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Artificial neural network models for predicting the solar radiation as input of a concentrating photovoltaic system

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ABSTRACT

The energy production analysis of a system based on renewable technology depends on the inputs estimation accuracy. The solar energy is a free resource characterized by high variability; hence, its correct evaluation is a strategic factor for the feasibility of a solar system. In this paper a new methodological approach is presented in order to evaluate more accurately the electric and thermal energy production of a point-focus concentrating photovoltaic and thermal system (CPV/T). Two Artificial Neural Network (ANN) models for predicting solar global radiation and direct normal solar irradiance (DNI) are developed adopting different parameters such as climatic, astronomic and radiometric variables. In particular, a new combination of parameters is proposed in this paper and adopted first of all for the global radiation evaluation whose ANN model can be easily compared with the literature; the data are trained and tested by a multi layer perceptron (MLP). Hence, the results validation for the global solar radiation evaluation has encouraged to design an ANN model for the DNI by means of a similar variables set. The MLP network is trained, tested and validated for the hourly DNI estimation obtaining the MAPE, RMSE and R^2 statistical indexes values respectively equal to 5.72%, 3.15% and 0.992. Finally, the electric and thermal outputs of a point-focus CPV/T system are evaluated varying the concentration factor and cells number, and adopting as input the DNI evaluation results obtained by the ANN model presented in this paper. The CPV/T system outputs are estimated referring to the city of Salerno (Italy) under different meteorological conditions.

1. Introduction

Renewable technologies play a relevant role in the energy production field. Their impact has become considerable in order to satisfy the energy demands of residential and industrial users [1]. Solar energy is widely recognized as the main renewable source; it constitutes a free resource largely available in the world [2]. The solar energy can be exploited by means of photovoltaic and solar systems in many applications as: demand balancing of electrical energy in national grids, reduction of environmental pollution, design and size of integrated energy systems. In particular, the concentrating photovoltaic and thermal systems (CPV/T) have been highly developed in the last years. Their main characteristic is to concentrate sunlight on a photovoltaic receiver by means of optical devices and then to decrease the solar cells area proportionally to the concentration factor (C) [3] equal to the ratio between the primary concentrator area and receiver area. High temperatures are also reached by means of the sunlight concentration [4]; so, it is necessary to cool the cells. The CPV/T systems usually adopt triple-junction cells, whose electric efficiency is less affected by the temperature increase [5]. Hence, the CPV/T systems allow the simultaneous production of electrical and thermal energy. These devices are more complex in comparison with the traditional photovoltaic systems and a standard configuration does not exist. In literature many CPV/T systems are present [6] and are different for optical [7], photovoltaic and thermal characteristics [8]. However, since the optics has to focus the sunlight on the cells, these systems can work only with the solar radiation direct component. For this reason it is basic to achieve an accurate evaluation of global and direct radiation. Many models have been developed in literature in order to evaluate the solar radiation. There are empirical [9], numerical and statistical models [10], physical models, etc., but the solar radiation prediction based on most of these models can't be accurate because of the intrinsic complexity of the problem.

The Artificial Neural Network (ANN) models are a very useful solution for problems which depend on many physical phenomena [11]. They adopt the long-term data series obtaining a higher level of reliability. Kalogirou has reported the ANN use in renewable energy systems applications [12]. Moreover, many ANNs have been developed in order to evaluate the global solar radiation. Azadeh et al. [11] estimated monthly the global solar radiation for six cities

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Nomenclature

A	area (m^2)
a	output layer bias
ANN	Artificial Neural Network
b_j	vector of hidden layer biases
BP	back propagation
C	concentrating factor
CPV/T	concentrating photovoltaic and thermal
DNI	direct normal irradiance (W/m^2)
E	energy (kW h)
f	output layer transfer function
G	global radiation (Wh/m^2)
g	hidden layer transfer function
H	daylight hours (h)
$\bar{h}_c$	mean heat transfer coefficient (W/m^2 K)
HRA	hour angle (°)
I	incident direct radiation (kW h)
InGaP/InGaAs/Ge	indium-gallium-phosphide/indium-gallium-arsenide/germanium
k_b	direct solar transmittance
k_t	clearness index
Lg	longitude (°)
LM	Levenberg–Marquardt
Lt	latitude (°)
MAE	mean absolute error
MAPE	mean absolute percentage error (%)
MLP	multilayer perceptron
MSE	mean squared error
N_{cell}	number of cells
NREL	national renewable energy laboratory
p_{ij}	array of hidden layer weights
p	loss factor
P	precipitation (mm)
PV	photovoltaic
R^2	goodness of fit
RMSE	root mean squared error
RTD	resistance temperature detector
SD	sunshine duration (h)
sf	safety factor
T	temperature (°C)
V	voltage (V)
w_j	vector of output layer weights
x	input array
n	cardinality of dataset
y	variable to estimate
$\bar{y}$	mean value of the variable to estimate
$\hat{y}$	estimated value of the variable to estimate

Greek symbol

μ	stochastic variable mean value
β	tension thermal coefficient (V/°C)
δ	solar declination angle (°)
ε	emissivity coefficient
η	efficiency
σ_{ST}	Stefan–Boltzmann constant ($W/m^2 K^4$)
σ	stochastic variable standard deviation
σ_t	temperature coefficient (%/°C)

Subscripts

oc	open circuit
c	cell
dir	direct
el	electric
gn	global normal
int	integrated
inv	inverter
o	environment
opt	optic
par	parasitic losses
ref	reference
th	thermal

in Iran using climatic and meteorological data collected for six years. They have developed a multilayer feed-forward network which has back propagation (BP) with momentum, pruning and weight decay as training algorithm. Model inputs are: average maximum temperature, average minimum temperature, mean relative humidity, mean vapor pressure, total precipitation, mean wind speed and mean duration of sunshine. Wang et al. [13] developed two BP neural networks to evaluate the hourly global irradiance using the data of the National Renewable Energy Laboratory (NREL), collected in four years, normalized in [0.1, 0.9] and preprocessed. Levenberg–Marquardt (LM) is the training algorithm, while the network topology includes two hidden layers with 18 and 13 neurons. The transfer functions are respectively hyperbolic tangent and sigmoid. In [14] a generalized regression neural network (GRNN) has been employed to evaluate the solar radiation on tilted surface. In particular, radiometric and astronomical variables such as global solar radiation on horizontal surface, declination angles and hourly angles have been employed. Moreover, Celik and Muneer [14] collected data by an experimental grid-connected photovoltaic system with a tilt angle of the modules equal to the latitude of a location in Turkey; finally, the LM algorithm and cross-validation are used. In [15] a Gaussian model has been applied to evaluate the daily solar irradiance. A radial basic function network (RBF) is developed to calculate the Gaussian function amplitude. The model has been tested to use the minimum number of inputs such as the weather conditions and the duration of daylight. Finally, Amrouche and Le Pivert [16] have applied two feed-forward ANNs with BP in order to estimate the daily global solar irradiance. The models exploit the local forecasting data; hence, the two ANNs can predict global radiation for locations where the measurements are not possible. The methodology is tested for two locations using US National Oceanic and Atmospheric Administration data.

Referring to systems that work only with the direct normal solar irradiance (DNI), the ANNs can also be used for predicting the DNI in order to estimate the amount of electrical and thermal energy produced by a CPV/T system. However, Yadav and Chandel [17] have reviewed different ANN techniques for the solar radiation evaluation, but no techniques able to estimate the DNI have been considered. Mellit et al. [18] developed a feed-forward ANN to evaluate the hourly DNI and to compare it with an adaptive model. The network inputs are hourly temperature, humidity, sunshine duration and irradiance for the hour j, while the network output is the direct irradiance at the hour $j + 1$; the neurons number in the hidden layer is 15. In [19] a feed-forward ANN has been applied for the clearness index evaluation of the DNI. The input data are chosen considering the functional dependence of the clearness index. The ANN has eight inputs: latitude, longitude, altitude, month of the year, local mean time, monthly mean hourly total rainfall, monthly mean hourly relative humidity, monthly mean