agnostic deep learning (DL) models to predict a hydrogen production system supported by PV technology. It showed that the DL model was well-matched with the observed data and its value of the coefficient of determination was 96.26%. Doucoure et al. [10] proposed a method based on an adaptive wavelet neural network (AWNN) and used Hurst coefficients to analyze the predictability of each element of input data. In the case study, an analysis of wind speed data for the RES was conducted. It showed that by removing two parts of the lower Hurst coefficient, the resources required to execute the algorithm could be reduced by about 29% without affecting the performance of the prediction algorithm. Dong et al. [11] proposed a new hybrid monitoring method using local convolutional neural network (LCNN) to maintain the convexity of the cost function and transform the non-convex problem into a convex problem. This article utilized the heuristic algorithm to solve the problems of optimal parameters, which was helpful to build a more stable model and realized the prediction of short-term time series of wind speed.

2.2. Output power prediction of renewable energy systems

In terms of the forecast of the output power of RES, it was performed in the literature [12-15]. Rodríguez et al. [12] established an ANN model to forecast the short-term wind power density in the next 10 minutes to realize the optimization of microgrid control. They verified the tool's effectiveness by testing the predicted results' root mean square error value. To improve the accuracy of wind power forecast, Hu [13] proposed a hybrid forecast method based on the numerical weather forecast, using a deep belief network (DBN) to process complex data and considering the advantages of spatial correlation between geographical location and terrain. Mellit et al. [14] developed a deep learning neural network (DLNN) to achieve accurate short-term prediction of photovoltaic power output power, which was of great significance for the control and design of micro-grid intelligent energy management systems. Shams et al. [15] used deep learning (DL) algorithm to forecast wind and solar power curtailment. Based on it, an original planning model was developed to minimize the waste of wind and solar power by utilizing the battery and hydrogen storage systems.

2.3. Load prediction of renewable energy systems

In the literature [16-19], the load demand of the RES was predicted. Ayoub et al. [16] established a neural network model for energy supply and demand prediction of the hybrid renewable energy systems (HRESs), including WT and PV, to predict the power generation and load demand in the following 24 hours. Zhang et al. [17] used multilayer perceptron-ANN (MLP-ANN) to realize the prediction of the load demand of a small independent hybrid power system and utilized the actual data for verification. The results showed that the use of load demand forecast data for the optimization scale of the HRES would affect the optimization results. Li et al. [18] utilized a recurrent neural network (RNN) to forecast the renewable energy systems' energy supply and water demand. They focused on the random behaviors of freshwater demand and renewable resources in the HRES. Hwangbo et al. [19] developed a supply-demand forecasting model to simulate a hydrogen self-sufficient integrated renewable grid based on DL algorithms. The case study in this paper showed that it would be positive to construct environmentally-friendly strategies for self-sufficient energy systems.

2.4. Electricity price prediction of renewable energy systems

The prediction of the electricity price of RES was proposed in the literature [20-22]. In order to obtain reliable price information in advance at the production planning period, Windler et al. [20] adopted the deep feedforward neural network (DFNN) to build a model to predict the day-ahead electricity price of German/Austrian European energy exchanges, with the prediction time up to one month. Zhang et al. [21] proposed the deep belief network (DBN), focusing on the large-scale integration of renewable energy into the power network, making the characteristics of electrovalence more complex. The results showed that this DBN model could significantly improve the correctness and stability of prediction. Wang et al. [22] proposed a new method that could dynamically determine bad samples. They applied the optimization algorithm, including dynamic choice artificial neural network (DCANN) and its updated version to day-ahead price prediction. The results showed that this model and its updated version could predict the regular electricity price or the actual price with high fluctuation.

3. Artificial intelligence methods in renewable energy systems for optimization

Two natural heuristic algorithms, biological heuristic algorithms (swarm and non-swarm biological heuristic algorithms) and physical or chemical heuristic algorithms, are used to obtain optimal goals such as economic, technical, environmental and social indicators.

3.1. Non-swarm biological heuristic algorithms for optimization

Upon searching the literature, some studies [23-27] have been identified to optimize the RES by non-swarm biological heuristic algorithms such as genetic algorithm, biogeography-based optimization algorithm, whale optimization algorithm and flower pollination algorithm.

The genetic algorithm (GA), an evolutionary heuristic algorithm, can solve optimization problems with multiple objectives. Because of its strength, GA has become the most widely used non-swarm biological heuristic algorithm. Maleki et al. [23] used GA to optimize the hybrid united heat and power systems which used solar, wind and fuel cell technologies to minimize the RES operating and maintenance costs. Beshr et al. [24] proposed a non-dominated sorting genetic algorithm (NSGA) to satisfy the load demand of the RES, which includes WT, PV, diesel generator with FC/electrolyser hydrogen storage system for short-term energy storage. Gupta et al. [25] applied biogeography-based optimization (BBO) algorithm in the small autonomous hybrid power system including PV/WT/battery to achieve the optimal size and minimum energy costs. The verification results displayed that the BBO algorithm could solve the optimal design parameters of the system effectively.

Yin et al. [26] presented a modified non-dominated sorting whale optimization algorithm (NSWOA) to accomplish the multi-objective optimization of the PV/WT/hydropower HRES. A group of solution sets was obtained by taking the total annual power generation and the fluctuation of system output power into account. The results showed that this algorithm would have a good effect as the dimension of the optimization problem increased, and hydropower could compensate the photovoltaic and wind power well. Moghaddam et al. [27] utilized a flower pollination algorithm (FPA) to analyze the PV/WT/FC HRES for the minimum of total net present cost (TNPC). The results showed that this methodology could find the ideal decision variables with the faster convergence, lower cost and better reliability indexes.

3.2. Swarm biological heuristic algorithms for optimization

Literatures [28-32] carried out swarm biological heuristic algorithms to optimize the RES, including particle swarm optimization, artificial bee swarm optimization, cuckoo search algorithm and firefly algorithms.

The particle swarm optimization (PSO) algorithm is a nature-inspired optimization technique that utilizes swarm intelligence to effectively solve large-scale nonlinear optimization problems. Due to its simplicity and fast convergence advantages, PSO has become the most widely used one among the swarm biological heuristic algorithms. By using the PSO algorithm, HassanzadehFard et al. [28] determined the optimal size and energy planning of the RES, which consisted of PV, WT, FC, reformer, electrolyser and hydrogen storage system. Eriksson et al. [29] proposed an improved particle swarm optimization (IPSO) algorithm that could accelerate search speed by keeping a historical lookup table and could optimize the RES for technical, economic, environmental and socio-political objectives. In particular, the socio-political objectives presented in the case study indicated certain social and political positions to a higher dependence on hydrogen FC. Based on the life cycle cost (LCC) of economic assessment and the loss of power supply probability (LPSP) of reliability, Maleki et al. [30] optimized the configuration of PV/WT/hydrogen/reverse osmosis desalination system by artificial swarm optimization (ABSO) algorithm. The consequences showed that it was the most profitable to set the maximum LPSP at 0-10%, and ABSO could effectively solve the optimal size problem. Mohamed [31] applied the optimization algorithm based on cuckoo search (CS) into the PV/WT/diesel/battery HRES to obtain the optimal size of system components under the conditions of the lowest generation cost and maximum reliability within the constraint range. The outcomes displayed that compared with iteration, GA and PSO algorithm, CS algorithm could reduce the time needed to find the optimal size and has better accuracy. Samy et al. [32] applied the firefly algorithm (FA) to optimize the size of the HRES composed of PV/WT/FC. Compared with the results of the shuffled frog leaping algorithm (SFLA) and PSO, it was found that FA's results had minimum net present cost (NPC) and running time.

3.3. Physical or chemical biological heuristic algorithms for optimization

By reviewing the literature, some studies [33-37] have been identified to optimize the RES by physical or chemical heuristic algorithms, such as simulated annealing algorithm, harmony search algorithm, discrete harmony search algorithm, mine blast algorithm.

Simulated annealing (SA) is a metaheuristic algorithm for approximate global optimization in an ample search space. This feature makes SA the most widely used physical or chemical biological heuristic algorithm. Ekren et al. [33] adopted the SA algorithm to realize the minimum total cost and optimize the PV/WT/battery HRES size. The optimal results gained by the SA algorithm were compared with previous research results, and it was found that the SA algorithm had a better performance than the traditional response surface methodology (RSM) method. Maleki [34] optimized the size of the PV/WT/FC/diesel HRES by using discrete simulated annealing (DSA) algorithm. They considered two scenarios, including different hybrid system reconfigurations and diesel fuel prices. The results showed that the PV/WT/FC/diesel HRES was the best choice for decreasing emissions and wastes, and the PV/FC/diesel HRES was the most cost-effective power generation system as diesel price rose. Brinda et al. [35] applied a harmony search algorithm (HS) to optimize the size and distribution system reconfiguration of FC/WT/PV HRES for maximizing voltage stability index (VSI) and minimizing the cost, power loss and pollution. Maliki et al. [36] used a discrete harmony search algorithm (DHS) to optimize the size of independent PV/WT/diesel systems with batteries or fuel cell storage devices to achieve minimum cost. The results showed that this algorithm could improve the convergence speed and search quality compared with the HS algorithm. Fathy [37] used the mine blast algorithm (MBA) to determine the optimal size of the PV/WT/FC HRES, minimizing the annual cost of the HRES within the load range. Compared with the solution results of PSO, CS and ABC, this method can perform better, saving the total annual cost of the system about 24.8%, 9.0% and 11.6%.

3.4. Promising hybrid algorithms for optimization

The hybrid optimization algorithms, including the combination of multiple algorithms and the optimization algorithm combining artificial neural networks, were carried out in literature [38, 39, 8] to improve the calculation speed, optimal performance. Although the hybrid optimization algorithms are complex and challenging to implement, they have a broad development prospect.

Roy et al. [38] presented a hybrid algorithm combining a bacterial foraging optimization algorithm (BFOA) and ANN to optimize the energy control strategy of photovoltaic and wind power microgrid systems. Compared with the optimization results of GA and ABC, it showed that the presented method made PV, WT, microturbines and batteries obtain the maximum generated power. Zhang et al. [39] optimized an HRES based on wind and solar with hydrogen and batteries storage to obtain the minimum LCC of the system by using an original hybrid chaotic search/harmony search/simulated annealing algorithm (HCHSA). The performance of the presented hybrid algorithm was compared with that of SA and hybrid HS-SA, and it was found that this hybrid algorithm had a lower index value and its robustness was better than other methods. Zhang et al. [8] proposed a novel hybrid optimization algorithm CS-HS-SA-ANN to optimize the size of PV/WT/hydrogen HRES. In addition, weather forecast and ANN model were used to forecast solar radiation, ambient temperature and wind velocity, which improved the accuracy of the results. Finally, by comparison to the simulation results of the single algorithm, the consequences showed the superiority of the hybrid optimization algorithm.

4. Case study for RES output power prediction with ANN model

Based on the review of the previous chapters, a case study of using an artificial neural network model to realize the prediction of the output power of RES is presented, including data source, establishment and verification procedure of the ANN model. The generation process of the predicted value of system output power is shown in Figure 1.

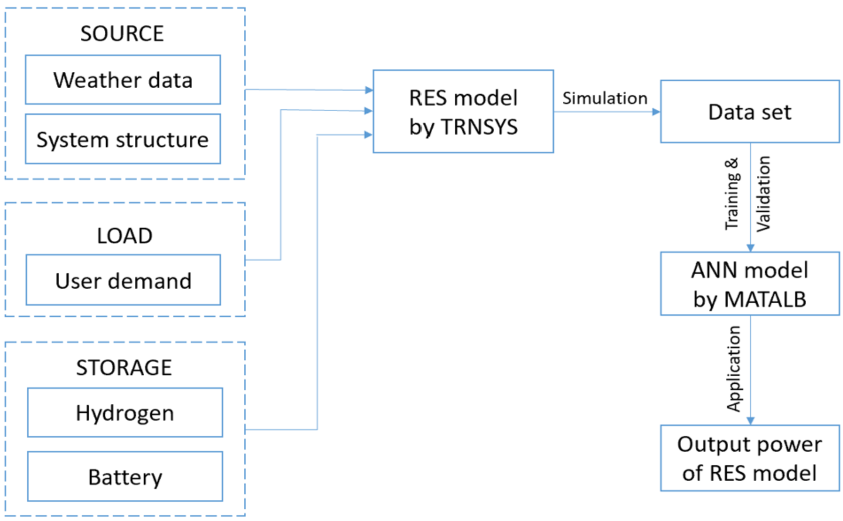


Figure 1. Flowchart of the methods used in this case study.

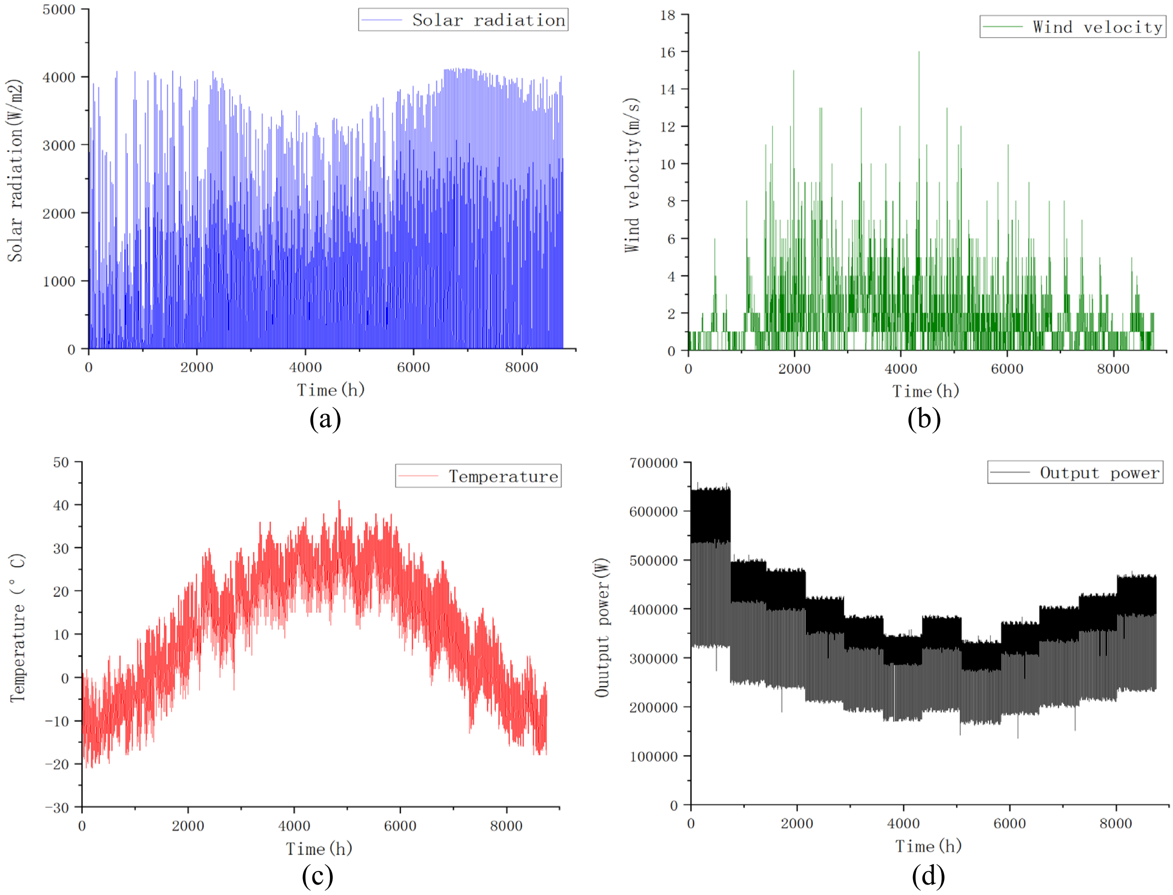


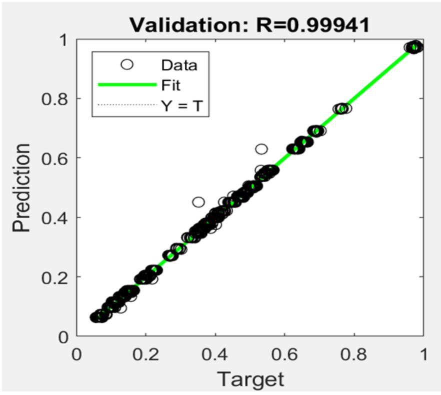
Figure 2. One-year data of (a) solar radiation, (b) wind velocity, (c) ambient temperature, and (d) total output power.

4.1. Data sources
Tikanlik is located in latitudes 87.70°N, longitudes 40.63°E, elevation 847m where is rich in wind and solar energy resources. The weather and system output power data are adopted as the basis of the training neural network model, which is shown in Figure 2.

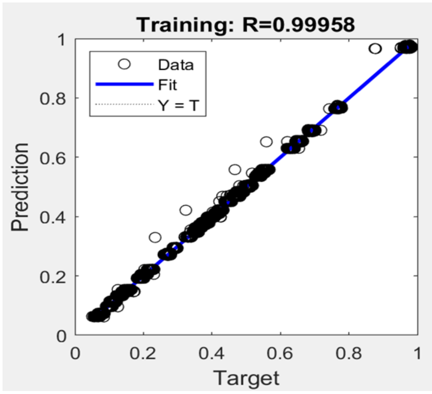
4.2. Implementation of ANN model
The training and test data are derived from the simulation outcomes with diverse original parameters, such as the weather data. There are 8760 data sets obtained from TRNSYS, divided into 75% for training sets and 25% for test sets. The proposed ANN has a three-layer structure. The five input parameters in the input layer of the ANN are three weather data variables (ambient temperature, wind velocity and solar radiation) and two time-related predictors (same hour load per day and month of the year), which can recognize the particular position of similar values in the demand time series [16]. The output layer contains one output variable, which is the total output power of this system. As for the hidden layer, it is a twenty-neuron computational layer. During the training process of the data set, the weight of each neuron is altered to minimize the error through the feedback mechanism, which calculates and adjusts the mean square errors of the results by the Levenberg-Marquardt algorithm.

4.3. Validation of ANN model
Figure 3 shows the consequences of the training and test sets. As shown in Figure 3 (d), the overall correlation coefficient of this ANN model is 0.99952, and the points of data distribution are close to the fitted straight line.

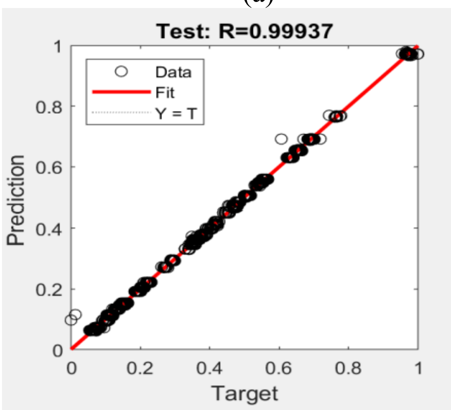
Figure 4 shows the relative error of this artificial neural network utilizing the test set, which was randomly chosen from the total data to verify the accuracy of the ANN model's predictions. The biggest value of the relative error is 15.8%, caused by the uncertainty of the ANN model. However, 99.32% of the relative error of the test set is less than 3%, which can identify that this model has good prediction results.



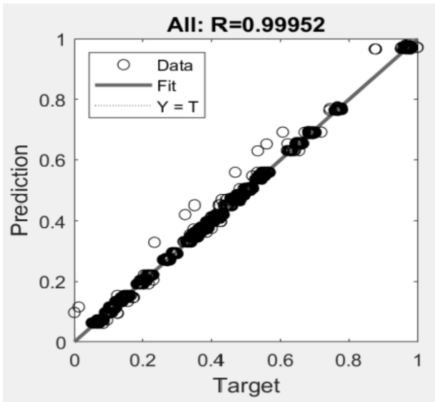
(a)



(b)



(c)



(d)

Figure 3. Correlation between ANN prediction and TRNSYS target within (a) validation set, (b) training set, (c) verification set and (d) all data set.

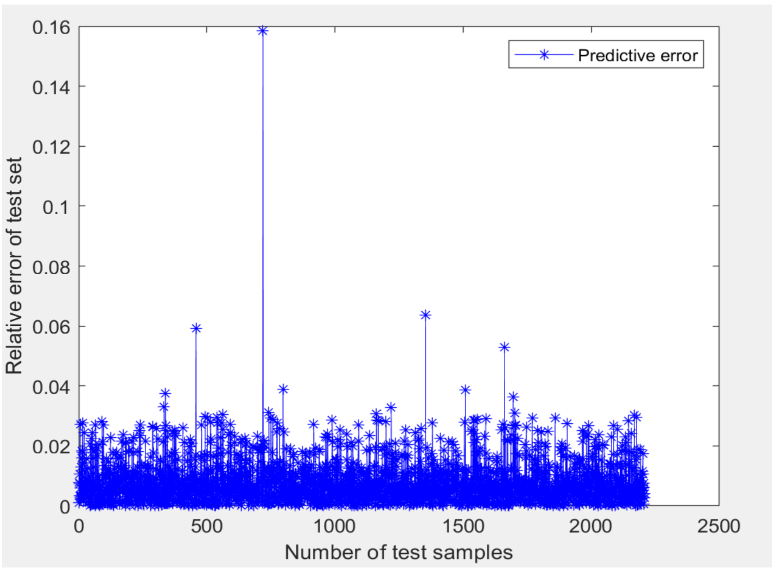


Figure 4. Distribution of test set relative error of RES output power forecast model.

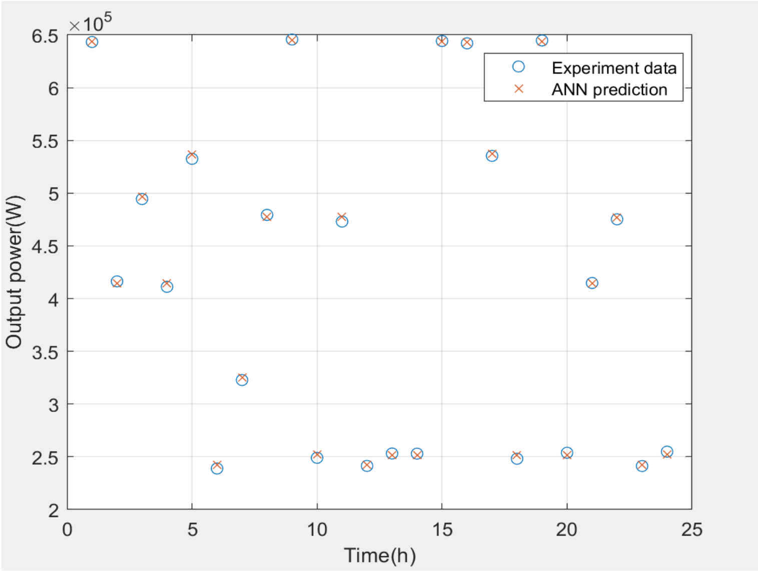


Figure 5. Comparison between prediction and experiment data of RES output power prediction model.

Figure 5 shows the verification of randomly selected 24 data sets from the test sets, making the forecast more visual. In general, the predicted values of system output power fit well with the test data, but there is some error in the model values. It can be regarded that this ANN model can meet the requirements of calculation and forecast.

In the subsequent work, various artificial intelligence algorithms can optimize the corresponding objective functions such as the economic, social, environmental and technical indicators based on a more accurate artificial neural network.

5. Conclusion

Artificial intelligence (AI) plays an essential role in modeling renewable energy systems (RES). The AI methods can achieve more intelligent planning, management, and control for energy generation and application for predicting the RES supply chain variables. Various AI optimization algorithms can make the RES achieve a more suitable configuration or size in optimizing RES indicators. The most meaningful conclusions in this review are as follow:

- The articles using an ANN model to predict the variables of hydrogen-based renewable energy systems are summarized. A new classification method is proposed based on the variables generated in different supply chain stages.
- The references that use AI optimization algorithms to optimize hydrogen-based RES are summarized. Among the AI optimization algorithms, particle swarm optimization algorithm, genetic algorithm, simulated annealing algorithm are the most popular ones.
- A case study for RES output power prediction with ANN model is carried out. The overall correlation coefficient and relative error of the verification set of this model are 0.99952 and almost less than 3%, respectively.
- Combining the ANN model and artificial intelligence optimization algorithms or applying them to more suitable and particular scenarios is a promising research direction.

Acknowledgments

Thanks to the Hydrogen Research Institute, Université du Québec à Trois-Rivières, for initializing a new research cooperation domain on renewable energy system simulation and optimization. This research is related to a hydrogen energy storage and safety project funded by the National Natural Science Foundation of China (52176191) and battery energy storage and safety projects funded by the Research Programme of Wuhan University of Technology Chongqing Research Institute (YF2021-08), and the Science and Technology Development Foundation of CMVR (China Merchants Vehicle

Research Institute) (20AKC3). Thanks also to the International Network Programme supported by the Danish Agency for Higher Education and Science for the PRESS project "Proactive Energy Management Systems for Power-to-Heat and Power-to-Gas Solutions" (No. 8073-00026B). Shenglin Su thanks the support from Wuhan University of Technology for the International Exchange Project of Postgraduate Independent Innovation Fund (2021-JL-008).

References

[1] Zahraee S M, Khalaji Assadi M, Saidur R 2016 *Renew Sust Energ Rev* **66** 617-30
[2] Come Zebra E I, van der Windt H J, Nhumaio G, Faaij A P C 2021 *Renew Sust Energ Rev* **144**
[3] Al-falahi M D A, Jayasinghe S D G, Enshaei H 2017 *Energy Convers Manage* **143** 252-74
[4] Xiao J, Bi C, Bénard P, Chahine R, Zong Y, Luo M, Yang T 2021 *Int J Hydrogen Energ* **46** 2936-51
[5] Xiao J, Li C, Fang L, Böwer P, Wark M, Bénard P, Chahine R 2020 *IJER* **44** 4475-92
[6] Ahmad T, Zhang D, Huang C, Zhang H, Dai N, Song Y, Chen H 2021 *J Clean Prod* **289** 125834
[7] Rangel-Martinez D, Nigam K D P, Ricardez-Sandoval L A 2021 *Chem. Eng. Res. Des.* **174** 414-41
[8] Zhang W, Maleki A, Rosen M A, Liu J 2019 *Energy Convers Manage* **180** 609-21
[9] Mert İ 2021 *Int J Hydrogen Energ* **46** 6272-85
[10] Doucoure B, Agbossou K, Cardenas A 2016 *Renew Energ* **92** 202-11
[11] Dong Y, Wang J, Xiao L, Fu T 2021 *Energy* **215** 119180
[12] Rodríguez F, Florez-Tapia A M, Fontán L, Galarza A 2020 *Renew Energ* **145** 1517-27
[13] Hu S, Xiang Y, Huo D, Jawad S, Liu J 2021 *Energy* **224** 120185
[14] Mellit A, Pavan A M, Lughi V 2021 *Renew Energ* **172** 276-88
[15] Shams M H, Niaz H, Na J, Anvari-Moghaddam A, Liu J J 2021 *J Energy Storage* **41**
[16] N. Ayoub F M, S. Pokharel and H. A. Gabbar 2018 *2018 IEEE International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada* 25-30
[17] Zhang W, Maleki A, Rosen M A 2019 *J Clean Prod* **241** 117920
[18] Li Q, Loy-Benitez J, Nam K, Hwangbo S, Rashidi J, Yoo C 2019 *Energy* **178** 277-92
[19] Hwangbo S, Nam K, Heo S, Yoo C 2019 *Energy Convers Manage* **185** 353-67
[20] Windler T, Busse J, Rieck J 2019 *J Clean Prod* **238** 117910
[21] Zhang J, Tan Z, Wei Y 2020 *ApEn* **258** 114087
[22] Wang J, Liu F, Song Y, Zhao J 2016 *Appl Soft Comput* **48** 281-97
[23] Maleki A, Hafeznia H, Rosen M A, Pourfayaz F 2017 *Appl. Therm. Eng.* **123** 1263-77
[24] Beshr E H, Abdelghany H, Eteiba M 2018 *PLoS One* **13** e0193224
[25] Gupta R A, Kumar R, Bansal A K 2015 *Renew Sust Energ Rev* **41** 1366-75
[26] Yin X, Cheng L, Wang X, Lu J, Qin H 2019 *Energy Procedia* **158** 6208-16
[27] Moghaddam M J H, Kalam A, Nowdeh S A, Ahmadi A, Babanezhad M, Saha S 2019 *Renew Energ* **135** 1412-34
[28] HassanzadehFard H, Tooryan F, Collins E R, Jin S, Ramezani B 2020 *Int J Hydrogen Energ* **45** 30113-28
[29] Eriksson E L V, Gray E M 2019 *Renew Energ* **133** 971-99
[30] Maleki A, Pourfayaz F, Ahmadi M H 2016 *Sol Energ* **139** 666-75
[31] Mohamed M A, Eltamaly A M, Alolah A I, Hatata A Y 2018 *Int J Green Energy* **16** 86-100
[32] Samy M M, Barakat S, Ramadan H S 2020 *Int J Hydrogen Energ* **45** 11471-83
[33] Ekren O, Ekren B Y 2010 *ApEn* **87** 592-98
[34] Maleki A 2018 *Int J Low-Carbon Tec* **13** 140-47
[35] Brinda M D, Suresh A, Rashmi M R 2018 *Cluster Comput* **22** 6849-54
[36] Maleki A, Pourfayaz F 2015 *J Energy Storage* **2** 30-42
[37] Fathy A 2016 *Renew Energ* **95** 367-80
[38] Roy K, Mandal K K, Mandal A C, Patra S N 2018 *Renew Sust Energ Rev* **82** 4296-308
[39] Zhang W, Maleki A, Rosen M A, Liu J 2018 *Energy* **163** 191-207