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SciVerse ScienceDirect

Solar Energy 86 (2012) 2001–2016

SOLAR ENERGY

www.elsevier.com/locate/solener

Global approach test improvement using a neural network model identification to characterise solar combisystem performances

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Received 7 April 2011; received in revised form 9 March 2012; accepted 8 April 2012
Available online 4 May 2012

Communicated by: Associate Editor C. Estrada-Gasca

Abstract

Solar CombiSystems (SCSs) are very efficient systems for reducing conventional energy consumption of building but their thermal performances are strongly dependent on the environment where they are installed (type of climate and thermal quality of the building). Currently it is impossible to predict the energy savings generated by a SCS as there is no standard test to characterise SCS performances.

Currently, the Short Cycle System Performance Test (SCSPT), based on a 12 days test of the complete SCS on a semi-virtual test bench, is able to predict annual energy savings with a good accuracy, but the performance prediction is limited to only one environment (the building and the climate corresponding with the test).

Based on the SCSPT procedure, this paper proposes an improvement of the method by identifying a global SCS model from the test data. Then, the identified model would be able to simulate the tested SCS in any environment and thus to characterise its performances.

The proposed model to identify is a "grey box" model, mixing a "White Box" model composed of known physical equations and a "Black Box" model, which is an Artificial Neural Network (ANN). A complete process is developed to train and select a relevant global SCS model from such a test.

This approach has been validated through numerical simulations of three detailed SCS models. Compared to those annual results, "Grey Box" SCS models trained from a twelve days sequence are able to predict energy consumption with a good accuracy for 27 different environments. An experimental application of this procedure has been used to characterise a real system.

Keywords: Neural network; Solar combisystem; Performance prediction; Test bench; Characterisation

1. Introduction

Solar combisystems are complex solar thermal systems that provide energy for Domestic Hot Water (DHW) preparation and space heating. Solar energy and auxiliary energy are managed in such a way that the thermal loads are covered to fulfil the comfort requirements of the user, but also to save as much as possible auxiliary energy. Each combisystem has its own feature concerning, for example, controller algorithm, hydraulic loops and storage design.

Nowadays, some combisystems can be very efficient and cover up to nearly 50% of the total heat demand with solar energy gains (Letz, 2006). However, such good results are met in very special cases because combisystem performances are very sensitive to climatic conditions and energetic quality of buildings. Besides, it is not unusual to see even poor design or installation mistakes making a

Abbreviations: ANN, Artificial Neural Network; CTSS, Component Testing – System Simulation; DHW, Domestic Hot Water; FSC, Fractional Solar Consumption; SCS, Solar CombiSystem; SCSPT, Short Cycle System Performance Test; SFH, Single Family House.

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0038-092X/$ - see front matter
http://dx.doi.org/10.1016/j.solener.2012.04.003

Nomenclature

Variables and parameters in the collector model

- A_{coll} collector area (m^2)
- c_1 heat loss coefficient at $(T_m - T_a) = 0$ ($W\ m^{-2}\ K^{-1}$)
- c_2 temperature dependence of the heat loss coefficient ($W\ m^{-2}\ K^{-2}$)
- c_3 wind speed dependence of the heat loss coefficient ($J\ m^{-3}\ K^{-1}$)
- c_4 sky temperature dependence of the heat loss coefficient (–)
- c_5 effective thermal capacity ($J\ m^{-2}\ K^{-1}$)
- c_6 wind dependence in the zero loss efficiency ($s\ m^{-1}$)
- E_L longwave irradiance ($\lambda > 3\ \mu m$) ($W\ m^{-2}$)
- F' collector efficiency factor (–)
- G total solar irradiance on the collector plane ($W\ m^{-2}$)
- G_b beam solar irradiance on the collector plane ($W\ m^{-2}$)
- G_d diffuse solar irradiance on the collector plane ($W\ m^{-2}$)
- $K_{\theta b}$ incidence angle modifier (–)
- $K_{\theta d}$ incidence angle modifier for diffuse radiation (–)
- $\dot{Q}_{coll}$ heat flow rate supplied by the collector (W)
- $\dot{Q}_{sol,net}$ net solar energy available at the bounds of the collector ($W\ m^{-2}$)
- $\dot{Q}_{sol,ref}$ reference solar irradiation (W)
- T_a ambient temperature (°C)
- T_{coll} mean temperature of the collector (°C)
- v collector surrounding air speed (ms^{-1})
- θ angle of incidence (°)
- σ Stephan–Boltzman constant ($W\ m^{-2}\ K^{-4}$)
- $(\tau\alpha)_{en}$ effective transmittance-absorptance product for direct solar radiation at normal incidence (–)

Variables and parameters in the radiator model

- C_{em} heat emitter effective heat capacity ($W\ h\ K^{-1}$)
- K heat emitter characteristic coefficient ($W\ K^{-n}$)
- n heat emitter characteristic exponent (–)
- $\dot{Q}_{em}$ heat flow rate supplied for the heat emitter (W)
- T_{em} mean temperature of the heat emitter (°C)

Variables and parameters in the building model

- $\dot{Q}_d$ standard heat load at design outdoor temperature for chosen location (W)
- $T_{a,d}$ ambient design temperature of heating system at chosen location (°C)
- T_{room} mean temperature of the room air (°C)
- $T_{set,room}$ room setpoint temperature (°C)

Variables and parameters in the store model

- C_{sto} storage tank effective heat capacity ($W\ h\ K^{-1}$)
- $\dot{Q}_{aux,sto}$ heat flow rate supplied by the auxiliary heater, at the bounds of the storage tank (W)
- $\dot{Q}_{dhw}$ heat flow rate supplied for the DHW demand (W)
- $\dot{Q}_{dhw,sto}$ heat flow rate supplied for the DHW demand, at the bounds of the storage tank (W)
- $\dot{Q}_{coll,sto}$ Heat flow rate supplied by the collector, at the bounds of the storage tank (W)
- $\dot{Q}_{em,sto}$ heat flow rate supplied for the heat emitter, at the bounds of the storage tank (W)
- $T_{a,sto}$ temperature of the air surrounding the storage (°C)
- T_{tap} temperature of water at input of tap water net (°C)
- T_{sto} mean temperature of the storage tank (°C)
- $T_{set,dhw}$ DHW setpoint temperature (°C)
- $(UA)_{aux,loop,hot}$ heat loss capacity rate of auxiliary loop hot side ($W\ K^{-1}$)
- $(UA)_{aux,loop,cold}$ heat loss capacity rate of auxiliary loop cold side ($W\ K^{-1}$)
- $(UA)_{coll,loop,hot}$ heat loss capacity rate of collector loop hot side ($W\ K^{-1}$)
- $(UA)_{coll,loop,cold}$ heat loss capacity rate of collector loop cold side ($W\ K^{-1}$)
- $(UA)_{dhw,loop,hot}$ heat loss capacity rate of DHW loop hot side ($W\ K^{-1}$)
- $(UA)_{dhw,loop,cold}$ heat loss capacity rate of DHW loop cold side ($W\ K^{-1}$)
- $(UA)_{em,loop,hot}$ heat loss capacity rate of heat emitter loop hot side ($W\ K^{-1}$)
- $(UA)_{em,loop,cold}$ heat loss capacity rate of heat emitter loop cold side ($W\ K^{-1}$)
- $(UA)_{sto}$ heat loss capacity rate of the storage tank ($W\ K^{-1}$)

Variables and parameters in the auxiliary boiler model

- a_{aux} boiler performance coefficient (W^{-1})
- b_{aux} boiler performance coefficient (–)
- c_{aux} boiler performance coefficient (W)
- $\dot{Q}_{aux}$ power consumed by the auxiliary heater (W)
- $\dot{Q}_{aux,nom}$ auxiliary heater nominal power (W)
- $\dot{Q}_{aux,out}$ heat flow rate supplied by the auxiliary heater (W)
- $T_{set,boil}$ set outlet temperature of auxiliary boiler (°C)

Symbols in system identification

- H Heissian matrix of the cost function
- J cost function
- N_i number inputs
- N_n number of neurones
- $N_{n,max}$ maximum number of neurones
- N_o number of outputs
- N_{tp} number of training patterns
- N_{sw} number of synaptic weights
- u input vector of system