Using an Artificial Neural Network to Predict Parameters for Frost Deposition on Iowa Bridgeways

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ABSTRACT

Forecasting frost formation on bridge-ways in Iowa is an important yet difficult problem. Frost forms when water vapor in the air sublimates onto a surface (which occurs when the dew point temperature of the air is greater than the surface temperature), and the surface temperature is below freezing. Only small amounts of moisture are needed to cover surfaces with frost and create hazardous travel conditions.

Recently, a frost model was devised by Knollhoff et al. (2001) to predict frost deposition based on moisture flux principles. The inputs required by the frost model include the following: (1) air temperature, (2) dew-point temperature, (3) wind speed, and (4) surface temperature.

An artificial neural network predicts these four inputs at 20-minute intervals for a 24-hour period. The output from the neural network models can then be used as input into the frost deposition model to predict frost formation on bridgeways in Iowa. The proper development of an artificial neural network requires the dataset to be subdivided into at least a training set and a validation set. A test set can also be used to test the model(s) even further.

Key words: artificial neural network—bridgeways—frost deposition

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INTRODUCTION

Forecasting frost formation on bridge-ways in Iowa is an important yet difficult problem. Frost forms when water vapor in the air sublimates onto a surface (which occurs when the dew point temperature of the air is greater than the surface temperature), and the surface temperature is below freezing. Only small amounts of moisture are needed to cover surfaces with frost and create hazardous travel conditions.

Background

There are two primary ways in which frost forms. The first is due to radiational cooling. As turbulent mixing decreases as the sun sets, the atmosphere near the surface begins to cool, eventually becoming stratified, as a nocturnal inversion forms (*1*). Within these inversion layers, the air near ground level is cooled by the surface and becomes cooler than the air elevated above the surface around 15–20 meters (*1*). As the surface and ambient air cools, the relative humidity increases in the air if the amount of moisture in the air remains constant. A moisture flux is then directed towards the surface when the dew-point temperature of the ambient air near the surface is higher than the surface temperature. If the surface temperature is below freezing, then frost will form due to deposition as opposed to dew from condensation. When dew forms and thereafter the temperature falls below freezing, the dew will freeze and potentially impact travel. These conditions are not accounted for in this study because they are different from the conditions of frost formation.

The second type of front formation has been referred to as the advection method and it often times occurs near active fronts/boundaries. If cold air cools the surface below freezing and a moist air mass moves into the area, moisture will begin to be deposited on surfaces which have temperatures below freezing. This type of event is not as common as frost that occurs because of radiational cooling, but it still occurs a few times each season.

Several different frost predictive systems have been developed in the past, many of which relate to linear regression techniques. In this study, we will use a non-linear regression approach to predicting frost through the use of an artificial neural network. The artificial neural network uses a non-linear modeling technique based on the hyperbolic tangent function, which allows for both positive and negative values as input. Artificial neural networks have been successfully used in the past to predict various aspects of meteorology including hail size (*2*), thunderstorms (*3*), tornadoes (*4*) and quantitative precipitation forecasts (*5, 6*) to name a few.

Recently, a frost model was devised by Knollhoff et al. (*7*) to predict frost deposition based on moisture flux principles. The inputs required by the frost model include the following:

- air temperature
- dew-point temperature
- wind speed
- surface temperature

Artificial Neural Networks

The artificial neural network predicts these four inputs at 20-minute intervals for a 24-hour period. The output from the neural network models can then be used as input into the frost deposition model to predict frost formation on bridge-ways in Iowa. The proper development of an artificial neural network requires the dataset to be subdivided into at least a training set and a validation set. A test set can also be used to test the model(s) even further.

METHODOLOGY

Since each model is predicting a different variable at a different time step, each model needed to be created independently (*8*). The models were set up in such a way that parameters are predicted at 20-minute intervals throughout the day. This means that each parameter is predicted using 72 different models predicting at different time steps. Since four parameters are predicted, a total of 288 models are used over the 24-hour period. The models were developed with application at the Iowa Department of Transportation (Iowa DOT) in mind, so that predictions are made after 1800 UTC observations are collected for the model run. Because the emphasis is on frost prediction, which generally occurs during the late night or early morning hours, the first forecast time for the suite of artificial neural network models is at 0000 UTC the following day (6 PM the same evening local standard time). The input data into the ANN includes the 1200 UTC nested grid model (NGM) model output statistics (MOS) (*9*) output paired with road weather information system (RWIS) observations from the cold seasons of 1995- 1998. For non-numerical input, categorical variables were used since all input into the ANN must be numerical. A cold season for purposes of this study is defined as October 1 through April 30. This time period was chosen because frost observations made by Iowa DOT personnel were readily available for these months at four stations across the state of Iowa. The four stations used in the development of the model were Waterloo (ALO), Des Moines southwest (DSM), Mason City (MCW), and Spencer. The model, once developed, was then later tested on data for Ames over the cold seasons of 2001-2002 and 2002- 2003.

Four different types of models were created to predict the input variables required by Knollhoff et al.'s model. Due to limitations on the number of variables that can be input into the neural network prior to ranking the variables, only one observed parameter other than the parameter itself was included as input. The two different types of RWIS observations used for the various models are shown in Table 1.

TABLE 1. RWIS Observations Used for Various Models

Forecasted Parameters	Observed Parameters (RWIS) Used as Input
Air temperature	Air temperature, dew point temperature
Dew point temperature	Dew point temperature, air temperature
Surface temperature	Surface temperature, air temperature
Wind speed	Wind speed, wind direction

Numerous models were created by varying the training time, architecture and number of inputs. It was noted that as more variables were added as input to the model, the performance eventually leveled off and often decreased. As can be seen from Figure 1, model performance increased very little with the addition of more than 8–10 input variables. To keep the complexity and the number of free parameters as low as possible, the number of inputs into each model was restricted to no more than 10. However, various architectures and training times were tried in various models with fewer inputs than this.

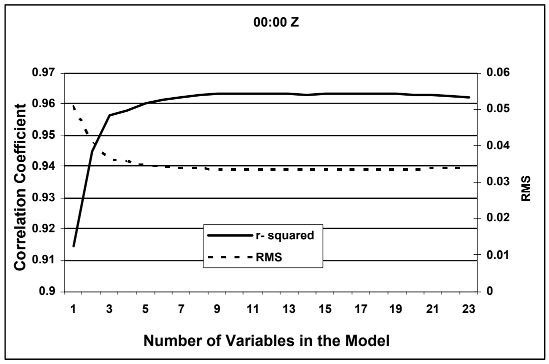

FIGURE 1. Model Performance and Input Variables

In total, 181 initial inputs were fed into the ANN for each model: 111 RWIS inputs, 65 1200 UTC NGM MOS inputs, and four unordered variables to test if the location of the RWIS sites was important to the model. Unordered variables had to be used to test if the location was important because the locations of the sites used are not related. From the 181 inputs, a general regression neural network was then used to rank the variables based on their relation to the output. Various time intervals were tried for training the model, and it was determined that a training time of 2 minutes gave the network ample time to learn the characteristics of the data. It was also found that using around eight ranked variables from the initial 181 as input into the ANN model itself produced the best results in terms of performance.

In total, there were anywhere from 1200–1500 cases included in the training and validation sets. The validation set comprised the last 15 percent of the original data set. This allowed for around 200 cases in each validation set, which adequately allowed us to test the performance of the models created.

RESULTS

Figures 2–5 show the results of a 6-hour forecast for each of the forecast variables. The first 85 percent of the data was used for training the model, and the last 15 percent was used as the validation set. The residual (error) is also plotted in yellow.

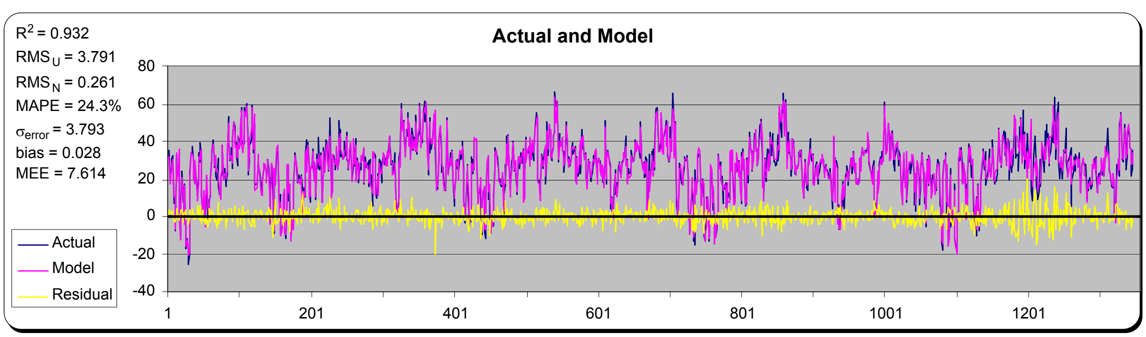

FIGURE 2. Dew Point

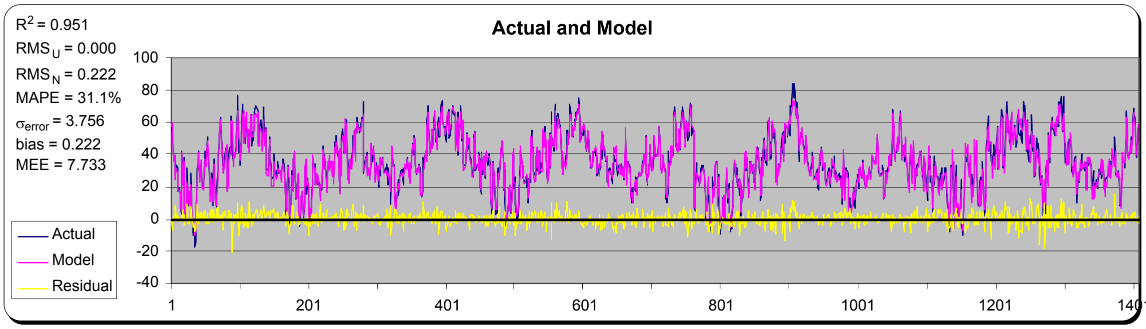

FIGURE 3. Air Temperature

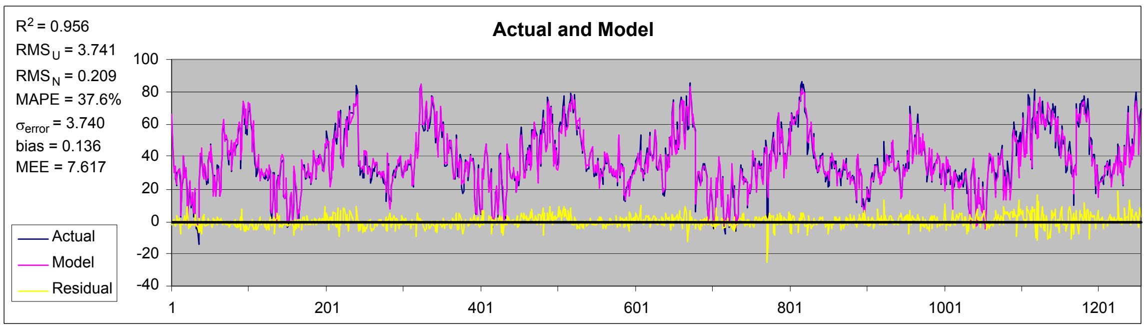

FIGURE 4. Surface Temperature

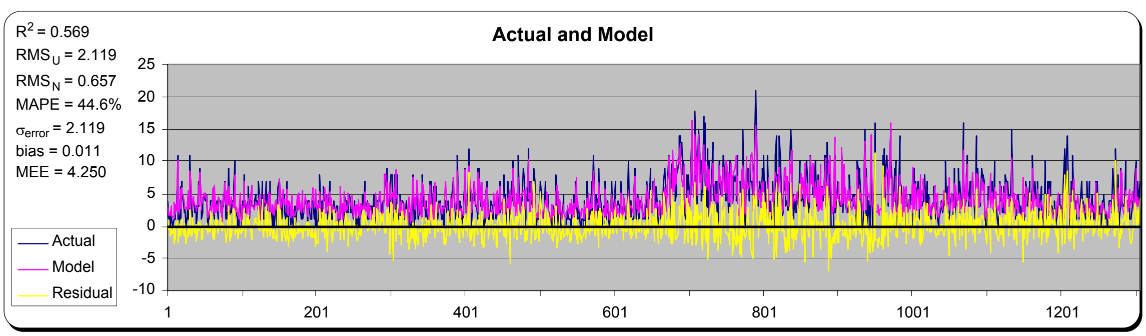

FIGURE 5. Wind Speed

Over all, the predictions correlate well with the RWIS observations, and generally perform better than the NGM-MOS output alone (for the similar forecasted variables).

Regarding a comparison of the predicted values with the MOS output alone, temperature errors using the artificial neural network were around 2 degrees F with MOS errors slightly higher, approaching three degrees. The greatest differences between MOS and neural network output were noted in the prediction of road surface temperature (because road surface temperature is not a direct MOS output, the forecasted air temperature was used as a proxy for road surface temperature). Errors with MOS again averaged close to three degrees F over the nighttime hours, but were much worse during the daytime when solar heating occurred, and road temperatures usually became much higher than 2m air temperatures. Errors with the artificial neural network were smaller, averaging just over 2 degrees. Similarly, the neural network error for the prediction of dew-point temperature overnight was close to one degree F, while it was over two degrees for MOS. Finally, the error in the prediction of wind speed was around 1–2 knots using the artificial neural network, while the errors associated with MOS averaged close to three knots across the entire time period.

CONCLUSIONS

Although not discussed in this present paper, it should be noted that although the nonlinear models usually performed best, for some parameters at some times, the linear models were better. These along with many other results will be presented at the conference.

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