Computation of daily solar radiation using adaptive neuro-fuzzy inference system in Illinois

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ABSTRACT

The objective of this study is to develop adaptive neuro-fuzzy inference system (ANFIS) model for estimating daily solar radiation using limited weather variables at Champaign and Springfield stations in Illinois. The best input combinations (one, two, and three inputs) can be identified using ANFIS model. From the performance evaluation and scatter diagrams of ANFIS model, ANFIS 3 (three input) model produces the best results for both stations. Results obtained indicate that ANFIS model can successfully be used for the estimation of daily global solar radiation at Champaign and Springfield stations in Illinois. These results testify the generation capability of ANFIS model and its ability to produce accurate estimates in Illinois.

Keywords: adaptive neuro-fuzzy inference system, daily solar radiation, Illinois, limited weather variables

INTRODUCTION

The availability of information about the solar radiation in the zone where a solar system is going to be installed is a necessary data for the designer of solar systems. This information, in case that it exists, can be available, in several ways. The most common is in tabular form with a lot of very useful information, usually large solar radiation sequences, but extremely difficult to handle. Another way can be solar radiation maps of the zone where the installation is going to be made. The neuro-fuzzy models were used by many researchers to estimate global solar radiation. Almost all the literatures concluded that neuro-fuzzy model is superior to other empirical regression models. The objective of the present study is to develop ANFIS model that can be used to estimate daily solar radiation at two locations (Champaign and Springfield stations) in Illinois.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The ANFIS is a combination of an adaptive neural network and a fuzzy inference system. The parameters of the fuzzy inference system are determined by the neural network learning algorithms. Since this system is based on the fuzzy inference system, reflecting amazing knowledge, an important aspect is that the system should always be interpretable in terms of fuzzy IF-THEN rules. The ANFIS is capable of approximating any real continuous function on a compact set to any degree of accuracy (Jang et al., 1997). The ANFIS identifies a set of parameters through a hybrid learning rule combining back propagation gradient descent error digestion and a least square error method. There are largely

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two approaches for fuzzy inference systems, namely the approaches of Mamdani (Mamdani et al., 1975) and Sugeno (Takagi and Sugeno, 1985). The differences between the two approaches arise from the consequent part. Mamdani's approach uses fuzzy membership functions (MFs), whereas Sugeno's approach uses linear or constant functions. The neuro-fuzzy model used in this study implements Sugeno's fuzzy approach (Takagi and Sugeno, 1985) to obtain the values for daily soil temperature from those of input variables. Figure 1 shows the general ANFIS structure.

The procedure described by Jang et al. (1997) was adopted for estimating daily solar radiation. As a simple example of the procedure adopted, a fuzzy inference system with two inputs x_1 and x_2 and one output y is assumed. Here, the input nodes, such as x_1 and x_2, may be considered as air temperature (TEM(t)) and relative humanity (HUM(t)), while the output node y would represent solar radiation (RAD(t)).

The ANFIS has five layers comprising different node functions. The output of the i_{th} node in layer 1 is denoted as $O_{1,i}$. Every node I in layer 1 is an adaptive node, with $O_{1,i}=\varphi A_i(TEM(t))$for i=1, 2 or $O_{1,i} = \varphi B_i(HUM(t))$ for i=3, 4, where TEM(t) (or HUM(t)) is the input node, and $A_i(orB_{i-2})$ is a linguistic label (e.g.,LOWorHIGH)associated with this node. The MFs for A and B can be written as

$$A_i(TEM(t)) = \frac{1}{1+[(TEM(t)-c_i)/a_i]^{2b_i}} \quad (1)$$

where $[a_i, b_i, c_i]$ = the parameter set. A similar equation may be considered for HUM(t). Any continuous and piecewise differential functions, such as commonly used triangular-shaped MFs, are also qualified candidates for node function in layer 1 (Jang, 1993). Parameters in layer 1 are called premise parameters.

Layer 2 consists of the nodes labeled Ⅱ, which multiplies the incoming signals and sends the product out. The output of layer 2 comprises the membership values of the premise part and can be written as

$$O_{2,i} = w_i = A_i(TEM(t))B_i(WIN(t)) \qquad i=1,\ 2 \qquad (2)$$

The nodes labeled N calculate the ratio of the i_{th}rule'sfiringstrengthtothesumofallrules' firing strengths in layer 3. Each node output represents the firing strength of a rule and can be written as

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i=1,\ 2 \qquad (3)$$

where $\overline{w}_i$ = the output of layer 3. The outputs of layer 3 are called normalized firing strengths. The nodes of layer 4 are adaptive with node functions and can be written as

$$O_{4,i} = \overline{w}_i y = \overline{w}_i (p_i TEM(t) + q_i WIN(t) + r_i) \qquad (4)$$

where $[p_i, q_i, r_i]$ = the parameter set. Parameters of layer 4 are referred to as consequent parameters. The single fixed node of layer 5 labeled Σ computes the final output as the summation of all incoming signals which can be written as

$$O_{5,i} = \sum_{i=1} \overline{w}_i y_i = \frac{\sum_{i=1} w_i y_i}{\sum_{i=1} w_i} \qquad (5)$$

Detailed information for ANFIS can be found in Jang (1993).

CASE STUDY

The daily weather data obtained from two weather stations, Champaign (latitude, 40.0840° N; longitude, 88.2404° W; altitude, 219 m) and Springfield (latitude, 39.7273° N; longitude, 89.6106°W; altitude, 177 m) operated by the Illinois State Water Survey (ISWS), were used in this study (http://www.isws.illinois.edu/warm/).

The ISWS is a division of the Prairie Research Institute of the University of Illinois at Urbana-Champaign and has flourished for more than a century by anticipating and responding to new challenges and opportunities to serve the citizens of Illinois. The weather data consisted of six years (January 2007 to December 2012, N=2,192 days) of daily records of air temperature (TEM), solar radiation (RAD), relative humidity (HUM), dew point temperature (DEW), wind speed (WIN), and potential evapotranspiration (ETO). Air temperature and relative humidity have been measured at 2 m above the ground, whereas wind speed has been measured at 10 m above the ground (prior to winter 2011/2012 measurement made at 9.1 m). Potential evapotranspiration has been calculated using the Food and Agricultural Organization (FAO) of the United Nations Penman–Monteith equation as outlined in FAO Irrigation and Drainage Paper No. 56 "Crop Evapotranspiration" (Allen et al. 1998) since 1 December 2012 (Water and Atmospheric Resources Monitoring Program 2011). Prior to that time, the Van Bavel method was used for calculating potential evapotranspiration (Van Bavel 1956). Figure 2 shows the comparison of the observed and estimated daily solar radiation values using ANFIS models (two and three inputs).

CONCLUSIONS

This study develops and evaluates data-driven models for estimating daily solar radiation at Champaign and Springfield stations in Illinois. The ANFIS model is developed for the best input combinations (one, two, and three inputs), respectively. Adding other input variables to the best input combinations (one, two, and three inputs) improves ANFIS model performance. In this study, it can be found that the data-driven models can estimate daily solar radiation.

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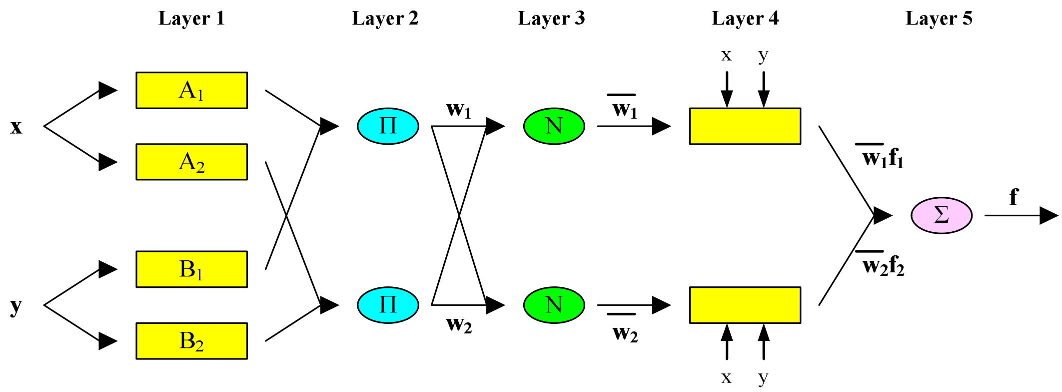
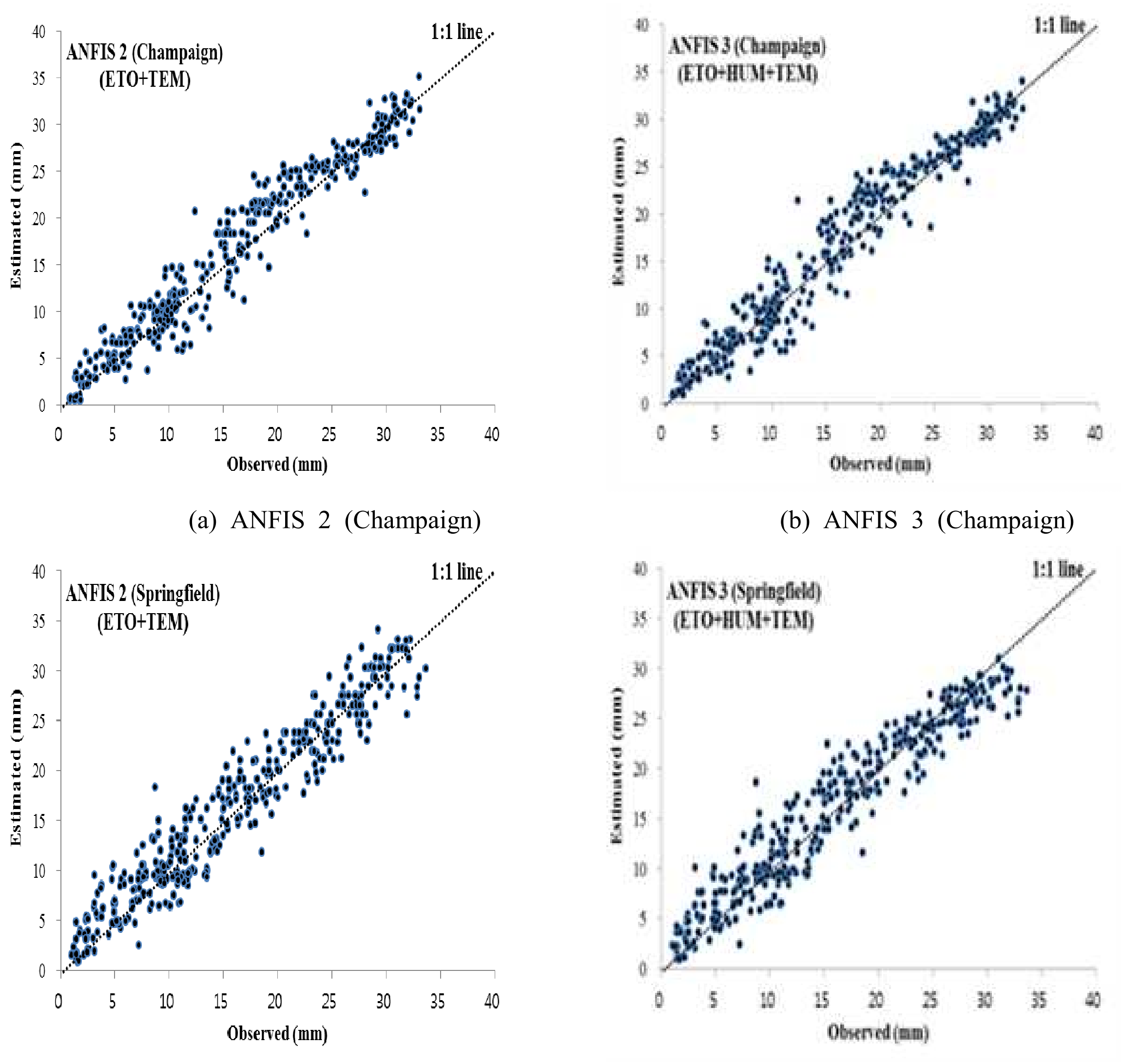


Figure 1 General ANFIS structure



(a) ANFIS 2 (Champaign) (b) ANFIS 3 (Champaign)

(c) ANFIS 2 (Springfield) (d) ANFIS 3 (Springfield)

Figure 2 Comparison of the observed and estimated daily solar radiation values using ANFIS models