ISSN: 2455 - 9172

EIJO Journal of Engineering, Technology And Innovative Research (EIJO–JETIR)

Einstein International Journal Organization (EIJO)

Available Online at: www.eijo.in

Volume – 8, Issue –3 , May - June - 2023 , Page No. : 01 - 04

A detailed review on solar collector

[1]Guddu Kumar, Dept. of Mechanical Engineering, Arya Institute of Engineering and Technology, Jaipur

[2]Gautam Kumar, Dept. of Mechanical Engineering, Arya Institute of Engineering and Technology, Jaipur

[3]Roop Chand Saini, Dept. of Mechanical Engineering, Arya Institute of Engineering and Technology, Jaipur

[4]Ankit Sharma, Dept. of Mechanical Engineering, Arya Institute of Engineering and Technology, Jaipur

Abstract

The solar collector is the heart of any solarenergy collection system the performance of solar is totally depend upon the design of solar collector system, gaining optimum performance is required. There are several different kinds of performance approaches for solar collector systems. Artificial neural networks, also called neural networks, are one of the intelligence techniques used in modelling, simulation optimization, and system control. Artificial neural network is very faster analysis and find out the complex and nonlinear problem as compare toanother techniques. Artificial intelligence neural network applied in various field engineering, energy sector, business and manufacturing sector. The primary function of the artificial neural network tool is structure training, which is carried out through experimentation with enormous amounts of data. this research paper is all about the using machine learning and deep learningtechnique to make accurate and predict the performance of the solar collector, which depends upon various factor that include time, metal of solar collector, location, temperature, angle, weather condition.

Keywords: Solar, Network, Data factor, ANN

Introduction

The usage of solar thermal collectors and renewable energy has grown significantly over the past few decades due to a number of important benefits, such as being a free, natural, ecologically friendly, and enduring energy source. Today, developing and optimising diverse solar thermal energy systems is more vital than ever. As a result, there are many methodologies and methods for examining these systems' performance, including experimental, numerical, and artificial intelligence (AI) method. It can forecast important and useful factors affecting solar collector efficiency. We have knowledge of the numerous machine learning methods to know that in this review study. which one is the best prediction method in that we used and gain energy efficiently .when we are talking about the renewable energy sources then we need to more focus on the solar collector system and other renewable energy sources because we are more depended on fossil fuel and it is causes of various things like -global warming, environment pollution so the government wants more investment on renewable energy and solar collector system is play big role in that which helps to generate the huge amount of the energy but in this method there are a lots of challenges that how to use it efficiently that helps us to generate the effectively and more energy. There are various technique to analysis the solar collector system and use it effectively but one of them using machine learning technique is very effective because of their analysis of the data and daily based data analysis through the sensors and predict through the various machine learning algorithms helps us to use it in more efficiently.

Application of ANN

Fundamentals of an ANN. Several machine learning methods have been successfully used. Applied to the ANN towards the prediction of energy system parameter values. Here, we merely cover the ANN's fundamental idea. Figure 1 depicts a general schematic ANN structure, with the input, hidden, and output layers each made up of a specific number of "neurons." In the input layer, every neuron (which is also referred to as a "node") corresponds to a particular independent variable. The dependent variable that needs to be predicted is represented by the neuron in the output layer. Typically, the independent variables ought to be those that are simple to measure and may be related to the dependent variable. Typically, the dependent variable is the one that is challenging to measure in experiments and is I expected to be accurately predicted. The hidden layer is the one who lies between the layers of input and output in Figure 1. The size of the dataset and the study object determine the appropriate number of neurons for the hidden layer. Each neuron has a connection to all of the neurons in the layer below it. The relation, known as the weight (which is frequently referred to as w), defines the ANN's ability to predict results through the use of its activation functions. The starting weights for an ANN's training are determined at random first, and the following iterations will help with selecting the ideal weight values that fulfils the prediction criteria. All data only move within itself similarly (as depicted in Figure 1, from left to right). An ideal number of hidden layer neurons, hidden layer(s), and weight values should be present in a well-trained ANN in order to sufficiently reduce the risk of either under- or overfitting. Several neural networks with enhanced algorithms are used in practical applications, including ELM, general regression neural networks and back-propagation neural networks. Despite the wide variety of network models, model training relies on the same fundamental ideas.

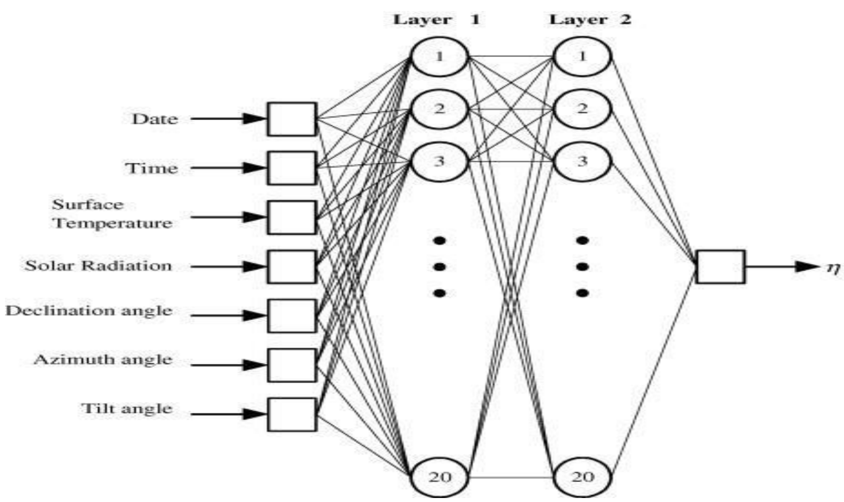

Figure 1: Schematic structure of a typical ANN. Circles represent the neurons in the algorithm.

An ANN's training: The following factors should be considered into account while training a robust ANN: (i) percentages of the training and testing sets; (ii) the number of hidden neurons; (iii) the number of hidden layers; and (iv) the quantity of training time needed. A large training set is` recommended to develop a practical ANN for applications in the real world. We develop a model to predict the heat gathering rates of WGET-SWHs. With a relatively big dataset (> 900 data groups), we discovered that a training set with a percentage higher than 85% could assist in the development of a model that performed well in the testing set. It would be a waste of data for real-world applications to utilize a small training set percentage, which is another justification for using a big training set. The explanation is straightforward: more training data groups usually result in better forecasting performance. It's crucial to try neuron numbers ranging from low to high when picking the number of hidden neurons. Underfitting would be possible if there are not enough buried neurons; overfitting would be possible if there are too many. Risk of overfitting and time-consuming would exist. Therefore, determining the optimal number of neurons by comparison is crucial. It should be indicated that in some unique neural network techniques, the number of hidden neurons can be fixed after the dataset is specified in some software tools. In this case, there is no longer a need to be associated about the hidden neuron settings.

In order to prevent either under- or overfitting, the same tests on the number of layers should be performed alongside to the hidden neuron numbers. We need to take into account the training time as a last aspect. The connectivity of neurons would occur according to the primary ANN concept (Figure 1) if the relationship between neurons would grow increasingly complex as the number of neurons increases. Therefore, the training period would be greater with a larger database, more independent variables, and buried neurons. This means that a time-consuming cross-validation test may occasionally be too much for a standard personal computer (PC). From our prior research using an ANN training, We found that if the database was large enough, repeated training and/or cross-validation training would produce little variation. So, after a simple sensitivity test, a cross-validation phase can be reasonably skipped to save time and money. If the database is substantial, the ANN training and testing causes would be strong for real-world applications. Consequently, following a straightforward sensitivity test, a the cross-validation procedure can be logically skipped to save on computing costs. evaluation of an ANN.

A well-trained ANN can accurately forecast the heat collecting rates of the data in the testing set, with comparatively small absolute residuals, as shown by a testing result using an ANN for the prediction of heat collection rate. Despite the fact that some estimated points still show variations, overall accuracy is still quite high and suitable for practical applications. The unrelated variables used for modelling a solar power system should always contain specific environmental variables like solar The temperatures outside and radiation strength. These factors are very reliant on the weather, location, and time of year. In other words, the data that is predicted should have similar environmental characteristics to the training data's external conditions. The ANN might not perform well in terms of prediction otherwise. All of the data observations in our most recent investigations were carried out in very similar locations, at very similar temperatures, and during very similar seasons, which is sufficient to guarantee accurate anticipated outcomes in both the testing set and any future experimental validation.

Conclusion

We have outlined our most recent research on the energy system's ability to forecast outcomes using machine learning techniques in this study. We have also provided a framework for ANN design that makes use of a machine learning algorithms based on HTS technique. This concept entails (i) creating a predictive model and (ii) eliminating candidates with subpar performance without having a thorough understanding of how the target performances are physically related. We anticipate that this study will be able to fill in the gaps left by HTS applications for energy system optimization and offer fresh perspectives on the development of energy systems with high performance.

References

1. S. Mekhilef, R. Saidur, and A. Safari, A review on solar energy use in industries, Renewable and Sustainable Energy Reviews, vol. 15, pp. 1777–1790, 2011.
2. Z. Wang and Y. Li, "Layer pattern thermal design and optimization for multistream plate-fin heat exchangers—a review," Renewable and Sustainable Energy Reviews, vol. 53, pp. 500– 514, 2016.
3. Predictive Power of Machine Learning for Optimizing Solar Water Heater Performance: The Potential Application of High-Throughput Screening
4. Geczy-Víg, P., Farkas, I., 2010. Neural network modelling of thermal stratification in a solar DHW storage. Sol. Energy 84 (5), 801-806
5. Kalogirou, S.A., 2004. Solar thermal collectors and applications. Prog. Energy Combust. Sci. 30 (3), 231e295. ISSN 0360-1285.
6. D. Kumar and S. Kumar. Simulation Analysis of Overall Heat Loss Coefficient Of Parabolic Trough Solar Collector At Computed Optimal Air Gap [J]. Energy Procedia, 2017, 109: 86–93. DOI: 10.1016/j.egypro.2017.03.057
7. J. Ramesh, J. K. Kumar and D. E. V. Subbareddy. Design, Fabrication and Performance Analysis of a Parabolic Trough Solar Collector Water Heater [J]. International Journal of Innovative Research in Science, Engineering and Technology, 2015, 4(7): 6038- 6043. DOI: 10.15680/IJIRSET.2015.0407122
8. P. K. V. Kumar, T. Srinath and V. Reddy. Design, Fabrication and Experimental Testing of Solar Parabolic Trough Collectors with Automated Tracking Mechanism [J]. International Journal of Research in Aeronautical and Mechanical Engineering, 2013, 1(4): 37-55.
9. S. K. Singh, A. K. Singh and S. K. Yadav. Design and Fabrication of Parabolic Trough Solar Water Heater for Hot Water Generation [J]. International Journal of Engineering Research &Technology (IJERT), 2012, 1(10): 1-9.
10. A. A. Ghoneim, A. M. Mohammedein and K. M. Kandil. Performance Analysis of Parabolic Trough Collector in Hot Climate [J]. British Journal of Applied Science & Technology, 2014, 4(14): 2038- 2058.