Solar Energy 142 (2017) 61–67

Contents lists available at ScienceDirect

Solar Energy

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

Design of high-performance water-in-glass evacuated tube solar water heaters by a high-throughput screening based on machine learning: A combined modeling and experimental study

Zhijian Liu [a,*,1], Hao Li [b,1], Kejun Liu [c,1], Hancheng Yu [d], Kewei Cheng [e]

[a] Department of Power Engineering, School of Energy, Power and Mechanical Engineering, North China Electric Power University, Baoding 071003, China
[b] College of Chemistry, Sichuan University, Chengdu 610064, China
[c] Department of Computer Science, Rice University, Houston, TX 77005-1892, USA
[d] Qinghai College of Architectural Technology, Xining 810002, China
[e] School of Computing, Informatics, Decision Systems Engineering (CIDSE), Ira A. Fulton Schools of Engineering, Arizona State University, Tempe, AZ 85281, USA

ARTICLE INFO

Article history:
Received 25 July 2016
Received in revised form 6 December 2016
Accepted 8 December 2016

Keywords:
Water-in-glass evacuated tube solar water heater (WGET-SWH)
Heat collection rate
High-throughput screening (HTS)
Artificial neural networks (ANNs)

ABSTRACT

How to design water-in-glass evacuated tube solar water heater (WGET-SWH) with high heat collection rates has long been a question. Here, we propose a high-throughput screening (HTS) method based on machine learning to design and screen 3.538125×10^8 possible combinations of extrinsic properties of WGET-SWH, to discover promising WGET-SWHs by comparing their predicted heat collection rates. Two new-designed WGET-SWHs were installed experimentally and showed higher heat collection rates (11.32 and 11.44 MJ/m^2, respectively) than all the 915 measured samples in our previous database. This study shows that we can use the HTS method to modify the design of WGET-SWH with just few knowledge about the highly complicated correlations between the extrinsic properties and heat collection rates of solar water heaters.

1. Introduction

Water-in-glass evacuated tube solar water heaters (WGET-SWH) are becoming the most prevalent technique to take advantage of solar energy (Mekhilef et al., 2011; Kalogirou, 2003; Morrison et al., 1984; Shah and Furbo, 2007; Liu et al., 2013). Solar collectors and concentrators are usually employed to collect the solar energy and then convert it into water or air for industrial, domestic and commercial buildings. As a promising technique, the evacuated tube thermal collector is a more recent development compared to the conventional flat plate collector. They have become more and more popular because of their high-performance and reliability in cold climates and commercial applications. During the past decade, the annual production of WGET-SWH kept expanding in Chinese areas, having a great amount of market share (Xiao et al., 2004; Tang et al., 2006).

During recent years, plenty of studies, in regard to the thermal performance assessment and prediction of WGET-SWH, had been reported (Morrison et al., 2005, 2014; Pei et al., 2012; Lin et al., 2012; Çomaklı et al., 2012; Govind et al., 2009; Xue, 2016; Bracamonte et al., 2015; Chow et al., 2011). These experiments were able to acquire precise assessments. However, they also require too much time and manpower. To assist these experimental assessments and reduce unnecessary consumptions, machine learning can help by using the knowledge from databases. Artificial neural networks (ANNs), as powerful machine learning techniques, have been widely employed in lots of complicated energy and solar energy storage systems during the past years (Kalogirou et al., 1999, 1998, 2014; Kalogirou, 2006; Kalogirou and Panteliou, 2000; Lecoeuche and Lalot, 2005). Using this technique, we can predict a series of coefficients for solar energy systems. So far, the heat collection rate (daily heat collection per square meter of a solar water system, MJ/m^2), a very important coefficient of thermal performance (CTP), is difficult to measure in many countries because of the complicated requirements for evaluating the thermal performance of WGET-SWH given by the standard of measurement, GB/T 19141-2011 (GB/T 19141, 2011) and ISO 9459-2 (ISO 9459-2, 1994). To address this problem, in our previous studies, we used "portable test instruments" (Table 1) Liu et al. (2015a) to measure the extrinsic properties of 915 WGET-SWHs. ANNs, support vector machine (SVM) and extreme learning machine (ELM) were shown to be good algorithms for predicting the heat

* Corresponding author.
E-mail address: lzj6035@163.com (Z. Liu).
[1] These authors contributed equally.

http://dx.doi.org/10.1016/j.solener.2016.12.015
0038-092X/

Nomenclature

q	heat collection rate, MJ/m^2
HTS	high-throughput screening
ANNs	artificial neural networks
WGET-SWH	water-in-glass evacuated tube solar water heaters
SWH	solar water heater
c_{pw}	specific heat of water, kJ/(kg °C)
ρ_w	water density, kg/m^3
t_b	water temperature at the beginning of heat collection, °C
t_e	water temperature at end of heat collection, °C
V_s	fluid volume in the thermal storage tank, m^3
A_c	solar collector area, m^2

Table 1
"Portable test instruments" for the measurement of parameters of WGET-SWHs.

Parameters	Portable test instruments	Accuracy
Final temperate of water	Digital thermoelectric thermometer	±0.5%
Tank volume	Electric platform scale	±1.0%
Diameter, tube center distance, tube length, collector area	Taper ZSH-3	±0.5%
Thermocouple	Type *T*	±0.5%

collection rates in testing sets (Liu et al., 2015a, 2016), with low root mean square (RMS) errors. Compared to the conventional measurements, machine learning provides a novel method for evaluating the CTP based on the knowledge from the measured database. Such a new technique reduces the measurement time from weeks to seconds, saving time, resources and manpower. The flow chart of the machine learning-based measurement is shown in Fig. 1. A software based on back-propagation (BP) algorithm, the *WaterHeater*, was developed in both Android and personal computer (PC) platforms for improving the user-friendliness in practical applications (Liu et al., 2015b).

In spite of the progress during recent years, there still remain some questions for scientists: how to efficiently select the combination of the extrinsic properties of solar water heaters (SWHs)? How to modify some of the extrinsic properties for improving the heat collection rate? Can we modify the performance of SWHs with just few knowledge about the highly complicated correlations between the extrinsic and intrinsic properties? These questions cause a big challenge for the practical design of WGET-SWH because of the highly complicated correlations between the extrinsic properties and heat collection rate, which is what we are not able to explicitly discover so far. Fortunately, ANN, as a powerful non-linear technique, is able to help us seek a numerical non-linear relationship by searching weights in an ANN structure. Here, to solve the questions mentioned at the beginning of this paragraph, we propose a novel design strategy of WGET-SWH using a high-throughput screening (HTS) method. Values of important extrinsic properties including the tube center distance, tube number, collector area, angle between tubes and ground, tube length, final temperature, and tank volume, were generated randomly and inputted into a well-trained ANN. The combinations of the generated input variables with high predicted heat collection rates would be considered as promising candidates. Then, the designed inputs were treated as the practical extrinsic properties and installed experimentally. Because the heat collection rate is the main coefficient that decides the performance of WGET-SWH while other coefficients (*e.g.*, heat loss coefficient) are highly dependent on the external environment, in the current stage of our study, we only discuss how to increase the heat collection rates during the design process.

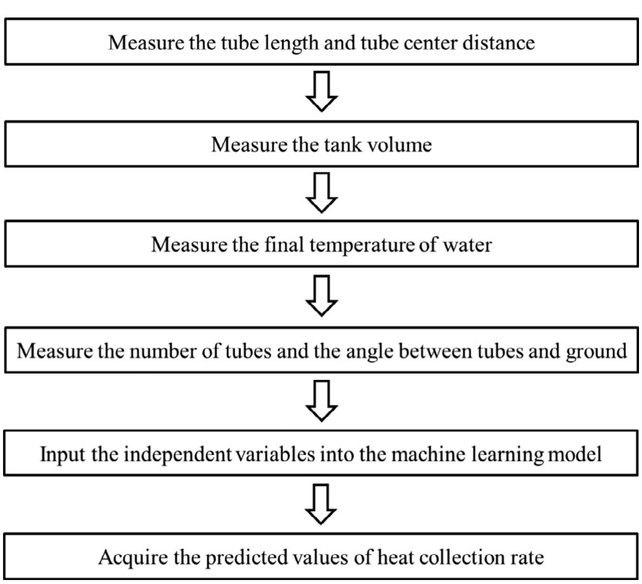

Fig. 1. Flow chart of the novel method using "portable test instruments" combined with machine learning models for measuring heat collection rates.

2. Methodologies

2.1. Data measurements

To collect data samples for modeling, the heat collection rates of 915 WGET-SWHs were measured by an inspection device (Model PDT2013-1), which was performed by China Academy of Building Research (CABR). All the measurements were performed in similar ambient conditions (*e.g.*, ambient temperature and season). The "portable test instruments" (Table 1) were used for measuring the extrinsic properties of WGET-SWHs. With the assumption that all these properties are correlated to the heat collection rate, they were set as the independent variables of ANNs. The descriptive statistics of all measured properties, as well as the experimentally measured heat collection rates of 915 WGET-SWHs are shown in Table 2 (Liu et al., 2015a,b, 2016). All these measured samples were regarded as the database for further comparisons.

2.2. ANN model

ANNs are widely used in numerical forecast and classifications (Hopfield, 1998; Dayhoff and DeLeo, 2001; Piaggi et al., 2010). According to the principle of the algorithm, an ANN structure is made up of "neurons" that are ordered into different layers. These layers can be divided into three parts, including input layer, output layer and hidden layer. The input layer is the first layer while the output layer is the last layer, and the hidden layer are the layer