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Using multi-pyranometer arrays and neural networks to estimate direct normal irradiance

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Abstract

Direct Normal Irradiance (DNI) is a critical component of solar irradiation for estimating Plane of Array (POA) irradiance on flat plate systems and for estimating photovoltaic and concentrating system power output. Current approaches to measuring or estimating DNI suffer from either high equipment costs or low precision and may require detailed environmental data. An alternative approach, using artificial neural networks to estimate DNI from the irradiance measurements of multiple pyranometers, is studied. We consider various neural network topologies and study the resulting errors. The neural network-based estimators are found to have higher accuracy than those obtained from empirical correlations of GHI measurements alone. Additionally, the use of a different GHI sensor than the one used to obtain the neural network training data does not induce significant errors. The ability of this method to be used as a quality-control instrument for pyrheliometer measurements is also discussed. We find that the proposed methodology is capable of detecting many instances of unreliable DNI measurements by considering the deviation between the predicted DNI and measured DNI. A more detailed analysis can be conducted by taking advantage of the data streams from the individual pyranometers.

Keywords: Direct normal irradiance; Multi-pyranometer arrays; Neural networks; Machine learning

1. Introduction

Direct Normal Irradiance (DNI) is a key variable in applications where the concentration of solar energy is important, such as for solar thermal energy systems, photovoltaic systems, or concentrating systems. There are several methods for measuring or calculating DNI. The most direct (and accurate) is to measure DNI using a system such as a pyrheliometer or a rotating shadowband pyranometer. However, these systems have a high investment cost and require regular monitoring to ensure accuracy. When these requirements are impractical, DNI can be estimated using Global Horizontal Irradiance (GHI) measurements as a part of one of many models. Gueymard (2010) surveyed eighteen clear-sky models. After comparing the output of the models to measured data, it was observed that models which are more physically based (and, therefore, require more atmospheric inputs) perform better and more consistently than simpler models. However, DNI model error statistics are generally optimistic, as the analysis often is restricted to the clear-sky conditions for which most of the models are developed. Additionally, it may be impractical to obtain enough

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Nomenclature

ANN	Artificial Neural Network
ASE	All-Seeing Eye
DNI	Direct Normal Irradiance
GHI	Global Horizontal Irradiance
MAE	Mean Absolute Error
MBE	Mean Bias Error
MPA	Multi-Pyranometer Array
RMSE	Root Mean Square Error
SERI QC	Software that provides quality control measures, information, and options on measurements for solar radiation. Developed by the Analytic Studies Division at the National Renewable Energy Laboratory (formerly *Solar Energy Research Institute*)
SRRL	*Solar Radiation Research Laboratory* at the National Renewable Energy Laboratory in Golden, Colorado, USA

atmospheric inputs for the more physical models to fully capture the anisotropy of the sky. In particular, the primary factors influencing DNI when the sun is not obscured are aerosols and precipitable water, both of which can vary significantly and are difficult to predict (Gueymard, 2010).

Another approach has been to use an array of multiple co-located pyranometers (a *Multi-Pyranometer Array*, or MPA) to measure irradiance at varying angles to separate it into components. The co-located pyranometer measurements are typically used to calculate DNI via a radiation model. An artificial horizon (a barrier that prevents the pyranometers from detecting nearby ground-reflected radiation) can be added to the MPA to simplify the inverted radiation model (Faiman et al., 1987; Munger, 1997). One potential limitation of this method is its reliance on a clear-sky model, which may reduce its effectiveness in everyday use. Additionally, even these simplified radiation models can be a computational challenge to invert, leading to the need for relatively complex postprocessing schemes.

To overcome this limitation, rather than invert a radiation model, we utilize Artificial Neural Networks (ANN), a tool from machine learning (see subSection 1.1 for a brief overview of neural networks). We sample data from five pyranometers for input into a trained neural network, which outputs an estimated DNI measurement. Neural networks are a useful tool for this type of problem, as while it might be virtually impossible (without extensive and expensive sensor measurements) to obtain enough atmospheric data to get a full model of the anistropic profile of the sky at any given point in time, through training on measured data a neural network can implicitly take these variables and their effects into account. Neural networks (a "black box" model) can fit almost any function to within a prescribed error bound, assuming the availability of input data that jointly captures all of the influential latent variables, and as long as there are no practical limits on the complexity of the network (Reed and Marks, 1999). Curtiss (1993) utilized a neural network approach to DNI estimation as a "nonconventional" beam irradiance estimator, while more recently ANNs have been used to estimate GHI (Mohandes et al., 1998; Zervas et al., 2008; Paoli et al., 2010; Wang et al., 2012; al Shamisi et al., 2013), estimate DNI from sky imager data (Eissa et al., 2013; Chu et al., 2013), estimate DNI from the National Weather Service database (Marquez and Coimbra, 2011), and construct synthetic irradiance time series (Hontoria et al., 2001). Additionally, while the training phase of neural network construction can be computationally intensive, the use of a trained network is trivial for any modern computer, making the entire setup extremely portable, while also being an order of magnitude less expensive than a pyrheliometer (and less expensive than a rotating shadowband radiometer if all of the pyranometers are photodiode sensors).

In this paper, we will present a brief background of the neural network technique before demonstrating how it can be applied to an MPA to solve for DNI, resulting in a sensor array we call an "All-Seeing Eye" (ASE). We will discuss our overall system design, including an analysis of the errors produced by the model. Our preliminary results show good accuracy across four full years of testing data, under both clear and cloudy conditions.

1.1. Neural network overview

ANNs are a machine learning method that generalizes logistic regression by passing n input variables $\mathbf{x} = [x_1, \ldots, x_n]$ through one or more hidden layers, consisting of *nodes* which implement an artificial neuron model, before recombining the hidden layer outputs into a final network output y.

Each hidden node takes inputs $\bar{\mathbf{x}} = [\bar{x}_1, \ldots, \bar{x}_m]$ (the bar-notation is used to distinguish these hidden layer inputs from the overall network inputs). As shown in

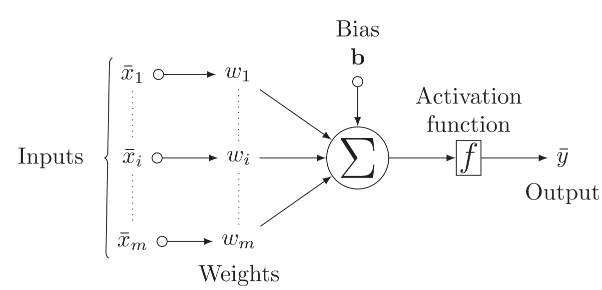

Fig. 1. Overview of the sigma function implemented within a single neural network node. The inputs x_i are linearly combined before the activation function is applied to the result.