DECISION SUPPORT FOR FREEZE PROTECTION USING ARTIFICIAL NEURAL NETWORKS

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Introduction

In rainfed agricultural production systems, up to 90% of the variability in the yield can be attributed to weather differences. Fruit crops such as blueberries and peaches are particularly susceptible to low air temperatures. Temperatures near but above freezing might slow plant growth and development but such conditions do not typically cause significant damage if the plants are exposed for a short duration. However, once the temperature drops below freezing, the plants are easily damaged, with the severity of damage being determined by the duration of low temperature as well as the temperature itself.

As an example, during the Spring of 2002, a large area in blueberry and peach production in South Georgia was damaged due to an unusually severe and unexpected late frost. Irrigation is the most widely practiced frost protection measure for southeastern U.S. crops including peaches and blueberries. Irrigation results in the formation of a layer of ice that keeps the temperature of the flower near freezing, preventing it from dropping to below freezing temperatures. Farmers need information about when to start irrigation, as the process has to be started before the temperature drops to freezing. In addition to the expected low temperatures, farmers also need information about local wind speed, dew point or vapor pressure deficit to determine the point to initiate the freeze protection measures. Thus there is a need for accurate local weather information and short-term weather forecasts.

The goal of frost/freeze protection is to prevent plant parts (particularly flower and fruit) from being damaged by temperatures that drop below a critical level. This critical temperature is a function of crop variety and growth stage. There are several factors that can affect the degree of injury due to low temperature including the following: 1) type of plant, 2) stage of development of the crop, 3) the amount of leaf cover over the blossoms and fruit, 4) severity and duration of the freeze, and 5) wind speed. The primary prevention mechanism used by horticultural growers is irrigation. However, there are some problems associated with irrigating to prevent frost and freeze damage. If the humidity is low and the wind speed is high during a freeze, insufficient irrigation may cause evaporative cooling, which may damage crops more than non-irrigated fields. There are a number of recommendations that have been published by the extension service regarding frost/freeze damage:

1) If relative humidity is greater than 90%, there is little likelihood of worsening freeze damage with irrigation.
2) Open blueberry flowers cannot survive temperature less than 28°F. At the petal fall, the developing berry can be damaged by temperatures less than 30°F.

3) Overhead irrigation can be effective in preventing damage to blueberries if there is very little wind when the temperature drops below freezing.
4) If the humidity is low, irrigation should begin when temperature drops to 37°F.
5) If the temperature drops to the low 20s or below, or if wind is higher than 5 miles an hour, irrigation can cause increased damage.
6) If wind rises to 5 miles an hour, an application rate of 0.5 inches per hour will be needed to give some protection from frost or freeze damage.
7) At wind speeds above 5 miles an hour, more damage may be done by irrigating than by non-irrigating.

The dewpoint temperature is an important factor in decision making related to frost/freeze protection. Producers need an accurate estimate of temperature, wind speed, relative humidity or dew point temperature during critical times of the freeze. The dewpoint temperature is useful for estimating moisture content of air during freezes. With little wind, the dewpoint temperature changes only slightly between noon and the following sunrise, which makes it a good indicator of humidity. Relative humidity, however, may have large fluctuations during such periods.

Traditionally the role of providing weather forecasts has been the responsibility of the National Weather Service (NWS). However, due to changes in the laws, the NWS no longer provides data for agricultural applications. The NWS collects data from urban centers, thus the data are less useful for rural areas where farming is mostly done. In response to this need, the University of Georgia initiated the Georgia Automated Environmental Monitoring Network (AEMN) (Hoogenboom, 1996; 2000a; 2000b; Hoogenboom et al., 2000). This is a network of automated weather stations that are mainly located in the rural areas of Georgia (www.Georgiaweather.net). These weather stations collect data every second on the following variables: air temperature, relative humidity, soil temperature at 5 cm, 10 cm and 20 cm depths, wind speed, wind direction, solar radiation, vapor pressure deficit and soil moisture. The averages, or totals depending on the variable, are calculated every fifteen minutes and stored in the data logger. In addition, daily summaries are also calculated. The 15-minute and daily summary data are downloaded automatically to a central computer located in Griffin. The website disseminates this information as well as simple calculators that can dynamically provide degree days, chilling hours or water balance for management of irrigation (Georgiev and Hoogenboom, 1998; 1999; Hoogenboom et al., 1998).

An Artificial Neural Network (ANN) is a computational intelligence technique that mimics the behavior of neurons in the brain. The basic components of an ANN are its nodes or neurons and the connections between the nodes. A node is primarily a computational unit. It receives inputs, calculates a weighted sum and presents the sum to an activation function. The nodes are generally arranged in layers. In the back propagation ANN architecture, the input layer nodes receive the inputs and pass the results of their computations to the nodes in the hidden layer by means of the connections. The hidden nodes sum these weighted values as inputs, calculate an activation level and pass the results to the output nodes.

For an ANN to be useful it should be able to learn or capture the complex relationships between inputs and outputs. This is done by searching for an optimal set of the weights of the connections between the nodes. It is achieved by first sending one set of inputs in the feed forward mode through the ANN. The error between the ANN output and the expected output is calculated. The error is then used to adjust the weights of the connections by using the method of gradient descent. The data that are used for this process are called the training data. The process is repeated until the error on another set of data called the testing data reaches a minimum. The testing data set is used in the feed forward mode only and are not used to adjust the weights. The training data and testing data comprise the model development data set. Once the training is complete, the ANN is then used with a separate model evaluation data set to determine its accuracy.

The overall goal of the research reported herein is to develop an ANN based Decision Support System (DSS) for predicting the occurrence of frost by predicting hourly temperatures during the subsequent twelve hour period. The most important inputs needed for the temperature predictions will be determined.

Methodology

Weather data for this study were obtained from the Georgia AEMN for the fruit producing areas of Georgia, including sites in peach producing areas (Fort Valley and Blairsville) as well as a blueberry producing area (Alma). The data from each location were divided into a model development set and model evaluation set. Data prior to 2001 were used for model development and data from years 2001 and 2002 were used for model evaluation. A final evaluation of the models was performed with data for 2003 since the 2001 and 2002 data, while not directly used for model development, were used to select the best configuration of hidden nodes. Only data from the months of January through April were used in the study. It is during this period that air temperatures vary between freezing and non-freezing and the crops are susceptible to freeze conditions.

The weather data consisted of observations of temperature, relative humidity, wind speed, solar radiation and rainfall. The current values of these variables were used as inputs along with corresponding prior values of these variables. The change in value of the weather variables from the prior values to current value (Δ) were calculated and also used as inputs.

To identify which weather variables are important, experiments were conducted with the hourly data from Fort Valley. The duration of prior data was held constant at four hours and the period of prediction was kept constant at four hours. The first set of experiments was performed to determine the best architecture when only temperature and its related inputs i.e. four hours of prior temperatures as well as their respective Δ values were used along with time of day. This set of inputs was called the core set of input variables. It was assumed that the current and prior air temperatures as well as time of day were important input variables. Subsequently, experiments were conducted for determining the best architecture when two weather variables are used as inputs. For this set of experiments the core set of inputs was used in conjunction with each of the other weather variables (relative humidity, solar radiation, rainfall and wind speed) one at a time to serve as the inputs. These experiments were then ranked based on the accuracy of their best architectures. The combination ranked first then became the new core set of inputs and subsequent experiments were conducted by adding a third weather variable. This process was carried out until the most important input variables were determined in order of importance.

Results

A study was performed to determine the most important input variables. When using only temperature and its associated Δ values as the only inputs, it was found that the lowest MAE was 1.41^{o}C when predicting four hours in the future. Each of the remaining weather variables and associated Δ values were included one at a time to determine the next most important input variables. Using this approach it was thus determined that the order of importance of the weather variable inputs considered was temperature, relative humidity, wind speed and solar radiation. The addition of rainfall slightly reduced the accuracy of the ANNs and it was thus excluded from all subsequent model development.

As expected, the accuracy of the ANNs decreased as the prediction period increased. Using the hourly format the MAE for predicting the temperature one hour in the future was 0.56^{o}C and was 2.36^{o}C for predicting temperature twelve hours in the future. A plot of predicted temperatures for a one hour period of prediction vs. the observed temperatures using the hourly data format for Fort Valley, GA, is shown. A linear regression line fit to this data gives an R^2 of 0.989. A similar plot of predicted temperatures for a twelve hour period is shown. As expected, the scatter is greater for the 12 hour period of prediction and the R^2 is 0.818.

The overall goal of this project was to develop ANN models for predicting temperatures which could be incorporated into a real time frost warning system. As such, all twelve ANNs predicting hourly temperatures for a given location were used to generate a simulated temperature forecast for the subsequent twelve hours. The outputs from the twelve networks that were developed were combined into a Decision Support System for frost prediction. Sample periods of data were selected for the simulation which included a freeze event. A Decision Point (DP) is defined as that point in time 't' when all networks are presented with the latest values of the input variables. For the simulation, the first decision point (DP1) was selected to be approximately ten hours prior to a freeze event. The subsequent decision points follow on an hourly basis.

Five day plots of predicted temperature and observed temperature versus time are shown using the eight hour prediction model. The data are for Ft. Valley, GA for February 24-March 1, 2002 and March 2-March 7, 2002. The model predicted the occurrences and durations of freezing conditions with reasonable accuracy. An animation of an actual twelve hour temperature prediction for Alma, GA in Bacon county is shown for the period January 5 through January 7, 2004. For this plot the prediction is updated every 45 minutes, although it could be performed every 15 minutes.

As an indication of the value of this frost/freeze decision support system, a quote from a UGA College of Agricultural and Environmental Sciences (CAES) county agent is included as an appendix. Robert T. Boland, Jr., county agent of Brantley County, Georgia, included this impact statement on the CAES website regarding the value of the AEMN weather network.

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Appendix

Freeze Protection for Southern Highbush Blueberries

Robert T. Boland Jr.
Brantley County

Situation

Brantley County's growth in Southern Highbush Blueberries acreage is on the increase. Southern Highbush Blueberries are harvested around April 15th in Brantley County. This is a time when Florida is finishing their blueberry harvest, and the price for early Georgia Southern Highbush Blueberries start around $36.00 a flat ($10.00/lb).

However, producing the early maturing Southern Highbush Blueberry is not without risk. Late winter freezes can wipe out an entire crop. To reduce this risk of late winter freezes growers must use irrigation to protect the fruit and blooms. This method of irrigation involves a process of water melting and freezing, which keeps the fruit and blooms at a temperature around 32°. The key variable with freeze protection is knowing when to start irrigating. This requires knowing temperature, relative humidity, and dew points. Brantley County Blueberry growers were getting their weather information from the Weather Channel web site and from NOAA Weather Station in Jacksonville, Florida. However, this data is not generated in Brantley County. Due to the lack of good weather information ZBLU Farms experience a loss of about 80% of the crop, which includes the early Southern Highbush Blueberry.

Response

To address this problem for future Blueberry crops, the Brantley County Extension Coordinator contacted Dr. Gerrit Hoogenboom, Coordinator of the UGA's College of Agriculture and Environmental Sciences/Georgia Automated Environmental Monitoring Network about locating a weather station in Brantley County. This weather station would give growers in Brantley County local weather information. The request was granted and a weather station was located in Brantley County at ZBLU Farms on March 22, 2002. ZBLU Farms provide the local phone line allowing Dr. Hoogenboom to collect weather data and post it on the web.

Results

Brantley County Southern Highbush Blueberry growers have an early market window during which they can receive higher prices , around $10.00 a pound. However, with early maturing varieties they face the risk of late freezes. Losses from the February 28, 2002 freeze were a whopping 80%, an estimated $115,000.00 loss to the Brantley County Blueberry crop to the early maturing varieties. The Georgia Automated Environmental Monitoring Network is, and will continue to be a management tool which Brantley County Southern Highbush Blueberry growers are using to monitor weather condition in the county. This weather station will allow growers to use current and local weather data to guide them on when to start freeze protection for their blueberries.