



Available online at www.sciencedirect.com





Solar Energy 118 (2015) 41-58

www.elsevier.com/locate/solener

## Predictive model for assessing and optimizing solar still performance using artificial neural network under hyper arid environment

Ahmed F. Mashaly<sup>a,\*</sup>, A.A. Alazba<sup>a,b</sup>, A.M. Al-Awaadh<sup>b</sup>, Mohamed A. Mattar<sup>b,c</sup>

<sup>a</sup> Alamoudi Chair for Water Researches, King Saud University, P.O. Box 2460, Riyadh 11451, Saudi Arabia

<sup>b</sup> Agricultural Engineering Department, College of Food and Agriculture Sciences, King Saud University, P.O. Box 2460, Riyadh 11451, Saudi Arabia <sup>c</sup> Agricultural Engineering Research Institute (AEnRI), Agricultural Research Center, P.O. Box 256, Giza, Egypt

Received 27 September 2014; received in revised form 13 January 2015; accepted 8 May 2015

Communicated by: Associate Editor G.N. Tiwari

#### Abstract

A mathematical model to forecast the solar still performance under hyper arid conditions was developed using artificial neural network technique. The developed model expressed by different forms, water productivity (MD), operational recovery ratio (ORR) and thermal efficiency ( $\eta_{th}$ ) requires ten input parameters. The input parameters included Julian day, ambient air temperature, relative humidity, wind speed, solar radiation, ultra violet index, temperature of the feed and brine water, and total dissolved solids of feed and brine water. The developed ANN model was trained, tested and validated based on measured data. The results showed that the coefficient of determination ranged from 0.991 to 0.99 and 0.94 to 0.98 for MD, ORR and  $\eta_{th}$  during training and testing process, respectively. The average values of root mean-square error for all water were 0.04 L/m<sup>2</sup>/h, 2.60% and 3.41% for MD, ORR and  $\eta_{th}$  respectively. Findings revealed that the model was effective and accurate in predicting solar still performance with insignificant errors. © 2015 Elsevier Ltd. All rights reserved.

Keywords: Artificial neural network; Solar still; Solar desalination; Water recovery; Modeling

#### 1. Introduction

Global water consumption is anticipated to increase by around 55% by 2050, primarily owing to growing demands from industry, electricity generation and municipal consumption. In light of this, more than 40% of the world population is anticipated to live under water stress by 2050. Moreover, still 768 million people have no access to potable water (WWAP, 2014), although that there are more than 16,000 desalination plants operating over the world

http://dx.doi.org/10.1016/j.solener.2015.05.013 0038-092X/© 2015 Elsevier Ltd. All rights reserved. with the total capacity reported at 66.4 million  $m^3/day$ , and it is anticipated to increase to 100 million  $m^3/day$  by 2015 (GWI/IDA, 2013). However, these mentioned indicators raise concern over current practices of water resource sustainability because desalination industry still depend mainly on fossil energy and with decline for 80% of world oilfields by 2030 (Höök et al., 2009). Alternative may need to be adopted to ensure steady water supplies, especially in the future following sustainable manner. Add to that, Kalogirou (2005) found that the production of 1000 m<sup>3</sup>/ day of desalinated water need 10,000 tons (toe) of oil per year. Accordingly, utilization of solar energy could be one of the promising renewable energy in desalinating

<sup>\*</sup> Corresponding author. Tel.: +966 14673737; fax: +966 14673739.

*E-mail addresses:* amashaly@ksu.edu.sa, mashaly.ahmed@gmail.com (A.F. Mashaly).

water particularly in arid areas where oil is consumed dramatically to operate desalination plants (Kalogirou, 2013). Therefore, the use of solar still in arid areas at small or large scale could help in desalinating necessary needs of water either by purifying seawater, groundwater or recycling of wastewater (Kabeel and Almagar, 2013). The ongoing efforts in this endeavor revealed that a solar still use evaporation and condensation process which in nature generate rainfall (Ahsan et al., 2010) and such device limited by the high capital cost required to be applied on a small scale. However, to optimize and enhance this configuration to be used widely with possible low cost, this may require further modeling processes to forecast optimal performance and identify critical parameters related to still performance to lower its costs. Based on the foregoing, there is a need to develop a predictive model that would be able to accurately estimate the performance. Khadir (2005), Tripathy and Kumar (2009) stated that classical modeling techniques are complex and a need long time for computing as well as occasionally are inaccurate to predict still performance effectively. Additionally, Santos et al. (2012) stated that amount of labor and equipment needed to achieve classical heat and mass transfer modeling for solar still performance oftentimes requires resources exceed the capability of many rural communities. Therefore, literature provides insufficient information on this aspect to develop novel models that could simplify the performance of still and optimize operational conditions (Dunkle, 1961; Mowla and Karimi, 1995; Tiwari and Tiwari, 2006; Dev and Tiwari, 2009). An artificial neural network (ANN) could be considered as a possible alternative to classical models in modeling thermal solar energy systems by incorporating meteorological data to precisely predict still performance (Kalogirou et al., 1999). Multiple uses of ANNs for a wide range of fields for modeling and prediction in energy engineering systems were reviewed by (Kalogirou 2001; Yang et al., 2003; Sözen et al., 2005; Mellita and Kalogirou, 2008; Kalogirou, 2006) and found that the results were effective and accurate. Moreover, in solar energy field, many researchers studied some applications of ANNs, for example, Kalogirou et al. (1998) used the ANN for modeling the heat-up response of a solar steam generating plant. Santos et al. (2012) determined the effectiveness of modeling solar still distillate production using ANNs and local weather data. They used only insolation, ambient temperature, distillate volume, wind speed, wind direction and cloud cover as inputs. The ANN method was also used by Sözen et al. (2008) in order to determine the efficiency of flat plate solar thermal collectors where the input data were the collector temperature, date, time, solar radiation, declination angle, azimuth angle and tilt angle. Porrazzo et al. (2013) used an ANN model for analyzing a solar powered membrane distillation system performance under several operating conditions, specifically distillate production versus feed flow rate, solar radiation and cold feed temperature. Farkas and Géczy-Víg (2003) developed ANN models for three different types of solar thermal collectors to predict the outlet temperature of the solar collectors based on solar radiation, ambient temperature and inlet temperature. Also, Lecoeuche and Lalot (2005) showed an application of ANNs to forecast the in-situ daily performance of solar air collectors where the output of the ANN is the outlet temperature of the collector, and inputs to the network are the solar radiation and the thermal heat loss coefficients. Hamdan et al. (2013) used three ANN models (Feed forward, Elman, and Nonlinear Autoregressive Exogenous (NARX) networks) to find the performance of triple solar still operating under Jordanian climate. They utilized nine input variables namely time, hourly variation of cover glass temperature, water temperature in the upper basin, water temperature in the middle basin, water temperature in the lower basin of the triple basin still, distillate volume, ambient temperature, plate temperature and hourly solar intensity as inputs to the network. They found that the achieved findings presented that feed forward model had the best ability to determine the required performance, on the other hand NARX and Elman network had the lowest ability to determine it. However, still there is a need for a comprehensive model to develop inputs and outputs for optimization of still performance by incorporating operational and meteorological parameters. For this reason, this study aims to examine the effectiveness of the solar still by modeling its performance with different types of water (seawater, groundwater and agricultural drainage water). Previous studies, for example, Santos et al. (2012) and Hamdan et al. (2013) indicated that there is a gap in this area on the development of inputs and outputs. All the main meteorological and operational data that may affect the desalination process and in particular the processes of evaporation and condensation were not included. Furthermore, the contribution of each component in the modeling process was not specified. So, this study will investigate development of an ANN model to predict the performance of solar still experimentally and theoretically through developed ANN model. Additionally, evaluate the performance of the developed ANN model in terms of certain statistical performance criteria in forecasting solar still performance and study the effectiveness of input variables on ANN model performance.

### 2. ANN theory

Artificial neural networks (ANNs) are information processing systems that are non-algorithmic, non-digital, and intensive parallel. By studying previously recorded data, they learn the relationship between the input and output variables (Caudill and Butler, 1993). ANNs consist of a large number of neurons (processing elements), which are arranged in different layers in the network: an input layer, an output layer and one or more hidden layers (Kumar and Singh, 2008). The neuron in the network essentially receives input signals, processes them then sends an output signal (Haykin, 1994). Every neuron is connected with no Download English Version:

# https://daneshyari.com/en/article/7937634

Download Persian Version:

https://daneshyari.com/article/7937634

Daneshyari.com