# IMPROVING AIR TEMPERATURE AND DEW POINT TEMPERATURE PREDICTION ACCURACY OF ARTIFICIAL NEURAL NETWORKS

by

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(Under the Direction of Walter D. Potter)

ABSTRACT

Air temperature and dew point temperature are two of the important atmospheric variables that affect the growth rate of plants as well as many other processes in agricultural and ecological systems. Extremely low air temperature and dew point temperature are harmful to the crops and might cause severe economic losses. Therefore, accurate predictions of air temperature and dew point temperature are necessary in order to prevent crops from being damaged by severe frost. Previous studies developed artificial neural network (ANN) models to predict air temperature and dew point temperature from one to twelve hours in advance. The goal of the research herein was to develop more accurate air temperature and dew point temperature prediction models. This research incorporated evolutionary approaches in the development of ANNs to refine the selection of input prior data for each applicable atmospheric variable.

INDEX WORDS: Artificial Neural Networks, Genetic Algorithm, Particle Swarm Optimization, Air Temperature, Dew Point Temperature

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# CHAPTER 1

# INTRODUCTION

Air temperature and dew point temperature are two of the important weather variables that affect crop growth. They have been considered as inputs to model the simulation of crop production (Hoogenboom, 2000a). Absalon and Slesak (2012) stated that air temperature should be carefully monitored and included in the assessment of the quality of human life in an urban area. Stull (2011) used air temperature along with relative humidity to calculate wet-bulb temperature at standard sea level pressure. White-Newsome et al. (2012) used outdoor air temperature and dew point temperature for the prediction of indoor heat to mitigate the effects of indoor heat exposure among the elderly people in Detroit. Dew point temperature is an essential weather variable for estimating various agro-meteorological parameters. Several agronomic, hydrological, ecological, and meteorological models require dew point temperature data (Hubbard et al., 2003). The 2007 spring freeze in the eastern U.S. killed newly formed leaves, shoots, and developing flowers and fruits (Gu et al., 2008). The severity of frost damage is influenced by the intensity and duration of low temperatures, the rates of temperature decrease and short-term temperature variations (Rodrigo, 2000). Therefore, accurate predictions of air temperature and dew point temperature are necessary to avoid severe economic losses due to weather events such as frost and freeze.

The Georgia Automated Environmental Monitoring Network (AEMN) was established in 1991, and currently consists of more than 80 weather stations distributed throughout Georgia

(Hoogenboom, 2000b). These solar-powered stations monitor weather data every second such as air temperature, dew point temperature, relative humidity, vapor pressure, wind speed, wind direction, solar radiation and rainfall. These data were summarized into hourly averages until March 1996. Subsequently, they have been aggregated into fifteen minute averages. The collection of dew point temperature data was started in 2002. These observations are downloaded to the server, and immediately made available on the website www.georgiaweather.net.

The data collected from AEMN have been used in several studies to create a number of ANN models that predict air temperature and dew point temperature and a decision support system that generates frost warnings using these predictions. Jain et al. (2003) created Artificial Neural Network (ANN) models to predict air temperature during winter. These models were trained using the patterns which included six hours of prior weather information such as air temperature, humidity, wind speed, and solar radiation as well as the time of the day. Smith et al. (2006) improved the prediction accuracies of winter-specific air temperature models by including seasonal information in the input pattern and extending the duration of prior data to 24 hours. Smith et al. (2009) also developed ANN models to predict air temperature throughout the year using the data collected through 2005. Shank et al. (2008a) created ANN models to predict dew point temperature up to 12 hours in advance using the weather variables dew point temperature, relative humidity, solar radiation, air temperature, wind speed, and vapor pressure. Shank et al. (2008b) created ensemble ANN models to improve the accuracy of dew point temperature prediction. The ANN models developed by Smith et al. (2009) and Shank et al. (2008b) were implemented at http://www.georgi aweather.net/, where the predictions are available for both air and dew point temperatures for every station in Georgia. These hourly predictions are made from one to twelve hours ahead and updated every 15 minutes. These predictions are mainly used by the Georgia farmers for agricultural decision making. Chevalier et al. (2012) created a decision support system to interpret these air temperature and dew point temperature predictions along with the observed wind speed as one of the five frost warnings determined related to blueberries and peaches.

Several studies have combined the evolutionary approaches with ANN techniques for tasks such as training the ANN, and determining the preferred network architecture etc. Montana et al. (1989) employed a genetic algorithm (GA) to evolve the connection weights of an ANN for the sonar image classification problem. Stanley et al. (2002) presented a method named NEAT (Neuro Evolution of Augmenting Topologies), which enabled parallel evolution of both network architecture and connection weights using an evolutionary algorithm. Aijun et al. (2004) used a GA to optimize the *chemical vapor infiltration* (CVI) processing parameters of Carbon/Carbon composites. The fitness function of their GA evaluated ANNs based on the candidate input parameters of the network. Saxena et al. (2007) applied a GA to choose the preferred combination of features to develop an ANN fault classification model for condition monitoring of mechanical systems. This GA also evolved the structure of the ANN in terms of the number of hidden nodes. Mohebbi et al. (2011) coupled a GA with the ANN to estimate the moisture content of dried banana. Their GA evolved the ANN parameters such as the number of hidden layers, and the number of hidden nodes, learning rate and momentum for each hidden layer. Lazzús (2011) created an ANN model to estimate auto ignition temperatures of organic compounds by training the models using a Particle Swarm Optimization (PSO) technique. Wu & Chen (2009) created nonparametric regression ensemble models for rainfall forecasting by coupling PSO with the ANN. Chau (2007) applied the PSO for the training of a three-layered perceptron network to predict the outcome of the litigation process in construction claims and concluded that the PSO-based perceptron network exhibited better performance than the back propagation-based perceptron network with regard to the convergence rate of training and the prediction accuracy.

Chapter 1 of this thesis outlines the problem of air temperature and dew point temperature prediction and provides an introduction to previous studies that approached this problem and other studies that applied computational evolutionary approaches to ANN prediction.This introduction briefly describes the AEMN which provided the environmental data for these studies. This chapter also provides the organization of the thesis. The overall goal of this research is to improve the prediction accuracies of air temperature and dew point temperature ANN models. Mean Absolute Error (MAE) is the measure of accuracy for all the ANN models. Specific research objectives to accomplish this overall goal are identified in Chapter 2 and Chapter 3.

Chapter 2 will describe the research that will apply a genetic algorithm (GA) to refine the way in which the input prior data for the ANN model are selected for air temperature prediction. The previous research by Smith et al. (2009) included a constant duration of input prior data in fixed intervals for all weather variables and for all prediction horizons. The objective of the research herein will be to determine the duration and resolution of input prior data for each input weather variable and for each prediction horizon.

Chapter 3 will describe the research that will apply a GA and a particle swarm optimization (PSO) technique to determine the duration and resolution of input prior data for dew point temperature prediction for one-, six- and twelve-hour prediction horizons. This research will also determine the effect of not including the constraint of every applicable weather variable being represented in the input prior data. The accuracies of the ANN models created using the GA and the two PSO based approaches will be compared to those of the ANN models created based on the existing constant duration and fixed resolution approach.

Chapter 4 summarizes the research performed in this study and provides conclusions for the findings. It also suggests possible future research that could further improve the accuracies of the air temperature and dew point temperature ANN models by fine-tuning various computational parameters involved.

# CHAPTER 2

# A GENETIC ALGORITHM TO REFINE INPUT DATA SELECTION FOR AIR TEMPERATURE PREDICTION USING ARTIFICIAL NEURAL NETWORKS[1]

[1] Venkadesh, S., Potter, W. D., McClendon, R. W., and Hoogenboom, G., To be submitted to *Applied Soft Computing*.

**Abstract**

Accurate prediction of air temperature is important to avoid severe economic losses due to frost damage of crops. Previous research focused on the development of artificial neural network (ANN) models to predict air temperature from one to twelve hours in advance. The inputs to these models included a constant duration of prior data with a fixed resolution for all environmental variables for all prediction horizons. The goal of the research herein was to develop more accurate ANN models to predict air temperature for each prediction horizon. The objective of this research was to apply a genetic algorithm (GA)for each prediction horizon to determine the preferred duration and resolution of input prior data for each environmental variable. Except for a few cases, the GA generally includeda longer duration for prior air temperature data and shorter durations for other environmental variables. The ANN models created based on this GA based approach provided smaller errors than the models created based on the existing constant duration and fixed data resolution approach for all twelve prediction horizons. For instance, the mean absolute errors (MAE's) on the evaluation input patterns for one, six and twelve hour prediction models created based on this GA based approach were $0.568^0$C, $1.567^0$C and $1.997^0$C. These MAE's were improvements of 3.22%, 2.39% and 2.73% over the models created based on the existing approach for one, six and twelve prediction horizon respectively. Thus, the GA based approach to determine the duration and resolution of input prior data proved to create more accurate ANN models than the existing ones for air temperature prediction. Future work could examine the effects of various GA and fitness evaluation parameters involved in this research.

## I. Introduction

Air temperature is one of the most important weather variables that affect crop growth and has been considered as a primary input to model the simulation of crop production (Hoogenboom, 2000a). Absalon and Slesak (2012) stated that air temperature should be carefully monitored and included in the assessment of the quality of human life in an urban area. Stull (2011) used air temperature along with relative humidity to calculate wet-bulb temperature at standard sea level pressure. White-Newsome et al. (2012) used outdoor air temperature and dew point temperature for the prediction of indoor heat to mitigate the effects of indoor heat exposure among the elderly people in Detroit. The 2007 spring freeze in the eastern U.S. killed newly formed leaves, shoots, and developing flowers and fruits (Gu et al., 2008). The severity of frost damage is influenced by the intensity and duration of low temperatures, the rates of temperature decrease and short-term temperature variations (Rodrigo, 2000). Therefore, it is necessary to accurately predict air temperature to help farmers in preventing crops from being damaged by freezing temperatures.

The Georgia Automated Environmental Monitoring Network (AEMN), established in 1991 (Hoogenboom, 2000b), currently consists of more than 80 weather stations distributed throughout Georgia. These solar-powered stationsmonitor weather data including air temperature, dew point temperature, relative humidity, vapor pressure, wind speed, wind direction, solar radiation and rainfall, every second. These data were summarized into hourly averages until March 1996. Subsequently they have been aggregated into fifteen minute averages. These observations are downloaded to the server, and immediately made available on the website www.georgiaweather.net.

Jain et al. (2003) created Artificial Neural Network (ANN) models to predict air temperature during winter. These models were trained using the patterns which included six hours of prior weather information such as air temperature, relative humidity, wind speed, and solar radiation as well as the time of the day. Smith et al. (2006) improved the prediction accuracies of winter-specific air temperature models by including seasonal information in the input pattern and extending the duration of prior data to 24 hours. Smith et al. (2009) also developed ANN models to predict air temperature throughout the year using the data collected through 2005. These ANN models have been implemented on www.georgi aweather.net as tools for temperature prediction. Shank et al. (2007) created ANN models to predict dew point temperature up to 12 hours in advance using the weather variables dew point temperature, relative humidity, solar radiation, air temperature, wind speed, and vapor pressure. Shank et al.(2008) created ensemble ANN models to improve the accuracy of dew point temperature prediction. These ANN models were also implemented on the same website, where the predictions are available for both air and dew point temperature for every station in Georgia. These hourly predictions are made from one to twelve hours ahead and updated every 15 minutes once new data have been received from each weather station. Chevalier et al.(2012) created a decision support system to interpret the air temperature and dew point temperature predictions along with the observed wind speed as one of the five frost warnings determined related to blueberries and peaches. All theexisting ANN models useda Ward-style ANN architecture and were trained using the well-known error back-propagation algorithm. Preferred values for the ANN parameters such as learning rate, number of hidden nodes, and initial weight range were determined by iterative search. The observations collected by weather stations were partitioned into different datasets for model development and evaluation purposes.

In the previous work by Smith et al. (2009) the duration of prior weather information for the inputs to the ANN model was determined by a limited iterative search. The durations considered were 2, 4, 6, 12, 18, 24, 30, 36, and 48 hours of prior data. A single duration was used to include the prior data for all five weather variables. Although the observed data were available for every fifteen minutes, prior work always included the data in one hour intervals. They did not explore the effects of including the prior data with a shorter or longer interval than one hour. Thus all twelve existing models included 24 hours of prior data for each weather variable in one hour intervals, resulting in a constant 258 input variables to the ANN models. In this paper, the term 'resolution' will be used further, instead of 'interval'. For instance, a 15-minute resolution or the highest resolution will denote that the prior data were included in fifteen minute intervals and a 4-hour resolution will denote that the prior data were included in four hour intervals.

Evolutionary algorithms, which are inspired by the biological evolutionary process, have been widely combined with ANNs to evolve the network architecture, connection weights and input features. Montana et al. (1989) employed agenetic algorithm (GA) to evolve the connection weights of an ANN for the sonar image classification problem. They have reported that their learning algorithm based on the GA outperformed the traditional back propagation algorithm. Stanley et al. (2002) presented a method named NEAT (Neuro Evolution of Augmenting Topologies), which enabled parallel evolution of both network architecture and connection weights. Aijun et al. (2004) used a GA to optimize the *chemical vapor infiltration* (CVI) processing parameters of carbon/carbon composites. The fitness function of their GA evaluated ANNs based on the candidate input parameters of the network. Saxena et al. (2007) applied a GA to choose the preferred combination of features to develop an ANN fault classification model for condition monitoring of mechanical systems. This GA also evolved the structure of the ANN in terms of the number of hidden nodes. Mohebbiet al. (2011) coupled a GA with the ANN to estimate the moisture content of dried banana. Their GA evolved the ANN parameters such as the number of hidden layers, and the number of hidden nodes, learning rate and momentum for each hidden layer. Čongradac and Kulić (2012) created a model to reduce the electricity consumption of chillers by coupling the ANN with a GA. They used the ANN to create a chiller model and then applied the GA to optimize the chiller model parameters. Irani and Nasimi (2011) used a hybrid GA-ANN strategy to predict the permeability of the Mansuri Bangestan reservoir. They used the GA to search for the best set of initial ANN weights for training using the back propagation and showed that the hybrid approach outperformed the traditional gradient-descent based approach for the ANN training. However, the best way to combine the evolutionary algorithm with an ANN is problem dependent.

In our current research, it was hypothesized that the information associated with each weather variable could contribute in varying degrees to the model prediction accuracy. Also, including too much unnecessary information might have a negative effect on the prediction accuracy. Tahai et al. (1998) claimed that incorporating too many input noise variables into the ANN prediction model would result in a poor ANN generalization capability. The amount of input information to the ANN model associated with a weather variable can be controlled with the duration and resolution of prior data for that particular weather variable. Longer duration and higher resolution requires more information to be included. The time series nature of the weather data also makes it intuitively appealing to explore variable resolution in prior data. The goal of our research was to improve the air temperature prediction accuracy of the existing ANN models developed by Smith et al. (2009), by optimizing the duration and resolution of prior data included as inputs. The objectives of this study were as follows: Using the evolutionary algorithm for each prediction horizon, determine the preferred total duration of prior data to be included, and the resolution with which the prior data should be included for that duration for each input weather variable.

## II. Methodology

This study was conducted in two phases: The evolutionary phase and the final model development phase. The evolutionary phase aimed at finding the duration and the resolution of prior data for each weather variable using the GA. The final model development phase developed the ANN models to be implemented for practical use, using the duration and the resolution identified in the evolutionary phase. All the networks were developed with the Ward-style architecture having three slabs in the hidden layer using Gaussian, Gaussian complement and hyperbolic tangent activation functions. Each ANN model was trained using the error back-propagation algorithm, a learning rate of 0.1, an initial weight range of ±0.15 and a range of (0.1, 0.9) to scale the inputs. These values were chosen based on the previous research conducted by Smith et al. (2009) and Shank et al. (2007). Mean absolute error (MAE) was the measure of accuracy for the ANN models.

The term model refers to a network with a certain number of input, hidden and output nodes with a specific set of input variables resulting from a particular duration and resolution of prior data. During model development, several network instantiations were created for a modelwhich differed only in the initial random weights and the order in which the training patterns were presented. Smith et al. (2006) showed that training and evaluating multiple instantiations of the same model provided a better foundation for the comparisonof model accuracies than a single network instantiation.

## 1. Input patterns and Datasets

A pattern is a set of values corresponding to the input and output nodes of the ANN model.The weather variables air temperature, relative humidity, wind speed, solar radiation and rainfall observed at different points in the time series were used to create an input pattern. These weather variables, observed at the time of prediction, were always included in the inputs. The input pattern also included the rates of change calculated as follows: global rates of change of a weather variable were the differences between the observation at the time of prediction and each of the included prior data observations. Local rates of change of a weather variable were the differences between every two adjacent observations that were included in the time series. Eight fuzzy logic variables to represent the time of day and the day of year information were also included in the input pattern similar to Smith et al. (2006).

It was intuitively assumed that more recent prior data observations were more important than historically older observations to predict air temperature. Thus, a variable resolution scheme which allowed higher resolution for recent observations, and lower resolution for historically older observations was explored in this study.This scheme encoded both the duration and the multiple resolutions of prior data for a weather variable as follows: the maximum allowed total duration of prior data for each weather variable was 48 hours. Although prior research work found that 24 hours of prior data was the preferred duration for the inputs, this decision was primarily based on including ‘all five weather variables’ of prior 24 hours. Our current study allowed 48 hours of prior duration for each weather variable to see if the ANN model could take advantage of the additional information, past 24 hours in the prior data for some weather variables. For each prediction horizon, each of the five weather variables represented the resolutions in segments of twelve hour duration. The various resolutions considered in this study were 15-minute, 1-hour, 2-hour, and 4-hour. These resolutions indicate the intervals between the observations included in the prior data. It should be noted that the highest possible resolution was 15-minute, as the observed data were aggregated into fifteen minute averages. *Thus four segments of twelve hour duration that allowed different or equal resolution were associated with each of the five weather variables.* An input weather variable had at least one segment, implying that the possible total durations of prior data are twelve, 24, 36 and 48 hours. It was assumed in this study that at least twelve hours of prior data with 4-hour resolution for each of the five input weather variables would be required for air temperature prediction. The first segment could have any of the four resolutions and a segment would always have the resolution equal to or less than its previous segment. Thus, for example, a typical candidate solution for solar radiation might be: "*15-minute*, *2-hour*, *4-hour*, *X* ",which means, 36 hours of prior solar radiation values should be included with 15-minute resolution for the first twelve hours of prior data (48 observations), 2-hour resolution from the 13$^{th}$ prior hour to the 24$^{th}$ prior hour (6 observations), and 4-hour resolution from the 25$^{th}$ prior hour to the 36$^{th}$ prior hour (3 observations), totaling to 57 prior observations of solar radiation. The *'X'* indicates no prior data was included past 36 hours. The maximum number of segments was restricted to four so as to have a reasonable GA search space size, yet produce realistic results.

Data collected from 2002 through 2010 at various weather stations geographically distributed throughout the state of Georgia were partitioned into model development and evaluation datasets. The ANN models were created using the patterns from the development dataset. Once these models were developed, they had to be evaluated on the patterns which were not presented to them during model development to perform an unbiased evaluation. Therefore, the evaluation dataset included years and locations which were mutually exclusive of the development dataset.

The development dataset was further partitioned into training and selection datasets. The patterns from the training dataset were used for ANN weight adjustment using back-propagation, and the patterns from the selection dataset were only used in feed-forward mode to choose the most accurate network instantiation for a model. The training and selection datasets shared the same years of data, but differed in the included locations as presented in Table 2.1. Using a stopping dataset to determine when to end the training was found to be unnecessary in the previous work by Smith et al. (2006) as the network performance on stopping and training datasets was qualitatively similar.

## 2. Evolutionary phase

The duration and the resolutions of prior data for each weather variable were identified in the evolutionary phase using the GA for one through twelve prediction horizons. Each GA run evolved the duration and the resolutions of prior data based onthe accuracy of the ANNs trained and evaluated on 10,000 patterns sampled from the training and the selection dataset respectively. During the course of one GA run, more than 5000 ANN models were created with the objective of determining the preferred duration and resolution. Thus, the evolutionary phase required many more computational resources than the final model development phase in this study.

### *2.1.The GA parameter settings*

The Java-based ECJ (Evolutionary Computation Journal) library developed by Luke et al. (2010) was used to implement the GA search. The time consuming nature of the fitness evaluation restricted the population size to 48 for all GA runs. The particular choice of 48 was due to its proportionality to the number of processors available on the computers on which the experiments were run. This proportionality allowed for efficiently parallelizing the fitness evaluations in the GA population. An individual in the GA population consisted of five components, one for each weather variable. Each component encoded the duration and the resolutions of prior data in four segments as explained earlier for the respective weather variable (genotype). Thus, an individual represented the way in which the input variables to the ANN model were to be included (phenotype). These ANN models were evaluated by the GA during the search for the preferred solution. One-point component level crossover with a probability of 0.5 was employed, for each component. Unlike the conventional one-point crossover, the point before the first segment (the starting point of a component) was considered as a possible crossover point, allowing a complete exchange of that particular component between two parents. One of two mutation schemes with a probability of 0.3 was applied at the component level, for each component. These probabilities for the variation operators were chosen based on the results from a set of preliminary runs. A step mutation either increased or decreased the resolution of a randomly chosen segment by one step, and a length mutation either removed the last segment, or added a new segment with a randomly chosen resolution. Both mutation schemes had equal selection probabilities. Repair schemes were implemented to ensure the integrity of an individual as follows: variation operators were not allowed to change a value beyond the defined boundary values. If a variation operator altered a segment to a resolution lower than the next segment in that component, all subsequent segments were changed to the new resolution of the altered segment, to maintain integrity.

### *2.2. Fitness evaluation*

Two sets of 10,000 observationswere randomly sampled from the training and the selection dataset respectively for the fitness evaluation. These random samples were equally distributed over all the selected stations and the years of the respective dataset as given in Table 2.1. Each pattern had its input variables to the ANN model selected as follows: five weather variables observed at the time of prediction, prior data for each of the five weather variables as represented in the respective components of the individual, global and local rates of change of the included prior data, and eight fuzzy seasonal variables. Fig. 2.1 shows the flow diagram of the fitness evaluation module. As can be seen from this figure, different individuals in the GA population not only created ANN models with a varying number of inputs, but also constructed different sets of 10,000 patterns for their fitness evaluation. Since a preliminary study revealed that the number of hidden nodes per slab had minimal impact on the ANN model accuracy, this value was fixed at 10 for all the ANN models developed in this phase so as to reduce the time required for ANN training. An ANN model which was the phenotype of an individual, instantiated 10 networks which were assigned different random initial weights. Each of the 10 networks was trained using the same set of patterns from the training data set, but presented in a different order. After each epoch of training, the network was evaluated on the training dataset. Training was stopped when the MAE decrease on the training dataset was less than or equal to 0.005 for three continuous epochs or a maximum of 20 epochs was reached. Once the training was completed, the network was evaluated on the selection dataset. Thus there were 10 selection dataset MAEs associated with an individual during its fitness evaluation. The lowest MAE among these 10 network evaluations on the selection dataset was assigned as the fitness value to the associated individual. In each GA generation, multiple individuals were evaluated in parallelon different processors available on the system so as to expedite the GA run.

The GA was terminated when the fitness improvement (MAE decrease) was not more than 0.005 in 100 continuous generations. None of the GA runs required more than 300 generations before termination.

### *2.3.Experiments*

Twelve GA instances were run for one through twelve hour prediction horizons. In rare scenarios, where the GA was stuck in the local optimum (where the best population fitness never improved from a generation less than 10), the GA was restarted for that prediction horizon. The runs were made on powerful computational servers that had at least eight processors. The fitness evaluation module of the GA was highly resource-intensive. A preliminary study using 10,000 patterns for fitness evaluation required approximately 5 to 7 days of run time, and a large working memory for one GA run, since, in addition to the network training and evaluation, the parallel fitness evaluation of multiple individuals necessitated the construction of different sets of 10,000 patterns to be held in memory. This also required the allocation of sufficient resources for the garbage collection process run in the background by the Java virtual machine (JVM) to clean up the heap memory once an individual was evaluated. This larger heap size requirement allowed the GA runs only on the machines which ran 64 bit JVM on a 64 bit operating system (for Windows). Because of the time constraints, this study did not explore and fine-tune various GA parameters. Some of the limitations of the GA runs include a smaller population size (48) and a smaller number of training patterns (10,000) for fitness evaluation. Finally, a limited study was conducted using a GA with an increased number of training patterns for fitness evaluation.

## 3. Final model development phase

In this phase, the final ANN models were developed and evaluated for each prediction horizon using a larger number of patterns sampled from the datasets given in Table 2.1. The final ANN models were trained based on the duration and resolution determined by the GA for each input weather variable and for each prediction horizon, and named the GASDR (GA Selected Duration and Resolution) models.For each prediction horizon, 300,000 randomly sampled patterns from the training datasetwere used for ANN training. In the same way, 100,000 patterns were randomly sampled from the selection dataset for ANN selection, and 1,000,000 patterns were randomly sampled from the evaluation dataset for model evaluation. For each prediction horizon, 30 networks were instantiated and trained using the training dataset.Then, the selection dataset patterns were presented to each network instantiation in feed-forward-only mode. The most accurate network instantiation on the selection dataset was selected to represent the ANN model for that prediction horizon.

This study also recreated the ANN models using the methodology followed by Smith et al. (2009) for the comparison of model accuracies. These ANN models included a constant 24 hours of prior data with a fixed one hour resolution for all the input weather variables and for all prediction horizons, and were named the CDFR (Constant Duration and Fixed Resolution) models. In order to allow for a fair comparison of model accuracies, the CDFR models were recreated and evaluated using the same datasets used to develop and evaluate the GASDR models. As mentioned earlier, from a preliminary study, it was observed that the number of hidden nodes per slab had minimal impact on the model prediction accuracy. Hence all the final ANN models were developed using 40 hidden nodes per slab, the value used by Smith et al. (2009). This study included the observations from different locations and years for the model development than the ones included in the previous study by Smith et al. (2009). The training dataset in this study consisted of data from fourteen locations and six years as opposed to nine locations and four years used in the previous study. Therefore, the existing ANN models developed in the previous study (which have been implemented on the website) were evaluated on the evaluation dataset and their accuracies were compared with those of the CDFR models for one- through twelve-hour prediction horizons. This comparison was performed to examine the effect of including the data from more locations and years for the ANN training on the model accuracy.

## III. Results

The results from the evolutionary phase for the twelve prediction horizons are presented in Table 2.2. The GA search included 48 hours of prior air temperature data with 4-hour resolution for the last two segments as inputs for one- through nine-hour prediction horizons. It included 36 hours of prior air temperature data for the ten-hour prediction horizon. The GA search included only twelve hours of prior relative humidity data with 2-hour or 4-hour resolution for all prediction horizons. For wind speed, generally, only the first segment (first twelve hours of prior data) was included in all the cases, except for the seven- and nine-hour prediction horizons, where two and four segments were included respectively. Except for the one-, six-, and ten-hour prediction horizons, only the first segment was included for solar radiation. For rain fall, five out of twelve prediction horizons included data past the first segment. In the cases where the highest resolution (15-min) was preferred for a weather variable, it was preferred only for the first twelve hours of prior data. The only exception was that the first two segments of air temperature were included with 15-min resolution for the nine-hour prediction horizon. No segment past 24 hours was included with a resolution higher than the lowest resolution (4-hour) for any weather variable and for any prediction horizon. For eleven- and twelve-hour prediction horizons, only the first segment was included for all weather variables. Some inconsistencies in the results are likely due to the limitations of the GA runs. It should be noted that only 10,000 training patterns sampled from more than 2.5 million patterns were used for fitness evaluation, compared to the 300,000 patterns used to train the existing ANN models implemented on the website and the GASDR and CDFR models in the final model development phase of this study. If there were sufficient resources available to run the GA with a much larger population size, and a larger number of training patterns for the fitness evaluation, the GA might have been able to evolve more consistent solutions. It is also possible that an intuitively more appealing solution was found during the GA run, but was assigned a fitness value (MAE) which was slightly larger than the best fitness value found, and otherwise could have been the best solution if more network instantiations were made for the fitness evaluation. Overcoming these concerns would require increased computational resources.

In the final model development phase, the GASDR models were more accurate than the CDFR models for nine out of twelve prediction horizons (one through six and eight through ten) on the training dataset. On the selection dataset, the GASDR models were more accurate than the CDFR models for one- through ten-hour prediction horizons. However, the CDFR models provided lower errors than the GASDR models on both training and selection datasets for eleven- and twelve-hour prediction horizons. The MAEs of the GASDR and CDFR models on model development (training, selection) and model evaluation datasets are presented in Table 2.3.

On the evaluation dataset, the GASDR models provided lower MAEs than the CDFR models for all prediction horizons except for the eleven-hour horizon. The accuracy improvement in predicting air temperature in the GASDR models was generally due to the inclusion of prior air temperature data past 24 hours (with a low resolution) in the inputs. The previous study by Smith et al. (2009) could not find this as they assigned equal roles to all weather variables in the input layer of the ANN model.

The GA with the restricted parameter settings did not evolve a solution that improved the prediction accuracy for the eleven-hour prediction horizon. Hence, an extended study was performed using the GA with an increased number (20,000) of ANN training patterns for fitness evaluation for one-, four-, eight-, eleven- and twelve-hour prediction horizons to examine the effect of the number of fitness evaluation training patterns on the GASDR model accuracy. The GASDR models developed using this extended GA were referred to as EGASDR (Extended GA Selected Duration and Resolution) models. Due to the limited availability of computational resources, the extended GA runs were not made for other prediction horizons.

As mentioned earlier, the regular GA runs did not include any prior data past twelve hours for eleven- and twelve-hour prediction horizons, but, the extended GA runs included 48 hours of prior air temperature data for these two prediction horizons. The extended GA preferred the highest resolution for the first twelve hours of prior air temperature data, except for the eight-hour prediction horizon (Table 2.4). As a result, the EGASDR models were more accurate than their corresponding GASDR models for one-, four-, eleven-, and twelve-hour prediction horizons (Table 2.3). Using the extended GA, the highest improvement in the accuracy was achieved at the four-hour prediction horizon with a 4.59% improvement over the models created based on the existing approach.

The CDFR models were more accurate than the existing models for two- through twelve-hour prediction horizons. The results indicated that the higher prediction horizons benefitted more from the inclusion of more locations and years in the training dataset than the lower prediction horizons (Table 2.3). However, for the one-hour prediction horizon, the CDFR model was slightly less accurate than the existing model due to the inclusion of more locations and years in the training dataset.

A strong correlation between the observed and predicted air temperature values was observed at the one-hour prediction horizon with a coefficient of determination ($R^2$) of 0.9918 for the EGASDR model. The correlation became weaker as the prediction horizon increased, and the predictions from the twelve-hour model had an $R^2$ value of 0.9151 (Fig. 2.4). The dotted line in Fig. 2.4 represents the ideal case of the 1:1 line of fit of a hypothetical model. The best line of fit for the one-hour prediction horizon had a slope of 0.183 and a Y-intercept of 0.990, whereas the best line of fit for the twelve-hour prediction horizon had a slope of 0.897 and a Y-intercept of 2.184 (Fig. 2.4). The $R^2$ values and regression equations of the GASDR / EGASDR and CDFR models have been presented in Table 2.5.

## IV. Summary and Future work

This study developed ANN models to predict air temperature which had higher accuracies than the ANN models developed based on the existing approach by performing a GA search for the optimal duration and resolution of prior data for each weather variable to be included as inputs. It identified the contributive roles of various weather variables in predicting the air temperature by using resource-intensive computational intelligence techniques. The ANN models based on the existing approach were recreated using the same datasets used to create the ANN models based on the new approach for a fair comparison. The GA based approach with a restricted parameter setting for the fitness evaluation produced more accurate models for one- through ten- and twelve-hour prediction horizons, but did not produce more accurate model for the eleven-hour prediction horizon. A limited study was performed that ran the GA with an increased number of ANN training patterns for the fitness evaluation for one-, four-, eight-, eleven-, and twelve-hour prediction horizons. Except for the eight-hour prediction horizon, the final ANN models developed using this extended GA based approach were the most accurate models developed in this study for their respective prediction horizons. Using the extended GA based approach, the highest improvement in the accuracy was achieved at the four-hour prediction horizon with a 4.59% improvement, compared to the accuracy of the model created based on the existing approach. However, the methodology used in this study could be further improved by exploring and fine-tuning various computational parameters. The extended GA runs showed that the GASDR model accuracies were generally improved by increasing the number of ANN training patterns used for the fitness evaluation. With additional computational resources, the number of ANN training patterns and the number of random network instantiations could be further increased for the GA fitness evaluation. Other possible parameters to explore include the GA population size, the crossover and the mutation operators and their probabilities, and the number of segments in the prior data for a weather variable. Future work will focus on this aspect of the study to tweak the parameters so as to effectively utilize the available computational resources.

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**Table 2.1:** Dataset partitioning by years and locations

| Dataset | | Sites | Years | Approximate number of observations |
|---|---|---|---|---|
| Development | Training | Atlanta, Brunswick, Pine Mountain, Covington, Dallas, Dawson, Dearing, Duluth, Homerville, Oakwood, Shellman, Tifton, Tiger, Woodbine | 2002<br>2003<br>2004<br>2005<br>2007<br>2009 | 2,500,000 |
| | Selection | Alma, Arabi, Williamson, Bowen, Dempsey, Dixie, Eatonton, Georgetown, Griffin, Howard, Jeffersonville, Lafayette, Plains, Sparta, Tennille | | 2,500,000 |
| Evaluation | | Alapaha, Alpharetta, Arlington, Attapulgus, Blue Ridge, Byromville, Cairo, Calhoun, Camilla, Clarks Hill, Cordele, Danville, Douglas, Ellijay, Moultrie, Nahunta, Newton, Odum, Ossabaw, Sasser, Savannah, Valdosta, Vidalia | 2006<br>2008<br>2010 | 2,500,000 |

**Table 2.2**: Prior data resolution determined by the GA search for each prediction horizon

| Prediction horizon (hour) | **Air temperature** | | | | **Relative humidity** | | | | **Wind speed** | | | | **Solar radiation** | | | | **Rain fall** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $rs^{a}_1$ | $rs_2$ | $rs_3$ | $rs_4$ | $rs_1$ | $rs_2$ | $rs_3$ | $rs_4$ | $rs_1$ | $rs_2$ | $rs_3$ | $rs_4$ | $rs_1$ | $rs_2$ | $rs_3$ | $rs_4$ | $rs_1$ | $rs_2$ | $rs_3$ | $rs_4$ |
| 1 | 15m | 2hr | 4hr | 4hr | 4hr | x | x | x | 2hr | x | x | x | 2hr | 4hr | x | x | 2hr | x | x | x |
| 2 | 15m | 1hr | 4hr | 4hr | 4hr | x | x | x | 2hr | x | x | x | 4hr | x | x | x | 2hr | 4hr | 4hr | x |
| 3 | 1hr | 4hr | 4hr | 4hr | 2hr | x | x | x | 15m | x | x | x | 2hr | x | x | x | 1hr | x | x | x |
| 4 | 15m | 1hr | 4hr | 4hr | 4hr | x | x | x | 2hr | x | x | x | 1hr | x | x | x | 1hr | x | x | x |
| 5 | 15m | 1hr | 4hr | 4hr | 4hr | x | x | x | 1hr | x | x | x | 15m | x | x | x | 1hr | x | x | x |
| 6 | 1hr | 1hr | 4hr | 4hr | 4hr | x | x | x | 15m | x | x | x | 4hr | 4hr | 4hr | x | 2hr | 4hr | x | x |
| 7 | 1hr | 2hr | 4hr | 4hr | 2hr | x | x | x | 1hr | 1hr | x | x | 4hr | x | x | x | 2hr | 2hr | x | x |
| 8 | 1hr | 2hr | 4hr | 4hr | 4hr | x | x | x | 1hr | x | x | x | 1hr | x | x | x | 15m | 2hr | 4hr | 4hr |
| 9 | 15m | 15m | 4hr | 4hr | 2hr | x | x | x | 15m | 2hr | 4hr | 4hr | 2hr | x | x | x | 2hr | 4hr | 4hr | 4hr |
| 10 | 1hr | 1hr | 4hr | x | 4hr | x | x | x | 15m | x | x | x | 4hr | 4hr | 4hr | 4hr | 1hr | x | x | x |
| 11 | 1hr | x | x | x | 2hr | x | x | x | 1hr | x | x | x | 2hr | x | x | x | 2hr | x | x | x |
| 12 | 15m | x | x | x | 4hr | x | x | x | 1hr | x | x | x | 1hr | x | x | x | 15m | x | x | x |

[a] Prior data resolution has been given in 12 hour segments for each weather variable: $rs_1$ - resolution for segment 1 (current-12 hours), $rs_2$ - resolution for segment 2 (12-24 hours), $rs_3$ - resolution for segment 3 (24-36 hours), $rs_4$ - resolution for segment 4 (36-48 hours); *'x'* indicates no prior data was included; 10,000 training patterns were used for fitness evaluation.

**Table 2.3:** Accuracies (MAE[a] s) of ANN models created using various approaches for one through twelve hour prediction horizons

| Prediction horizon (hour) | Training dataset ($^0$C) | | | Selection dataset ($^0$C) | | | **Evaluation dataset** ($^0$C) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | CDFR[b] model | GASDR[c] model | EGASDR[d] model | CDFR model | GASDR model | EGASDR model | CDFR model | GASDR model | EGASDR model | *Existing model [e]* | % of improvement[f] |
| 1 | 0.566 | **0.547** | <u>0.543</u> | 0.562 | **0.545** | <u>0.542</u> | 0.587 | **0.568** | <u>0.564</u> | *0.562* | 3.98% |
| 2 | 0.886 | **0.877** | - | 0.889 | **0.859** | - | 0.902 | **0.899** | - | *0.918* | 0.31% |
| 3 | 1.130 | **1.103** | - | 1.115 | **1.084** | - | 1.149 | **1.122** | - | *1.190* | 2.34% |
| 4 | 1.309 | **1.288** | <u>1.268</u> | 1.279 | **1.260** | <u>1.246</u> | 1.325 | **1.294** | <u>1.264</u> | *1.423* | **4.59%** |
| 5 | 1.469 | **1.430** | - | 1.432 | **1.407** | - | 1.482 | **1.446** | - | *1.629* | 2.47% |
| 6 | 1.595 | **1.571** | - | 1.549 | **1.530** | - | 1.605 | **1.567** | - | *1.798* | 2.39% |
| 7 | **1.699** | 1.703 | - | 1.666 | **1.651** | - | 1.714 | **1.702** | - | *1.940* | 0.67% |
| 8 | 1.785 | <u>**1.770**</u> | 1.773 | 1.749 | **1.724** | <u>1.718</u> | 1.812 | <u>**1.766**</u> | 1.773 | *2.072* | 2.55% |
| 9 | 1.867 | **1.863** | - | 1.827 | **1.815** | - | 1.868 | **1.854** | - | *2.193* | 0.73% |
| 10 | 1.942 | **1.913** | - | 1.894 | **1.886** | - | 1.951 | **1.899** | - | *2.299* | 2.65% |
| 11 | **1.963** | 2.025 | <u>1.927</u> | **1.931** | 1.962 | <u>1.903</u> | **1.957** | 2.025 | <u>1.932</u> | *2.395* | 1.29% |
| 12 | **2.036** | 2.047 | <u>**2.027**</u> | **1.987** | 1.995 | <u>1.977</u> | 2.053 | **2.037** | <u>2.018</u> | *2.458* | 1.70% |

[a] Mean Absolute Error. [b] Constant Duration (24 hours) with a Fixed Resolution (1 hour). [c] GA Selected Duration and Resolution. [d] Extended GA Selected Duration and Resolution. [e] Models created by Smith et al. (2009). [f] improvement in the most accurate model over CDFR model; Lower error between CDFR and GASDR models is bolded; Lowest error among CDFR, GASDR and EGASDR models is underlined.

**Table 2.4**: Prior data resolution determined by the extended GA

| Prediction horizon (hour) | Air temperature | | | | Relative humidity | | | | Wind speed | | | | Solar radiation | | | | Rain fall | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $rs^a_1$ | $rs_2$ | $rs_3$ | $rs_4$ | $rs_1$ | $rs_2$ | $rs_3$ | $rs_4$ | $rs_1$ | $rs_2$ | $rs_3$ | $rs_4$ | $rs_1$ | $rs_2$ | $rs_3$ | $rs_4$ | $rs_1$ | $rs_2$ | $rs_3$ | $rs_4$ |
| 1 | 15m | 1hr | 1hr | x | 2hr | x | x | x | 2hr | x | x | x | 2hr | 2hr | x | x | 2hr | 2hr | 2hr | x |
| 4 | 15m | 1hr | 4hr | x | 2hr | 2hr | x | x | 1hr | 1hr | 4hr | 4hr | 15m | 4hr | x | x | 1hr | 1hr | 1hr | 4hr |
| 8 | 1hr | 1hr | 1hr | x | 1hr | 4hr | 4hr | x | 1hr | x | x | x | 1hr | x | x | x | 15m | 4hr | 4hr | x |
| 11 | 15m | 15m | 4hr | 4hr | 4hr | 4hr | 4hr | 4hr | 2hr | 4hr | 4hr | 4hr | 1hr | 4hr | x | x | 1hr | 4hr | 4hr | x |
| 12 | 15m | 4hr | 4hr | 4hr | 4hr | x | x | x | 15m | 2hr | 2hr | 2hr | 1hr | x | x | x | 2hr | 4hr | 4hr | 4hr |

[a] Prior data resolution has been given in 12 hour segments for each weather variable: $rs_1$ - resolution for segment 1 (current-12 hours), $rs_2$ - resolution for segment 2 (12-24 hours), $rs_3$ - resolution for segment 3 (24-36 hours), $rs_4$ - resolution for segment 4 (36-48 hours); *'x'* indicates no prior data was included; 20,000 training patterns were used for fitness evaluation.

**Table 2.5:** Coefficient of determination ($R^2$) and Regression equation for the GASDR[a] and CDFR[b] models

| Prediction horizon (hour) | $R^2$ | | Linear fit | |
|---|---|---|---|---|
| | GASDR / EGASDR[c] model | CDFR model | GASDR / EGASDR model | CDFR model |
| 1 | 0.9918 | 0.9913 | *Y = 0.183 + 0.990 * X* | *Y = 0.241 + 0.989 * X* |
| 2 | 0.9818 | 0.9817 | *Y = 0.583 + 0.973 * X* | *Y = 0.436 + 0.980 * X* |
| 3 | 0.9722 | 0.9713 | *Y = 0.755 + 0.961 * X* | *Y = 0.448 + 0.969 * X* |
| 4 | 0.9649 | 0.9632 | *Y = 0.385 + 0.980 * X* | *Y = 0.948 + 0.955 * X* |
| 5 | 0.9562 | 0.9544 | *Y = 0.993 + 0.951 * X* | *Y = 1.178 + 0.943 * X* |
| 6 | 0.9483 | 0.9474 | *Y = 0.836 + 0.956 * X* | *Y = 1.359 + 0.942 * X* |
| 7 | 0.9392 | 0.9411 | *Y = 1.417 + 0.945 * X* | *Y = 1.615 + 0.926 * X* |
| 8 | 0.9350 | 0.9324 | *Y = 1.446 + 0.942 * X* | *Y = 1.700 + 0.922 * X* |
| 9 | 0.9278 | 0.9286 | *Y = 1.530 + 0.931 * X* | *Y = 1.892 + 0.904 * X* |
| 10 | 0.9256 | 0.9228 | *Y = 1.395 + 0.920 * X* | *Y = 2.084 + 0.912 * X* |
| 11 | 0.9184 | 0.9190 | *Y = 2.135 + 0.904 * X* | *Y = 1.758 + 0.917 * X* |
| 12 | 0.9151 | 0.9154 | *Y = 2.184 + 0.897 * X* | *Y = 2.364 + 0.884 * X* |

[a] GA Selected Duration and Resolution. [b] Constant Duration with a Fixed Resolution. [c] Extended GASDR (1, 4, 11 and 12 hour prediction horizons); *Y* = Predicted air temperature; X = Observed air temperature.

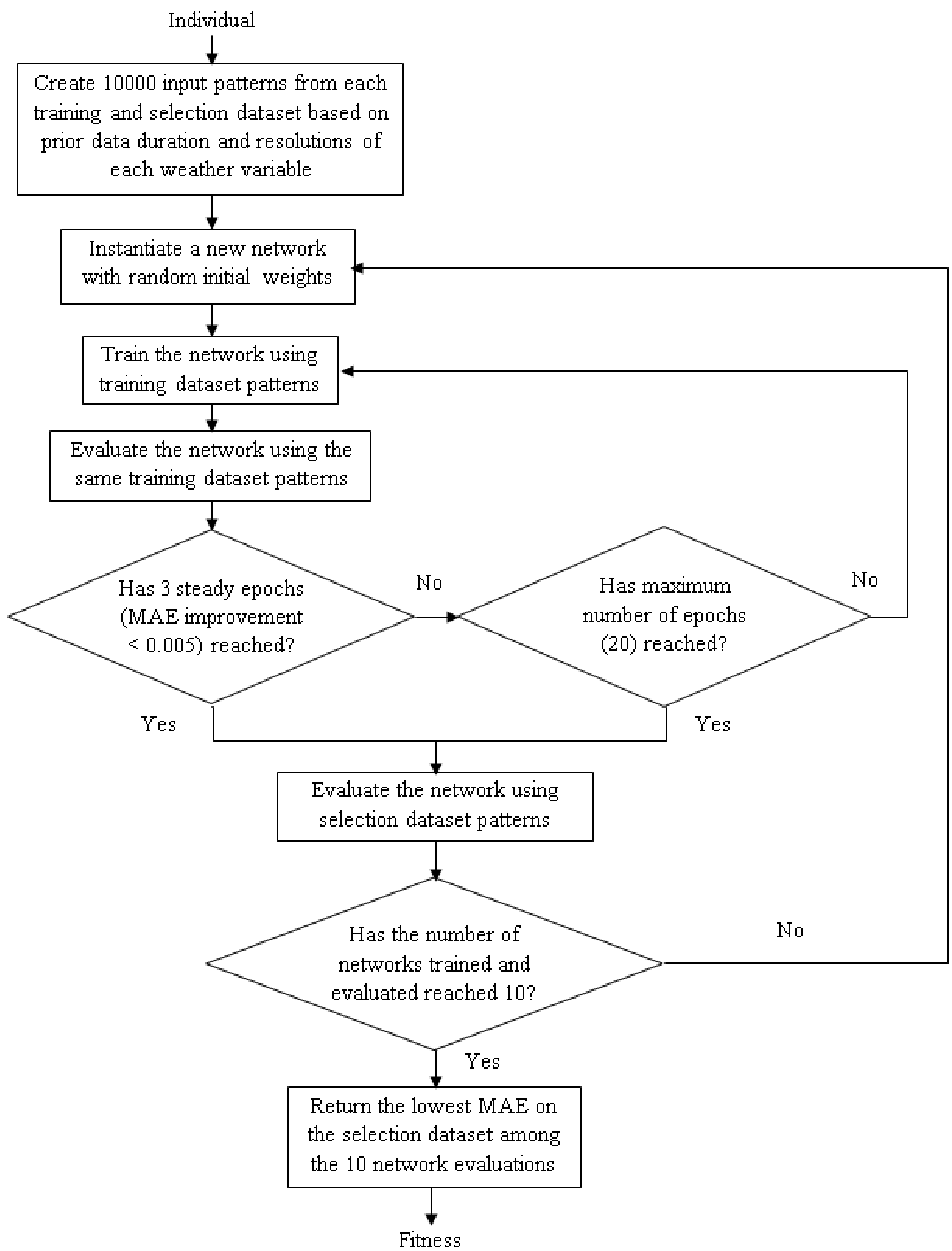


**Fig. 2.1.** Flow chart – Fitness evaluation of an individual in the GA population

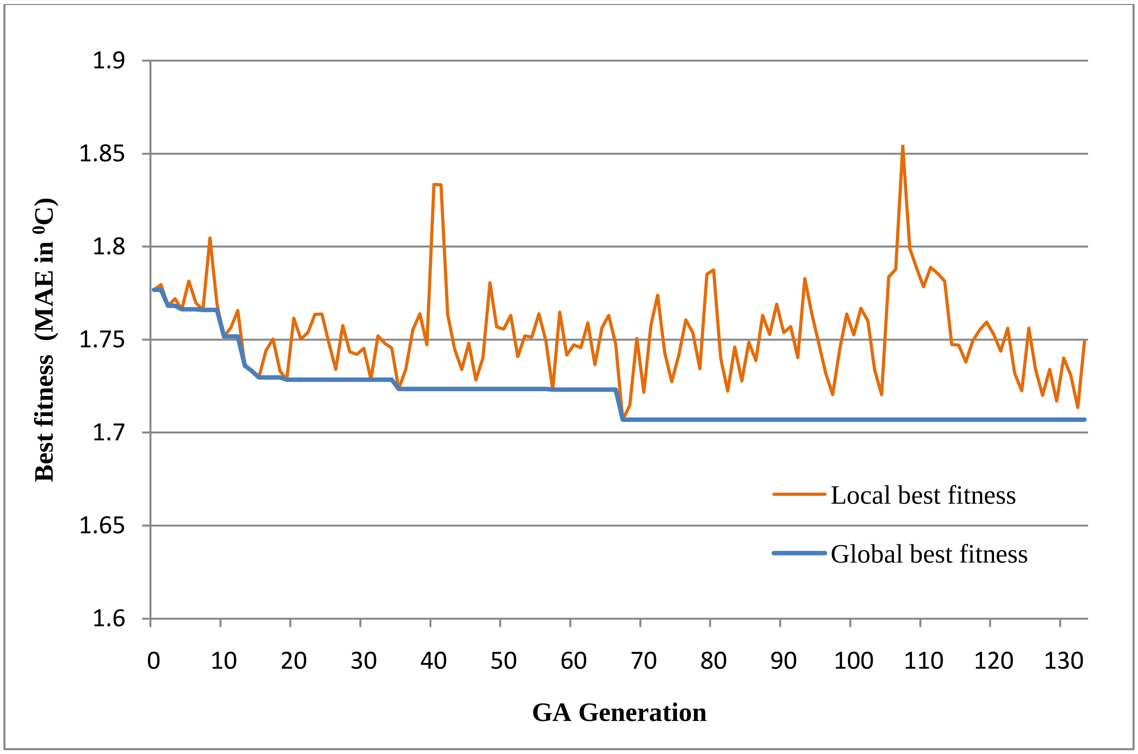


**Fig. 2.2.** Local and global best fitness values for each GA generation for 6-hr prediction horizon

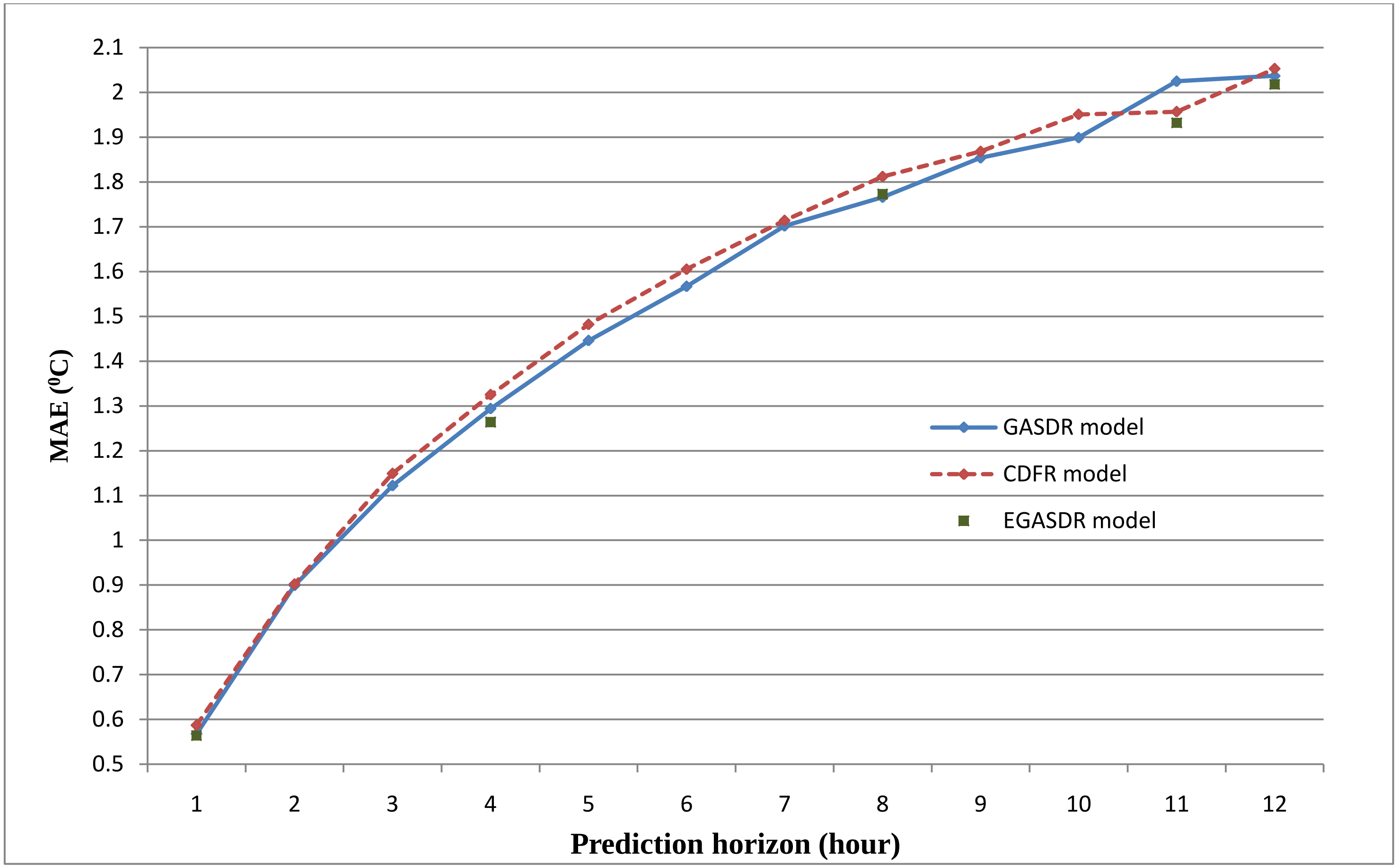


**Fig. 2.3.** MAE for each prediction horizon, CDFR, GASDR, and EGASDR models, Evaluation dataset

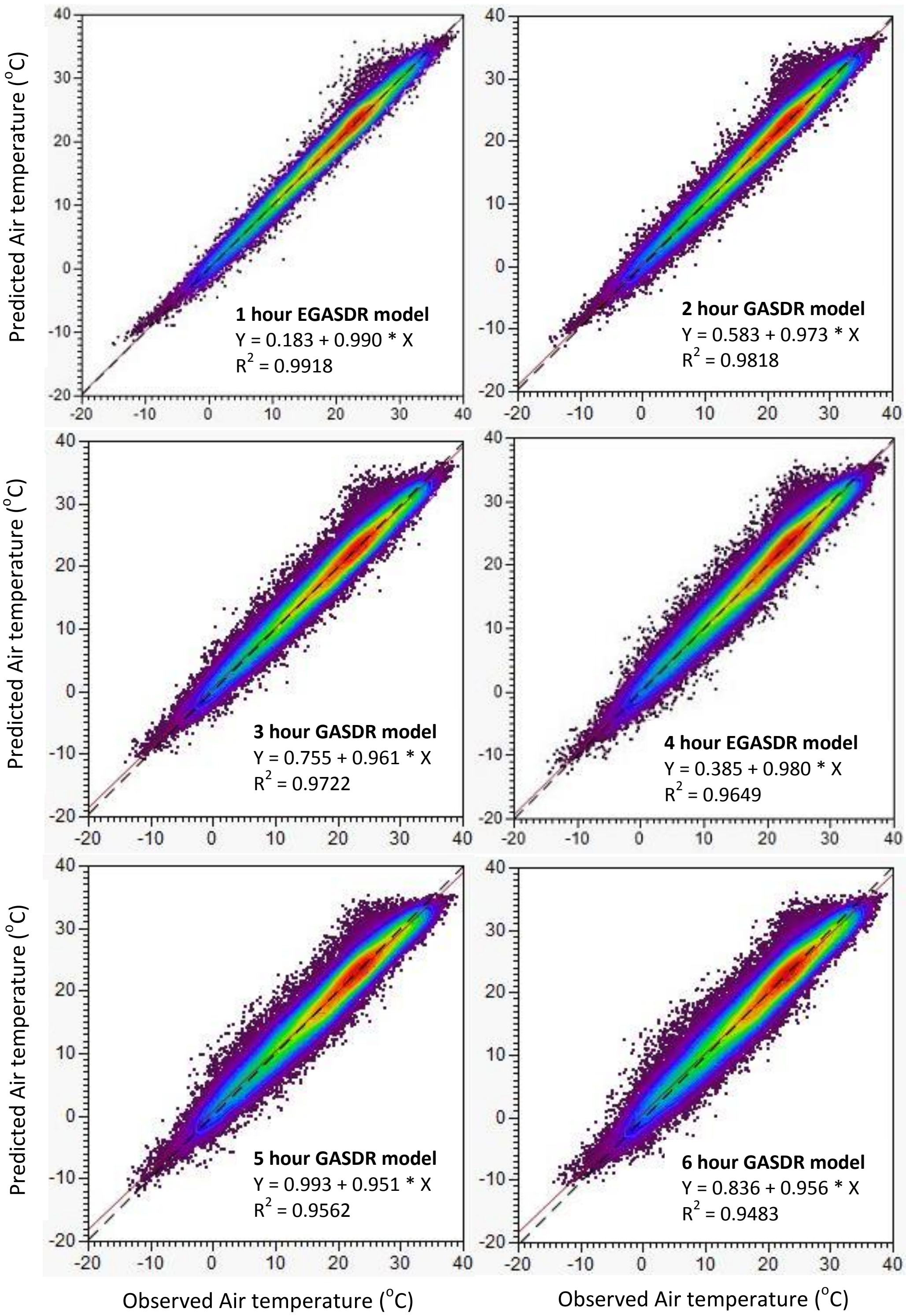


**Fig. 2.4.1.** Observed and Predicted air temperatures for the evaluation dataset for one through six hour GASDR/EGASDR models (Dotted line represents the ideal case of Y = X)

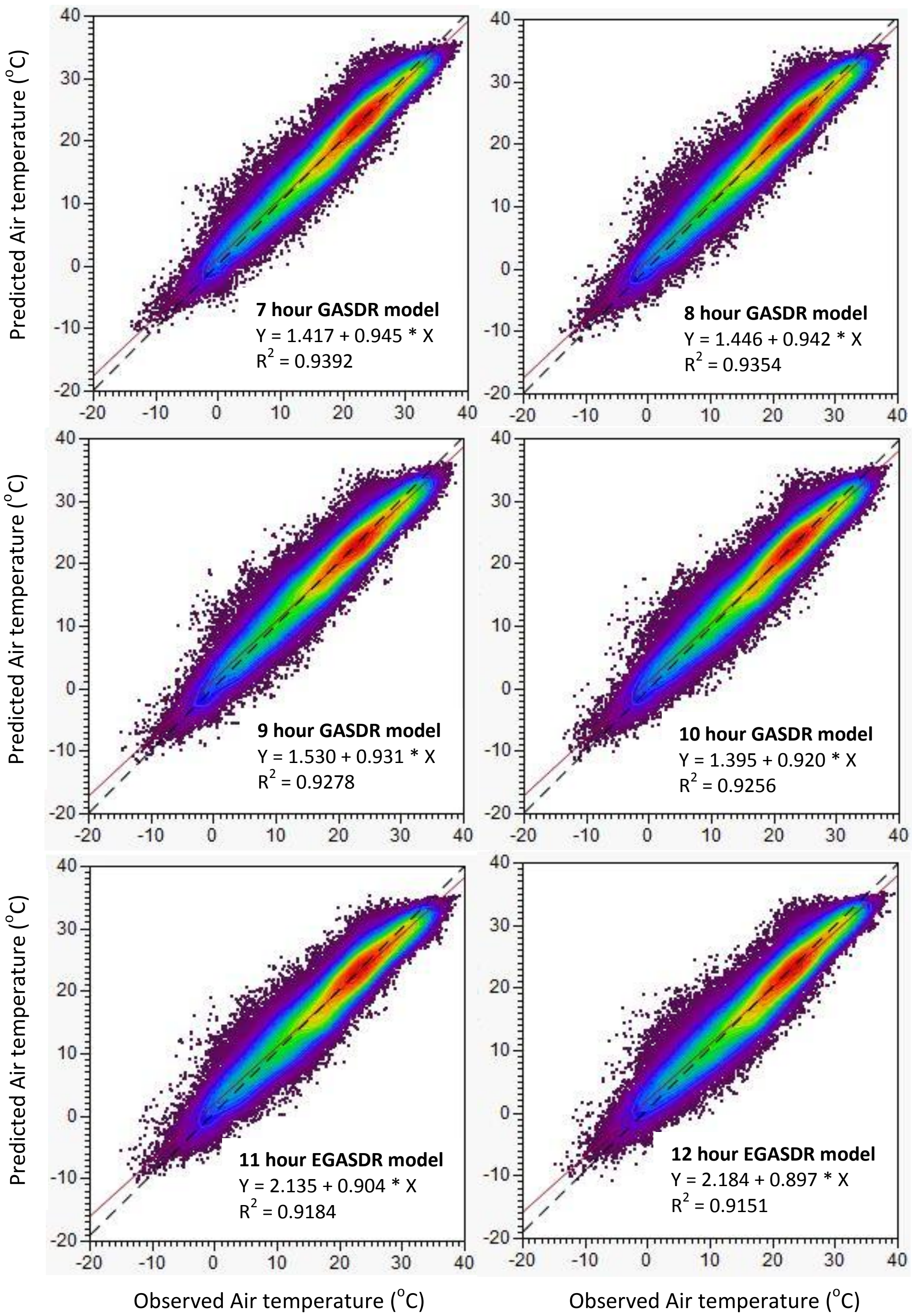


**Fig. 2.4.2.** Observed and Predicted air temperatures for the evaluation dataset for seven through twelve hour GASDR/EGASDR models (Dotted line represents the ideal case of Y = X)

# CHAPTER 3

# COMPUTATIONAL EVOLUTIONARY APPROACHES TO REFINE INPUT DATA SELECTION FOR DEW POINT TEMPERATURE PREDICTION USING ARTIFICIAL NEURAL NETWORKS[2]

[2]Venkadesh, S., Potter, W. D., McClendon, R. W., and Hoogenboom, G. To be submitted to the *International Journal of Computational Intelligence*.

**Abstract**

Dew point temperature is an important weather variable that affects crop growth and development as well as many other processes in agricultural and ecological systems. Accurate prediction of dew point temperature is necessary to avoid severe economic losses due to weather events such as frost and freeze. Previous research focused on the development of artificial neural network (ANN) models to predict dew point temperature from one to twelve hours in advance. The inputs to these models included a constant duration of prior data with a fixed resolution for all atmospheric variables. The goal of the research herein was to develop more accurate ANN models to predict dew point temperature for one-hour, six-hour and twelve-hour prediction horizons. This study employed stochastic optimization techniques including the genetic algorithm (GA) and particle swarm optimization (PSO) to refine the way in which the prior data were included as inputs for the ANN. Specific objectives of this research were to (i) determine the preferred duration and resolution of input prior data using the GA and PSO based approaches, and (ii) study the effect on the ANN prediction accuracy when eliminating the constraint of every weather variable being represented based on the PSO search. The PSO based approach that did not mandate the inclusion of at least some prior observations for every weather variable created an ANN model with a Mean Absolute Error (MAE) of 0.533 $^0$C on the evaluation patterns for the one hour prediction horizon. This was a slight improvement from the accuracy of the ANN model created based on the existing constant duration and fixed resolution approach which provided an MAE of 0.535 $^0$C on the same set of evaluation patterns. By exploiting a variable resolution scheme for the input prior data, this study found that for the accurate prediction of dew point temperature for the one-hour prediction horizon, the prior data for relative humidity and wind speed (included in the ANN inputs by the existing approach) were

not required, if the input prior data for other weather variables were included with appropriate resolutions. This study also found that the highest resolution air temperature data, in some cases along with relative humidity, complemented the highest resolution dew point temperature data for the inputs for all the prediction horizons considered in this study. Future work could study the effects of various evolutionary parameters involved in this research.

## I. Introduction

Dew point is the temperature at which the water vapor in the air will condense into water at a constant atmospheric pressure. Dew point temperature is an essential weather variable for estimating various agrometeorological parameters. Several agronomic, hydrological, ecological, and meteorological models require dew point temperature as input (Hubbard et al., 2003). White-Newsome et al. (2012) used outdoor air temperature and dew point temperature for the prediction of indoor heat to mitigate the effects of indoor heat exposure among the elderly people in Detroit. Dew point temperature is one of the weather variables that affects crop growth and has been considered as an input for the simulation of crop production (Hoogenboom, 2000a).

The Georgia Automated Environmental Monitoring Network (AEMN) was established in 1991, and currently consists of more than 80 weather stations distributed throughout Georgia (Hoogenboom, 2000b). These solar-powered stations record atmospheric variables at a one second frequency. The weather variables that are being monitored include air temperature, dew point temperature, relative humidity, vapor pressure, wind speed, wind direction, solar radiation and rainfall. These data were summarized as hourly averages and totals until March 1996. Subsequently the aggregated interval was reduced to fifteen minute averages. The collection of dew point temperature data was started in 2002. These observations are downloaded to a server for data processing, and immediately made available on the website www.georgiaweather.net.

ZareNezhad and Aminian (2011) developed an ANN model to predict the dew points of acidic combustion gases to prevent corrosion failures in process and power plants. Their model was trained using the Levenberg–Marquardt back propagation algorithm and a trial-and-error approach was taken to determine the best network architecture. Shank et al. (2008a) created ANN models to predict dew point temperature up to twelve hours in advance using the weather variables dew point temperature, relative humidity, solar radiation, air temperature, wind speed, and vapor pressure as inputs. The observations were partitioned into different datasets for model development and evaluation purposes. Shank et al. (2008) created ensemble ANN models to improve the accuracy of dew point temperature prediction. These ANN models were implemented on the website www.georgiaweather.net. Smith et al. (2009) developed ANN models to predict air temperature for one through twelve hour prediction horizons. These ANN models were also implemented on the same website, where the predictions are available for both air and dew point temperatures for every weather station that is part of the Georgia. These hourly predictions are made from one to twelve hours ahead and updated every 15 minutes. Chevalier et al. (2012) created a decision support system to interpret these air temperature and dew point temperature predictions along with the observed wind speed as one of the five frost warnings determined related to blueberries and peaches.

In the previous research conducted by Shank et al. (2008a), the duration of prior weather information for the inputs to the ANN model was determined by a limited iterative search for each prediction horizon. For this search, the duration was varied from six to thirty hours in increments of six hours for each prediction horizon. It was assumed that all six weather variables were required for the accurate prediction of dew point temperature for all prediction horizons. Thus, a single duration was used to include the prior data for all six weather variables. Although the observed data were available for every fifteen minutes, prior research only included the data in one hour intervals and the effect of including the prior data with either a shorter or a longer interval than one hour was not explored. In this paper, the term ‘resolution’ will be used further, instead of ‘interval’. For instance, a 15-minute resolution or the highest resolution will denote that the prior data were included in fifteen minute intervals and a 4-hour resolution will denote that the prior data were included in four hour intervals.

In several studies, evolutionary approaches such as the genetic algorithm (GA) and Particle Swarm Optimization (PSO) have been coupled with ANN techniques for tasks such as training the ANN, and determining the preferred network architecture etc. The PSO is a stochastic optimization technique introduced by Eberhart & Kennedy (1995). Like evolutionary algorithms, PSO is a population based search technique that begins with a set of randomly initialized particles each of which represents a candidate solution. During each iteration, a velocity is applied to a particle to update its position in the search space. The velocity of a particle is calculated based on two factors: the local best position, which is the best position that the particle has achieved so far ($P_{lb}$), and the global best position which is the position of the best particle in the current population ($P_{gb}$). The velocity is controlled by cognitive ($C_1$) and social ($C_2$) coefficients which are applied to $P_{lb}$ and $P_{gb}$ respectively, and an inertial weight ($W$). The velocity ($V_{id}$) and the position ($X_{id}$) of the $d^{th}$ dimension of the $i^{th}$ particle in the population are updated using the following two equations:

$$V_{id} = W * V_{id} + C_1 * R_1 * (P_{lb} - X_{id}) + C_2 * R_2 * (P_{gb} - X_{id}) \ldots. (1)$$

$$X_{id} = X_{id} + V_{id} \ldots. (2)$$

where, $R_1$ and $R_2$ are two randomly generated numbers.

Stanley et al. (2002) presented a method named NEAT (Neuro Evolution of Augmenting Topologies), which enabled parallel evolution of both network architecture and connection weights using an evolutionary algorithm. Aijun et al. (2004) used a GA to optimize the *chemical vapor infiltration* (CVI) processing parameters of Carbon/Carbon composites. The fitness function of their GA evaluated ANNs based on the candidate input parameters of the network. Mohebbi et al. (2011) coupled a GA with the ANN to estimate the moisture content of dried banana. Their GA evolved the ANN parameters such as the number of hidden layers, and the number of hidden nodes, learning rate and momentum for each hidden layer. Wu & Chen (2009) created nonparametric regression ensemble models for rainfall forecasting by coupling PSO with the ANN. In their study the PSO was used to evolve the ANN structure and the weights. Chau (2007) applied the PSO for the training of a three-layered perceptron network to predict the outcome of the litigation process in construction claims and concluded that the PSO-based perceptron network exhibited better performance than the backpropagation-based perceptron network with regard to the convergence rate of training and the prediction accuracy. Lazzús (2011) created an ANN model to estimate autoignition temperatures of organic compounds by training the models using the PSO. In his study, each particle in the PSO population represented the connection weights and was evaluated using a predefined fitness function which incorporated the resulting ANN accuracy.

Venkadesh et al. (2012) applied a genetic algorithm (GA) to determine the duration and resolution of prior data for each input weather variable to predict air temperature for one through twelve hour prediction horizons. They assumed that all the input weather variables that were considered were necessary to accurately predict air temperature. Therefore, one of the constraints that was added to the GA in evolving the preferred duration and resolutions was to include at least twelve hours of prior data (the shortest duration considered) with 4-hr resolution (the lowest resolution considered) for each weather variable. The previous GA based approach created ANN models that provided lower error than the ANN models created based on the existing ‘constant duration with a fixed resolution’ approach.

The goal of this research project was to improve the dew point temperature prediction accuracy of the existing ANN models. Specific objectives were: for the one-hour, six-hour and twelve-hour prediction horizons, (i) determine the preferred duration and resolution of input prior data using the GA and PSO based approaches, and (ii) study the effect on the ANN prediction accuracy while eliminating the constraint of every weather variable being represented based on the PSO search.

## II. Methodology

This study consisted of an input optimization phase and a final model development phase. The input optimization phase aimed at determining the duration and the resolution of prior data for each input weather variable using GA and PSO searches. The final model development phase created the ANN models to be implemented for practical use, using the duration and the resolution identified in the input optimization phase and compared the results of this study with the existing ANN models for dew point temperature prediction developed by Shank et al. (2008a). All the ANNs were developed with the Ward-style architecture having three slabs in the hidden layer using Gaussian, Gaussian complement and hyperbolic tangent activation functions. Each ANN model was trained using the error back-propagation algorithm, a learning rate of 0.1, an initial weight range of ±0.15 and a range of (0.1, 0.9) to scale the inputs. These values were chosen based on the previous work by Shank et al. (2008a) in which dew point temperature prediction models were created. Mean absolute error (MAE) was the measure of accuracy for these ANN models.

The term model refers to an ANN with a certain number of input, hidden and output nodes with a specific set of input variables resulting from a particular duration and resolution of prior data. During model development, several network instantiations were created for a model which differed only in the initial random weights and the order in which the training patterns were presented. Smith et al. (2006) showed that training and evaluating multiple instantiations of the same model provided a better foundation for the comparison of model accuracies than a single network instantiation.

### 1. Input patterns and Datasets

A pattern is a set of values corresponding to the input and output nodes of the ANN model. The weather variables of dew point temperature, relative humidity, air temperature, wind speed, solar radiation and vapor pressure observed at different points in the time series were used to create an input pattern. These weather variables, observed at the time of prediction, were always included in the inputs. The input pattern also included the rates of change calculated as follows: local rates of change of a weather variable were the differences between every two adjacent observations that were included in the time series. Eight fuzzy logic variables to represent the time of day and the day of year information were also included in the input pattern as done by Shank et al. (2008a).

The variable resolution scheme employed in Venkadesh et al. (2012) to represent the duration and resolution for each weather variable for air temperature prediction was used in this study. However, unlike the previous work, this study considered only twelve hours of total duration of prior data for each weather variable for the one hour prediction horizon. This was because Shank et al. (2008a) concluded that only six hours of prior data was required for the accurate prediction of dew point temperature for the one hour prediction horizon. Since their conclusion was based on including a constant total duration of prior data for all six weather variables during the search for the preferred total duration of prior data, the current study allowed twelve hours of prior duration for each weather variable for the one hour prediction horizon to determine if the ANN model could take advantage of the additional information past six hours in the prior data for some weather variables. Hence, each of the six weather variables represented the resolutions in three segments of four hour duration (three segments of four hours each equates to twelve hours) for the one hour prediction horizon. Since the existing ANN models for six and twelve hour prediction horizons were developed using eighteen hours of prior data, the GA and the PSO search included a maximum of 48 hours of prior data for each weather variable. Thus, the maximum duration of 48 hours for the prior data allowed four segments of twelve hour duration for each weather variable for six- and twelve-hour prediction horizons. The various resolutions considered in this study were 15-minute, 1-hour, 2-hour, and 4-hour.

Data collected from 2002 through 2010 at various weather stations geographically distributed throughout the state of Georgia were partitioned into model development and evaluation datasets. The ANN models were created using the patterns from the development dataset. Once these models were developed, they were evaluated on the patterns which were not used during the model development. Therefore, the evaluation dataset included years and locations which were mutually exclusive of the development dataset. The development dataset was further partitioned into training and selection datasets. The patterns from the training dataset were used for ANN weight adjustment using back-propagation, and the patterns from the selection dataset were only used in feed-forward mode to choose the most accurate network instantiation for a model. The training and selection datasets shared the same years of data, but differed in the included locations. Table 1 shows the dataset partitioning by years and locations. Using a stopping dataset to determine when to end the training was found to be unnecessary by Smith et al. (2006) as the network performance on stopping and training datasets was qualitatively similar.

## 2. The Input Optimization phase

The overall goal of the input optimization phase was to determine the duration and the resolution of prior data for each weather variable using the GA and the PSO. The GA and the PSO searches determined the duration and the resolutions of prior data based on the accuracy of the ANNs trained and evaluated on a smaller number patterns sampled from the training and the selection dataset respectively. During the course of each of the GA and the PSO runs, more than 3000 ANN models were created with the objective of determining the preferred duration and resolution.

From a set of preliminary runs it was found that the preferred values for the cognitive ($C_1$) and social ($C_2$) coefficients were 2.2 and 1.8 respectively when the velocity limit ($V_{lim}$) of 2.0 was used for the PSO algorithm. These preliminary runs were made for the one hour prediction horizon using only 10,000 ANN training patterns for fitness evaluation. Shi & Eberhart (2009) found that for a number of PSO applications, an inertia weight in the range (0.9, 1.2) resulted in a higher chance of finding the global optimum within a reasonable number of iterations, when the maximum velocity allowed was set as two. Hence a value of 0.9 was used for the inertia weight for all the subsequent PSO runs in this study. The PSO runs were made for 150 iterations with a swarm size of 50. The resolutions of 15-min, 1-hr, 2-hr and 4-hr were represented as the real values of 0.25, 1.0, 2.0 and 4.0 respectively in a particle. Once the computed velocity was applied to a segment of a particle, the new position of the segment was adjusted to the nearest valid resolution. For example, a velocity of 0.70 applied to a 15-min resolution (0.25) would result in 1-hr resolution, and a velocity of -3.9 applied to a 4-hr resolution (4.0) would result in 15-min resolution.

An individual in the GA population consisted of one component for each weather variable totaling to six components, similar to the previous study by Venkadesh et al. (2012). A one-point component level crossover with a probability of 0.5 and one of two mutation schemes with a probability of 0.3 were applied at the component level for each component. A step mutation either increased or decreased the resolution of a randomly chosen segment by one step, and a length mutation either removed the last segment, or added a new segment with a randomly chosen resolution. Both mutation schemes had equal selection probabilities.

It was observed in Venkadesh et al. (2012) that sampling 20,000 patterns from each training and selection dataset for fitness evaluation as opposed to 10,000 samples was helpful in evolving the solutions that resulted in more accurate final ANN models. Therefore, the current study used 20,000 patterns for the fitness evaluation in both the GA and the PSO. However, using 20,000 patterns for fitness evaluations required roughly two weeks of run time for the GA runs in the previous study. Hence, the current study was limited to only one-, six- and twelve-hour prediction horizons. The number of network trials was also reduced to five as opposed to ten used in the previous study to expedite the runs.

In the first set of experiments, the GA and the PSO runs were made for one, six and twelve hour prediction horizons. These runs included a constraint that an input weather variable would have at least one segment with the lowest resolution (4-hr) for each weather variable. Therefore, inclusion of four hours of prior data with 4-hr resolution (one prior observation) was the minimum requirement enforced for each weather variable for the one-hour prediction horizon. Similarly, for the six- and twelve-hour prediction horizons, inclusion of twelve hours of prior data with 4-hr resolution (3 prior observations) was the minimum requirement enforced for each weather variable. The variation operators in these runs were not allowed to modify the duration and resolution for a weather variable beyond these minimum bounds which would result in not including any prior observation for a weather variable. *The PSO with this constraint will be denoted as $PSO_1$ herein.*

In the second set of experiments, the effect of eliminating the above constraint during the search for the duration and resolution was studied. This portion of the study was performed using only the PSO search, since the PSO generally converges faster than the GA. The PSO runs were made for one, six and twelve hour prediction horizons without enforcing the minimum requirement to include at least one segment of prior data with the lowest resolution. During a run, if the new velocity of the first segment had to lower its resolution from a value of 4-hr, no prior observations from that particular weather variable were included in the inputs. *This PSO without the constraint will be denoted as $PSO_2$ herein.*

## 3. Final model development phase

In this phase, the final ANN models were developed and evaluated for one-, six- and twelve-hour prediction horizons using a larger number of patterns sampled from the datasets (Table 1). For each prediction horizon, four final ANN models were developed: The ANN models trained based on the duration and resolution determined by the GA were named the GASDR (GA Selected Duration and Resolution) model. The ANN models trained based on the duration and resolution determined by the PSO that had the constraint to include at least one segment of prior data with the lowest resolution were named the $PSOSDR_1$ (PSO Selected Duration and Resolution) model. The ANN models trained based on the duration and resolution determined by the PSO that did not add the above constraint were named the $PSOSDR_2$ model. Finally, the ANN models created using the methodology followed by Shank et al. (2008a) by including a constant duration of prior data with a fixed resolution for all weather variables as inputs were named the CDFR (Constant Duration with a Fixed Resolution) model. The training dataset in this study consisted of data from different locations and years than the ones used in the previous study (Shank et al., 2008a). Therefore, the three CDFR models were evaluated on the evaluation dataset used in the previous study (data from the year 2005) to compare their accuracies with those of the existing models. This comparison was performed to ensure that the CDFR models which were used as the baseline models in this study were not less accurate than the existing models.

For each prediction horizon, 300,000 randomly sampled patterns from the training dataset were used for ANN training. In the same way, 100,000 patterns were randomly sampled from the selection dataset for ANN selection, and 1,000,000 patterns were randomly sampled from the evaluation dataset for model evaluation. For each prediction horizon, 30 networks were instantiated and trained using the training dataset. Then, the selection dataset patterns were presented to each network instantiation in feed-forward-only mode. The most accurate network instantiation on the selection dataset was selected to represent the ANN model for that prediction horizon. All the final ANN models were developed using 20 hidden nodes per slab, the value used by Shank et al. (2008a). The GASDR, $PSOSDR_1$ and $PSOSDR_2$ models were evaluated on the evaluation dataset and their MAEs were compared with the MAE of the CDFR model for each prediction horizon.

## III. Results

In the input optimization phase for the one-hour prediction horizon, the prior data past four hours were generally not preferred for any weather variable to be included in the inputs (Table 2). The exceptions were that the $PSO_1$ included one observation past four hours (4-hr resolution for the second segment, where the duration of a segment is four hours) for relative humidity and the GA and the $PSO_1$ included two observations past four hours for solar radiation. The $PSO_1$ which added the constraint to include at least one segment with 4-hr resolution included one prior observation for wind speed and two prior observations for relative humidity, but the $PSO_2$ which did not include the above constraint did not include any prior data for wind speed and relative humidity. Both $PSO_1$ and $PSO_2$ preferred the highest resolution (15-min) for the prior dew point temperature data. Certain inconsistencies could be observed from the duration and resolution included for a weather variable across the three different search techniques considered. For example, vapor pressure was included with three different resolutions by the three approaches. This inconsistency could be attributed to the possibility of different points in the search space being similarly fit, and the fact that these search techniques are stochastic and start with a different initial population.

Similarly, for the six-hour prediction horizon, the prior data past twelve hours were not generally preferred for any weather variable (Table 3). However, the $PSO_1$ included the second segment for solar radiation, air temperature and vapor pressure with the lowest resolution

(Segment duration was twelve hours for the six-hour prediction horizon, resulting in three observations if the lowest resolution was preferred for a segment). The GA preferred the highest resolution for the prior dew point temperature data where as both the $PSO_1$ and $PSO_2$ preferred the highest resolution for the prior air temperature data. The $PSO_2$ also preferred the highest resolution for the prior relative humidity data, and did not include any prior data for dew point temperature. Since the dew point temperature is calculated from the air temperature and relative humidity, the inclusion of these two weather variables with the highest resolution might have resulted in not requiring any prior dew point temperature data by the $PSO_2$.

For the twelve-hour prediction horizon, longer durations of prior data were preferred in some cases (Table 4). The GA preferred 48 hours of prior data for air temperature and both the $PSO_1$ and $PSO_2$ included the prior data for solar radiation past 24 hours. However, no prior data were included past twelve hours with a resolution higher than the lowest resolution for any weather variable. All three algorithms preferred the highest resolution for the first segment of air temperature, and lower resolutions for the dew point temperature segments (Segment duration was twelve hours for the twelve-hour prediction horizon). The $PSO_2$ did not include any prior data for relative humidity and vapor pressure. A general observation from the results of one-hour, six-hour and twelve-hour prediction horizons was that the highest resolution air temperature data, in some cases along with relative humidity, complemented the highest resolution dew point temperature data for the inputs: In all the cases, except for the GA for the one-hour prediction horizon, either some prior dew point temperature observations were included with the highest resolution, or some prior air temperature observations, in some cases along with relative humidity, were included with the highest resolution, but not both.

In the final model development phase, the CDFR models were more accurate than the existing models for all three prediction horizons (Table 5). This accuracy improvement was due to the inclusion of data from six years for the ANN training, whereas only three years of data were available for the ANN training in the previous study. Among the four approaches considered in this study for the one-hour prediction horizon, the $PSOSDR_2$ and $PSOSDR_1$ models provided the lowest MAE's on the training and selection datasets respectively (Table 6). However, for the six and twelve hour prediction horizons the CDFR models provided the lowest MAE's on both the training and selection datasets. This trend was in general observed from the evaluation dataset MAE's as well. On the evaluation dataset, among the three new approaches considered in this study (GA, $PSO_1$ and $PSO_2$), the $PSO_2$ which did not add the constraint to include at least one segment for a weather variable created the most accurate model ($PSOSDR_2$) for the one-hour prediction horizon. Among these three new approaches, the $PSOSDR_1$ and GASDR models created by the GA and $PSO_1$ based approaches which added the constraint to include at least one segment for a weather variable were the most accurate models respectively for the six- and twelve-hour prediction horizons. Therefore, eliminating the constraint of every applicable weather variable being represented for the ANN inputs did not improve the accuracy from the approaches that included this constraint for the six- and twelve-hour prediction horizons.

The $PSOSDR_2$ model for the one-hour prediction horizon provided an MAE of 0.533 $^0$C on the evaluation dataset, a slight improvement from the corresponding CDFR model's MAE of 0.535 $^0$C (Table 6). It should be noted that unlike the previous approach by Shank et al. (2008a), this MAE was obtained by the one hour $PSOSDR_2$ model without including any prior data inputs for relative humidity and wind speed. This implied that prior relative humidity and wind speed observations were not required for the accurate prediction of dew point temperature one hour in advance, if the prior input observations for dew point temperature, air temperature, solar radiation and vapor pressure were included with appropriate resolutions. However, for the higher prediction horizons of six-hour and twelve-hour, the CDFR models provided the lowest MAE's on the evaluation dataset among the four approaches considered. It was concluded that the search for the six-hour and twelve-hour prediction horizons would require a less restricted parameter setting such as a larger population size, and an increased number of training patterns for the fitness evaluation, since the prediction becomes more problematic for the higher prediction horizons. However, because of the time and working memory constraints, this study could not exploit a more resource-intensive search to determine the preferred duration and resolutions for the six-hour and twelve-hour prediction horizons. Therefore, the $PSOSDR_2$ model for the one-hour prediction horizon and the CDFR models for the six- and twelve-hour prediction horizons were selected as the final models.

A strong correlation between the observed and predicted dew point temperature values was observed for the lowest (one hour) prediction horizon with a coefficient of determination ($R^2$) of 0.9926, and the predictions from the twelve hour model had an $R^2$ value of 0.8946 as shown in Figures 1a through 1c. The dotted line represents the ideal case of the 1:1 line of fit of a hypothetical model. The slopes of the best line of fit for the one-, six-, and twelve-hour prediction horizon were 0.996, 0.951, and 0.898 respectively. The one-, six-, and twelve-hour prediction horizons had the best line of fit with a Y-intercept of 0.024, 0.728, and 1.680 respectively.

## IV. Summary and Future work

This study compared three approaches to determine the input prior data duration and resolutions for various weather variables to predict dew point temperature with the existing approach. The first and second approaches employed a GA and PSO respectively and mandated the inclusion of some prior data for every weather variable and the third approach employed a PSO technique which did not incorporate this constraint. This study was performed for the one-hour, six-hour and twelve-hour prediction horizons. The ANN models based on the existing constant duration and fixed resolution approach were recreated using the same datasets used to create the ANN models based on the new approaches for a fair comparison. The GA and PSO based approaches created the ANN models with accuracies comparable to those of the ANN models based on the existing approach. This study found that for the accurate prediction of dew point temperature for a lower prediction horizon, the prior data for relative humidity and wind speed (included in the ANN inputs by the existing approach) were not required, if the input prior data for other weather variables were included with appropriate resolutions. This study also found that for the dew point temperature prediction for any prediction horizon, the highest resolution air temperature data, in some cases along with relative humidity, and the highest resolution dew point temperature data were complementary to each other for the ANN inputs. With additional computational resources, it might be possible to create more accurate models for each prediction horizon. Future work could focus on fine-tuning the GA parameters such as the population size, and variation operators and their probabilities, and the PSO parameters such as the swarm size, inertia weight, and social and cognitive coefficients for each prediction horizon. Future work could use a less restricted parameter setting for the fitness evaluation such as more than 20,000 patterns for the ANN training and more random network instantiations. The effects of these fitness evaluation parameters on creating more accurate ANN models for the higher prediction horizons could also be studied.

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**Table 3.1:** Dataset partitioning by years and locations

| Dataset | | Sites | Years | Approximate number of observations |
|---|---|---|---|---|
| Development | Training | Atlanta, Brunswick, Pine Mountain, Covington, Dallas, Dawson, Dearing, Duluth, Homerville, Oakwood, Shellman, Tifton, Tiger, Woodbine | 2002 2003 2004 2005 2007 2009 | 2,500,000 |
| | Selection | Alma, Arabi, Williamson, Bowen, Dempsey, Dixie, Eatonton, Georgetown, Griffin, Howard, Jeffersonville, Lafayette, Plains, Sparta, Tennille | | 2,500,000 |
| Evaluation | | Alapaha, Alpharetta, Arlington, Attapulgus, Blue Ridge, Byromville, Cairo, Calhoun, Camilla, Clarks Hill, Cordele, Danville, Douglas, Ellijay, Moultrie, Nahunta, Newton, Odum, Ossabaw, Sasser, Savannah, Valdosta, Vidalia | 2006 2008 2010 | 2,500,000 |

**Table 3.2**: Prior data resolution in four hour segments for the one-hour prediction horizon selected by the GA and PSO

| Algorithm | **Dew point temperature**[a] | | | **Relative humidity** | | | **Solar radiation** | | | **Air temperature** | | | **Wind speed** | | | **Vapor pressure** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Duration of 12hrs*** | | | ***Duration of 12hrs*** | | | ***Duration of 12hrs*** | | | ***Duration of 12hrs*** | | | ***Duration of 12hrs*** | | | ***Duration of 12hrs*** | | |
| GA | 2hr | x | x | 2hr | x | x | 2hr | 2hr | x | 1hr | x | x | 15m | x | x | 1hr | x | x |
| $PSO_1$ | 15m | x | x | 4hr | 4hr | x | 4hr | 4hr | 4hr | 4hr | x | x | 4hr | x | x | 15m | x | x |
| $PSO_2$ | 15m | x | x | x | x | x | 15m | x | x | 4hr | x | x | x | x | x | 2hr | x | x |

[a] A weather variable had three segments of 4 hour duration each. The first, second and third segments correspond, respectively, to the current-4 hours, 4-8 hours, and 8-12 hours of prior data; The GA and $PSO_1$ added a constraint to include at least one segment with 4-hr resolution for each weather variable. $PSO_2$ did not include this constraint; *'x'* indicates no prior data was included for that segment; A total of 20,000 training patterns were used for fitness evaluation.

**Table 3.3**: Prior data resolution in twelve hour segments for the six-hour prediction horizon selected by the GA and PSO

| Algorithm | Dew point temperature[a] | | | | Relative humidity | | | | Solar radiation | | | | Air temperature | | | | Wind speed | | | | Vapor pressure | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Duration of 48hrs* | | | | *Duration of 48hrs* | | | | *Duration of 48hrs* | | | | *Duration of 48hrs* | | | | *Duration of 48hrs* | | | | *Duration of 48hrs* | | | |
| GA | 15m | x | x | x | 4hr | x | x | x | 2hr | x | x | x | 1hr | x | x | x | 2hr | x | x | x | 4hr | x | x | x |
| $PSO_1$ | 4hr | x | x | x | 4hr | x | x | x | 4hr | 4hr | x | x | 15m | 4hr | x | x | 4hr | x | x | x | 4hr | 4hr | x | x |
| $PSO_2$ | x | x | x | x | 15m | x | x | x | 2hr | x | x | x | 15m | x | x | x | 4hr | x | x | x | 4hr | x | x | x |

[a] A weather variable had four segments of 12 hour duration each. The first, second, third and fourth segments correspond, respectively, to the current-12 hours, 12-24 hours, 24-36 hours, and 36-48 hours of prior data; The GA and $PSO_1$ added a constraint to include at least one segment with 4-hr resolution for each weather variable. $PSO_2$ did not include this constraint; '*x*' indicates no prior data was included for that segment; A total of 20,000 training patterns were used for fitness evaluation.

**Table 3.4**: Prior data resolution in twelve hour segments for the twelve-hour prediction horizon selected by the GA and PSO

| Algorithm | **Dew point temperature**[a] | | | | **Relative humidity** | | | | **Solar radiation** | | | | **Air temperature** | | | | **Wind speed** | | | | **Vapor pressure** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Duration of 48hrs*** | | | | ***Duration of 48hrs*** | | | | ***Duration of 48hrs*** | | | | ***Duration of 48hrs*** | | | | ***Duration of 48hrs*** | | | | ***Duration of 48hrs*** | | | |
| GA | 1hr | x | x | x | 2hr | x | x | x | 1hr | x | x | x | 15m | 4hr | 4hr | 4hr | 2hr | x | x | x | 1hr | x | x | x |
| $PSO_1$ | 4hr | 4hr | x | x | 15m | x | x | x | 1hr | 4hr | 4hr | 4hr | 15m | x | x | x | 4hr | x | x | x | 4hr | x | x | x |
| $PSO_2$ | 2hr | x | x | x | x | x | x | x | 4hr | 4hr | 4hr | x | 15m | x | x | x | 1hr | x | x | x | x | x | x | x |

[a] A weather variable had four segments of 12 hour duration each. The first, second, third and fourth segments correspond, respectively, to the current-12 hours, 12-24 hours, 24-36 hours, and 36-48 hours of prior data; The GA and $PSO_1$ added a constraint to include at least one segment with 4-hr resolution for each weather variable. $PSO_2$ did not include this constraint; '*x*' indicates no prior data was included for that segment; A total of 20,000 training patterns were used for fitness evaluation.

**Table 3.5:** Accuracies (MAEs) of the Existing models and CDFR models on the previous evaluation dataset[1]

| Prediction horizon (hour) | Existing model[1] ($^0C$) | CDFR model[2] ($^0C$) |
|---|---|---|
| 1 | 0.550 | **0.528** |
| 6 | 1.566 | **1.483** |
| 12 | 2.281 | **2.089** |

[1]Shank et al. (2008a). [2]Constant Duration with a Fixed Resolution.

**Table 3.6:** Accuracies (MAE's) of the ANN models created based on different approaches for each prediction horizon

| Prediction horizon (hr) | Training dataset ($^0C$) | | | | Selection dataset ($^0C$) | | | | **Evaluation dataset** ($^0C$) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GASDR model[a] | $PSOSDR_1$ model[b] | $PSOSDR_2$ model[c] | CDFR model | GASDR model | $PSOSDR_1$ model | $PSOSDR_2$ model | CDFR model | GASDR model | $PSOSDR_1$ model | $PSOSDR_2$ model | CDFR model |
| 1 | 0.511 | 0.509 | **0.505** | 0.511 | 0.510 | **0.505** | 0.507 | 0.508 | 0.540 | 0.535 | **0.533** | 0.535 |
| 6 | 1.504 | 1.508 | 1.521 | **1.473** | 1.499 | 1.487 | 1.513 | **1.479** | 1.533 | 1.508 | 1.548 | **1.489** |
| 12 | 2.134 | 2.161 | 2.158 | **2.109** | 2.121 | 2.148 | 2.153 | **2.091** | 2.123 | 2.162 | 2.162 | **2.102** |

[a] GA Selected Duration and Resolution. [b] PSO (which had the added constraint to include at least one segment with 4-hr resolution for a weather variable) Selected Duration and Resolution. [c] PSO (which did not add the above constraint) Selected Duration and Resolution; Highest accuracy results are bolded.

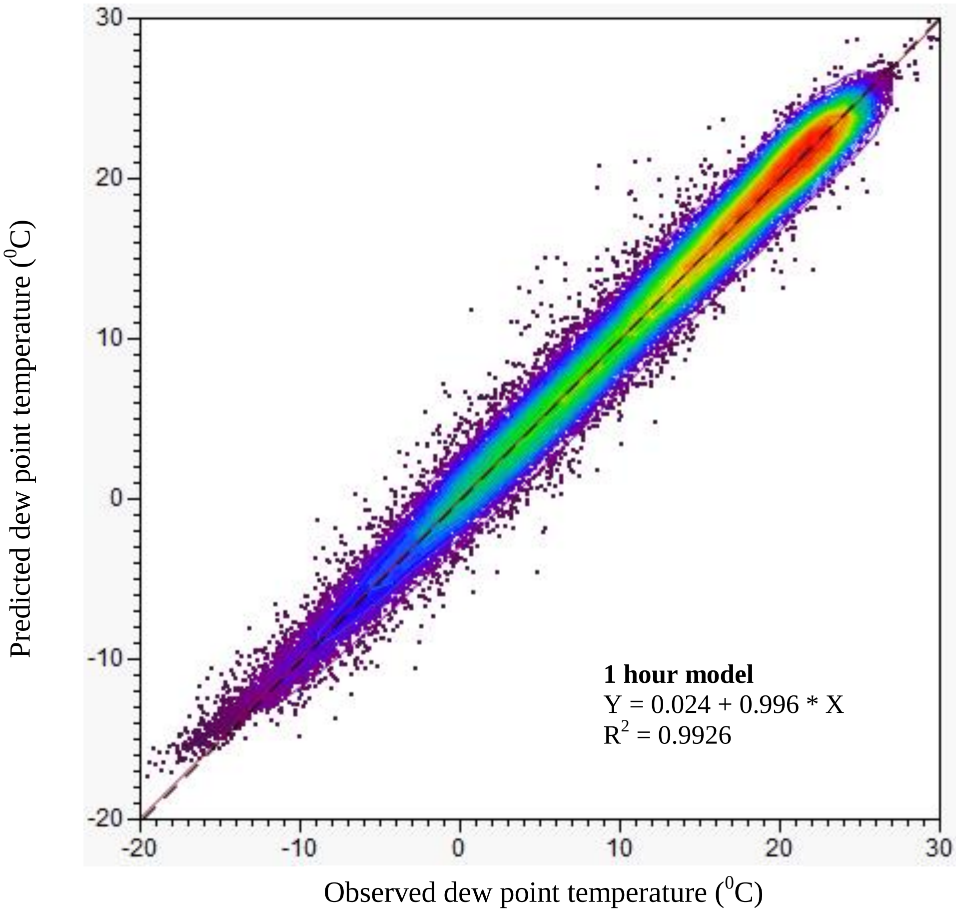


**Fig. 3.1.1.** Observed and Predicted air temperatures for the evaluation dataset for the one-hour $PSOSDR_2$ model (Dotted line represents the ideal case of Y = X)

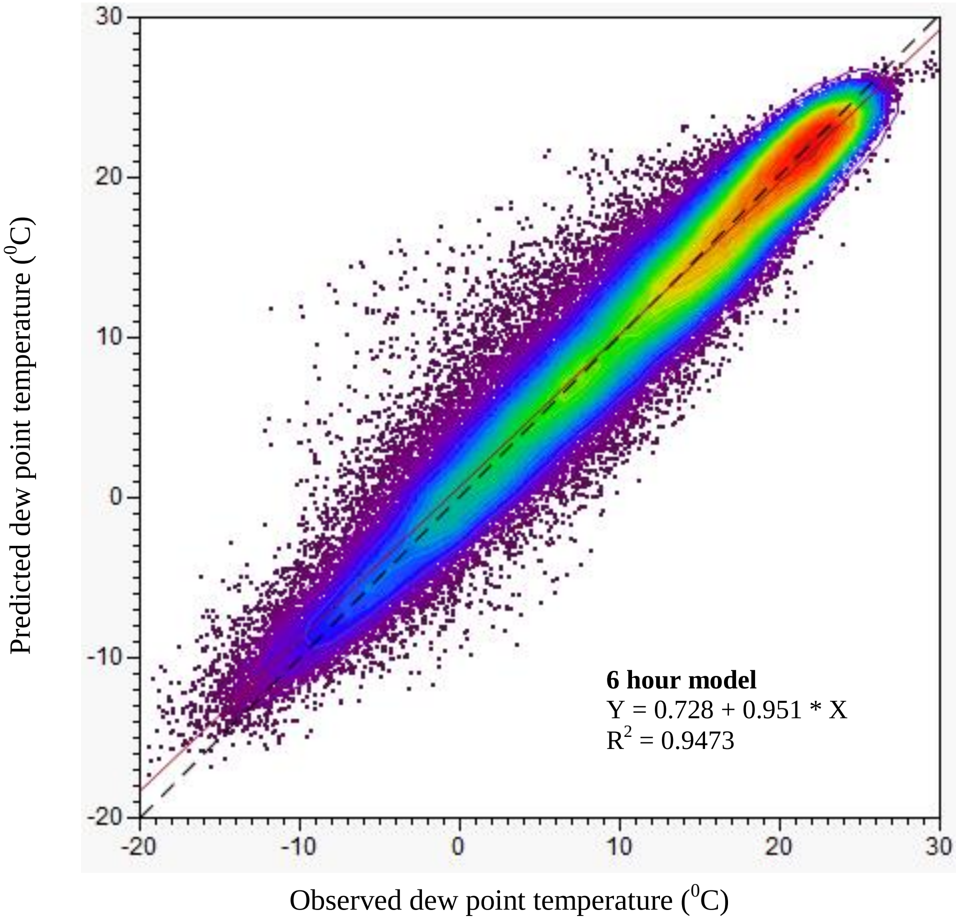


**Fig. 3.1.2.** Observed and Predicted air temperatures for the evaluation dataset for the six-hour CDFR model (Dotted line represents the ideal case of Y = X)

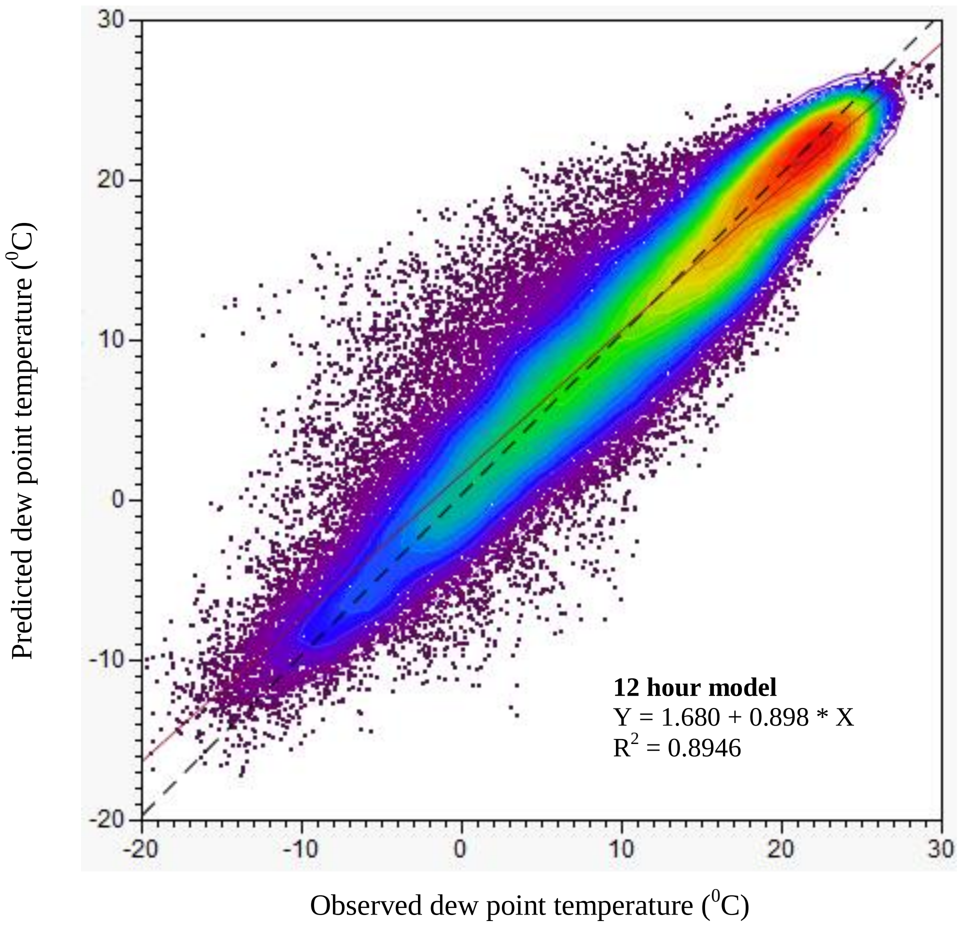


**Fig. 3.1.3.** Observed and Predicted air temperatures for the evaluation dataset for the twelve-hour CDFR model (Dotted line represents the ideal case of Y = X)

# CHAPTER 4

## SUMMARY AND CONCLUSIONS

The goal of this research was to improve the prediction accuracies of the existing air temperature and dew point temperature ANN models. Specific objectives of this research were to determine the preferred duration and resolution of prior data for each weather variable using computational evolutionary approaches and compare the accuracies of the ANN models created based on various approaches.

The objective of the research described in chapter 2 was to perform a GA search to determine the preferred duration and resolution of prior data for each weather variable to be included as inputs for the air temperature prediction ANN models. This study consisted of an evolutionary phase and a final model development phase. The evolutionary phase determined the duration and various resolutions for each input weather variable and for each prediction horizon using the GA search. The final model development phase trained the ANN model using a larger dataset based on the GA selected duration and resolution for each prediction horizon. The ANN models based on the existing constant duration and fixed resolution approach employed by Smith et al. (2009) were also recreated using the same datasets used to create the ANN models based on the new approach for a fair comparison. Using the GA based approach, the highest improvement in the accuracy was achieved at the one hour prediction horizon with a 3.22% improvement, compared to the accuracy of the model created based on the existing approach. The GA based approach with a restricted parameter setting such as 10,000 ANN training patterns and ten random network instantiations for the fitness evaluation generally proved to produce more accurate models for one- through ten-hour prediction horizons, but did not produce more accurate models for the eleven- and twelve-hour prediction horizons. This problem was addressed using an approach that ran the GA with a less restricted parameter setting such as 20,000 ANN training patterns and thirty random network instantiations for the fitness evaluation for the eleven- and twelve-hour prediction horizons. The eleven- and twelve-hour ANN models created based on this extended GA approach were more accurate than the existing models. Thus the GA based approach to determine the duration and resolution of input prior data for each weather variable proved to create more accurate ANN models for all prediction horizons.

The specific objective of the research described in chapter 3 was to compare the accuracies of various approaches to determine the input prior data duration and resolutions for various weather variables to predict dew point temperature with those of the existing approach. The first and second approaches employed a GA and PSO respectively and had a constraint of every weather variable being included in the ANN inputs. The third approach employed a PSO technique which did not incorporate the above constraint. This study was performed for the one-hour, six-hour and twelve-hour prediction horizons. The ANN models based on the existing constant duration and fixed resolution approach employed by Shank et al. (2008a) were recreated using the same datasets used to create the ANN models based on the new approaches for a fair comparison. The GA and PSO based approaches created the ANN models with accuracies comparable to those of the ANN models created based on the existing approach. This study found that for the accurate prediction of dew point temperature for the one-hour prediction horizon, the prior data for relative humidity and wind speed were not required, if the input prior data for other weather variables were included with appropriate resolutions. This study also found that for the dew point temperature prediction for any prediction horizon, the highest resolution air temperature data, in some cases along with relative humidity, complemented the highest resolution dew point temperature data for the ANN inputs.

Future work could explore various computational parameters involved in this study. The possible parameters to explore in the GA based approach include the GA population size, the crossover and the mutation operators and their probabilities, and the number of segments in the prior data for a weather variable. For the PSO based approach, the parameters such as the swarm size, inertia weight, and social and cognitive coefficients could be fine-tuned for each prediction horizon. With additional computational resources, it might be possible to further improve the accuracies of air temperature and dew point temperature ANN models by employing a more resource-intensive GA and PSO searches. Future work could use a less restricted parameter setting for the fitness evaluation such as more than 20,000 patterns for the ANN training and more random network instantiations. The possible research objectives for the future work could be to determine the preferred GA and PSO parameters to search for the best duration and resolution of input prior data and examine the effects of the fitness evaluation parameters such as the number of ANN training patterns and random network instantiations on creating more accurate ANN models for each prediction horizon.

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