Renewable Energy 40 (2012) 71–79

Contents lists available at SciVerse ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Modeling solar still production using local weather data and artificial neural networks

Noe I. Santos[a], Aly M. Said[a], David E. James[b,*], Nanda H. Venkatesh[a]

[a] Department of Civil and Environmental Engineering, Howard R. Hughes College of Engineering, University of Nevada, Las Vegas, 4505 S. Maryland Pkwy, Box 454015, Las Vegas, NV 89154-4015, USA
[b] Office of the Vice Provost for Academic Affairs, University of Nevada, Las Vegas, 4505 S. Maryland Pkwy, Box 451099, Las Vegas, NV 89154-1099, USA

ARTICLE INFO

Article history:
Received 11 February 2011
Accepted 7 September 2011
Available online 15 October 2011

Keywords:
Artificial neural networks
Weather data
Solar
Predicting
Water
Purification

ABSTRACT

A study has been performed to predict solar still distillate production from single examples of two different commercial solar stills that were operated for a year and a half. The purpose of this study was to determine the effectiveness of modeling solar still distillate production using artificial neural networks (ANNs) and local weather data. The study used the principal weather variables affecting solar still performance, which are the daily total insolation, daily average wind velocity, daily average cloud cover, daily average wind direction and daily average ambient temperature. The objectives of the study were to assess the sensitivity of the ANN predictions to different combinations of input parameters as well as to determine the minimum amount of inputs necessary to accurately model solar still performance. It was found that 31–78% of ANN model predictions were within 10% of the actual yield depending on the input variables that were selected. By using the coefficient of determination, it was found that 93–97% of the variance was accounted for by the ANN model. About one half to two thirds of the available long term input data were needed to have at least 60% of the model predictions fall within 10% of the actual yield. Satisfactory results for two different solar stills suggest that, with sufficient input data, the ANN method could be extended to predict the performance of other solar still designs in different climate regimes.

1. Introduction

With anticipated future increases in energy costs, water purification processes such as multistage flash, multiple effect, vapor compression, reverse osmosis, electrolysis, phase change, and solvent extraction will see their price per unit of water increase drastically over time. Furthermore, rising energy prices will also increase the costs required for pumping desalinated water and transporting it to the desired location. One low cost, point of use alternative to energy-intensive approaches for purification of brackish, saline, or polluted waters is passive solar distillation [1]. Kalogirou [2] reviewed solar distillation technologies and costs and concluded that, because of fairly low energy fluxes from sunshine, space requirements for solar stills are high compared to other technologies. At the current state of still development, for daily water yields ranging from one to 7 L per square meters of still area, a small community requiring 200 m^3/day [2] would require 3–20 ha of still area. Due to the high capital costs involved with solar distillation, primarily land and equipment, accurate prediction of expected distillate production is vital to the success of a project to optimize capital expenses and maximize production.

While previous design and testing work has emphasized methods to improve distillate quantity, there is still a need to develop a predictive model that would be able to accurately estimate long term distillate production. The amount of labor and equipment needed to perform heat and mass transfer modeling often requires resources beyond the capacity of many rural communities. In response to this need, an artificial neural network model was considered as a possible technique that could use easily accessible weather data to accurately predict still performance.

The ability of solar stills to produce water for small communities is highly beneficial for remote and arid regions. With advancements in computational technology, the application of Artificial Neural Networks (ANNs) in the field of passive solar distillation could yield results that are not easily obtained with classical modeling techniques. In this paper, the effectiveness of artificial neural networks in modeling the performance of solar stills is studied using locally available daily weather data that contributes to the energy gains

* Corresponding author. Tel.: +1 702 895 5804; fax: +1 702 895 3670.
E-mail addresses: Santosn3@unlv.nevada.edu (N.I. Santos), Aly.Said@unlv.edu (A.M. Said), Dave.James@unlv.edu, drdavej@unlv.nevada.edu (D.E. James), Nandavenkatesh@gmail.com (N.H. Venkatesh).

0960-1481/$ – see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.renene.2011.09.018

and losses that solar stills experience during operation. This study will evaluate the overall performance of an ANN model in predicting solar still production and will also identify the effect that each input variable has on ANN model performance.

1.1. Background

Research into solar distillation goes as far back as the fourth century B.C. when Aristotle described a method to evaporate and condense polluted water for potable use [3]. However, the earliest documented work on solar distillation came from Arab alchemists in the 16th century [3] and later with the use of wide earthen pots exposed to the sun [3]. Faced with rapidly growing populations, many regions across arid temperate zones and in the tropics are short on potable water supplies. Available ground and surface waters may have biological or chemical contaminants in excess of potable primary standards or may be too saline [2]. Some water-short populations are located in coastal areas. The oceans are nearly inexhaustible sources of water; however, their high salinity renders them unsuitable for human consumption. In order to treat the water for human consumption, desalination is used. However conventional means of desalination such as steam distillation and reverse osmosis both require significant quantities of energy to separate sea salt and water. Due to the high recurring energy costs to perform desalination, few of the water short areas of the world, besides some countries in the Middle East that have enough money to perform desalination due to oil income, can afford conventional desalination approaches [2].

Renewable energy systems are capable of producing energy from sources that are freely available and are also characteristically environmentally friendly [2]. Although renewable energy powered desalination systems, at current fossil fuel prices, cannot compete with conventional systems in terms of the cost of water produced, they are applicable in certain areas and are likely to become accepted as a feasible solution in the near future [2].

Most of the current research in solar distillation has focused on modifying the solar still design to introduce components that would allow water to either evaporate or condense faster. Some of the modifications that were studied include using internal and external condensers [4,5], using black walls with cotton cloth [1], the use of black dye and charcoal in the distilland [6], multi-wick solar stills [7] and condensing cover cooling [8]. For this paper, “distilland” refers to the water in the basin undergoing distillation and “distillate” refers to the condensed water produced as a result of distillation.

Kalogirou [2] reviewed multiple desalination techniques using renewable energy citing previous research studies to predict solar still performance involving computer simulation [9], thermic circuit and sankey diagrams [10], periodic and transient analysis [11,12], iteration methods [13], and numerical methods [14,15]. Despite the different numerical techniques, all of the above cited methods rely on mechanistic internal heat and mass transfer (HMT) models which were first published by Dunkle [16] in the 1960s and subsequently revisited by other researchers such as Tiwari [17]. Evaluation of heat and mass transfer equations using first order accurate backward difference formulae [8] has proven to be one of many ways to model solar still performance. However, these models usually require simplifying assumptions regarding the relative magnitude of several components of HMT. The HMT model, as developed by Dunkle [16] and Tiwari [17], relies on many variables such as density, specific heat, thermal conductivity of the still materials, the viscosity, latent heat of vaporization, partial saturated vapor pressure of water, and heat and mass transfer coefficients derived from the HMT models. These coefficients are derived from intensive data logging of several solar still thermal characteristics including the outer glass temperature, inner glass temperature, vapor temperature, distilland temperature, internal solar still humidity, distillate output and also environmental data such as ambient air temperature, ambient air velocity, and total and diffused radiation [16,17]. Due to the large amount of data needed to validate the HMT model, the ability to forecast distillate production is limited by the ability to measure the variables needed to assess the HMT model. While the HMT model has been used successfully in the past, the amount of time, data storage, and the frequency of measurements may put this approach out of reach in many parts of the developing world. ANNs have a potential advantage for predicting the performance of solar stills by using fewer variables compared to HMT models.

1.2. Artificial neural networks

Multi-layer Perceptron (MLP) networks in artificial neural networks have been used in the past for engineering applications due to their ability to use non-linear transformations and to learn patterns of behavior between inputs and outputs [18]. Kalogirou [19] has reviewed multiple uses of ANNs for a wide range of fields for modeling and prediction in energy engineering systems. The architecture of a neural network helps to determine how a network transforms the inputs into an output [19]. Furthermore, Kalogirou states that it is essential to be able to identify the most important variables in a process [19]. These networks are highly data driven and are capable of capturing complex behavior by learning from the user supplied input and target (output) data.

The MLP network can consist of input, output, and several hidden layers. Each layer can have many computational hidden nodes or neurons. The hidden layers’ neurons connect the input and target layers by using a specified training function [18]. Each layer has units that are partially or fully connected to units in consecutive layers. Initially the connections between consecutive units are assigned random weights to represent their strength or activity with regards to the noted patterns. The output from the first hidden layer is transferred to the second hidden layer whose outputs are then transferred to the subsequent hidden layers. This process is repeated for the rest of the network until reaching the final output layer which is the complete response of the ANN to the patterns and trends that were provided in the input layer.

ANNs are able to derive their predictive power through their parallel structure as well as their ability to learn and generalize. The generalization that occurs within a neural network allows for the prediction of reasonable outputs given inputs that were not originally included in the training data set [18]. After an ANN architecture has been designed, the network must be trained in order to create the optimum set of weights for each connection until there is no more change in the synaptic weights. This results in a minimized difference between the actual and predicted target variable. ANNs have an advantage over traditional empirical models and multivariable regression analysis because they are able to account for the total interaction between input variables [20].

2. Materials and methods

Solar still experimental data were collected between February 2006 and August 2007 using single basin solar stills from two different manufacturers [21]. The data were originally collected to evaluate the long term performance of single basin solar stills in Las Vegas, Nevada. The test site was located on the roof of the Howard R. Hughes College of Engineering building at the University of Nevada, Las Vegas (36.11°N, 115.142°W). The hourly weather data that were used as inputs for the ANN were retrieved from the U.S. National Weather Service (NWS) station located at McCarran