Modeling and Forecasting the Daily Maximum Temperature Using Abductive Machine Learning

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ABSTRACT

The abductory induction mechanism (AIM®) is a modern machine-learning modeling tool that draws from the fields of neural networks, abductive networks, and multiple regression analysis. This paper introduces AIM as a useful weather modeling and forecasting utility and reports on its use with daily maximum temperatures in Dhahran, Saudi Arabia. Compared with other statistical methods and neural network techniques, this approach has the advantages of faster and highly automated model synthesis as well as improved prediction and forecasting accuracies. AIM models developed using daily data for 18 weather parameters over 1 yr that were used to predict the maximum temperature on a given day from other parameters on the same day. Evaluated on data for another full year, these models give 97% yield in the ±3°C error category. Various models for 3-day forecasting have been developed and evaluated. First-day forecasts give 77% yield in the same error category, and they compare favorably with official forecasts for the region, particularly for the warm seasons, as well as with forecasts based on persistence and climatology. Model relationships and performance statistics are compared with those previously obtained for the minimum temperature. The effect of increasing the AIM model complexity is investigated for both modeling and forecasting.

1. Introduction

Forecasting the minimum and maximum daily temperatures is an important requirement at many meteorological installations worldwide. Statistical as well as mixed statistical/dynamical techniques have been widely used for short-range prediction (Abdel-Nabi and Elhadidy 1991; Kruizinga and Murphy 1983). Model output statistics (MOS) methods (e.g., Klein and Hammons 1975; Woodcock 1984) have been the most commonly used approach since 1973. More recently, artificial intelligence approaches have been adopted for the prediction of weather parameters. These fall into two main categories: knowledge-based (or expert) systems and machine-learning techniques. Examples of the first category have been described by McArthur et al. (1987) and by Peak and Tag (1989). Of the second category, artificial neural networks (ANN) based on the back propagation paradigm have been used for forecasting the minimum temperature (Schizas et al. 1991). This latter approach has a number of limitations, which include heavy computational requirements and the lack of design methodologies for selecting the model architecture and parameters. Another route for machine-learning through self-organization has followed the track of the group method of data handling (GMDH) algorithm (Farlow 1984) and the closely related adaptive learning network (ALN) approach (Barron et al. 1984; Barron 1984). GMDH techniques have been used for forecasting meteorological time series of precipitation and 700-mbar geopotential heights (Lebow et al. 1984). Based on the ALN approach, the abductory induction mechanism (AIM)[1] was recently developed and is now available for use as a modeling tool on a number of computer platforms (Abtech 1990). AIM has been applied to the modeling and forecasting of the daily minimum temperature (Abdel-Aal and Elhadidy 1994). With the AIM approach, model synthesis is fast and highly automated, requiring little or no user intervention, and forecasting accuracy is superior to statistical and neural network methods. This paper reports on the application of AIM to the maximum temperature.

Dhahran (26.32°N, 50.13°E) is located a few kilometers inland from the Arabian Gulf. Over the period 1951–1976, average annual precipitation was about 80 mm and the absolute maximum and minimum temperatures recorded were 51° and −1°C, respectively. Average daily maxima range between 21° and 42°C and exceed 40°C for four months of the year. Average daily minima vary between 12°C in December/January and 29°C in July/August and fall below 20°C only during the months November–March. An account

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of the climate at the Dhahran area is given by Williams (1979). For the past 15 years, the Research Institute (RI) of King Fahd University of Petroleum and Minerals (KFUPM) has operated a computerized meteorological and radiation monitoring station (Kruss et al. 1989) where the evaporation rate as well as 6 meteorological and 12 radiation parameters are measured. Both statistical and machine-learning models for forecasting the minimum temperature in the region using the data measured have been described (Abdel-Nabi and Elhadidy 1990; Abdel-Aal and Elhadidy 1994). The present study describes the use of the AIM abductive network modeling tool (Version 1.0 for the Macintosh) with the maximum temperature. Daily data for 18 weather parameters over a maximum of 1 year are used for model synthesis, and evaluation is performed using data for different years. Prediction and forecasting by the generated models can be easily implemented on-line using the station computer.

In this paper, the GMDH-type modeling approach is reviewed and contrasted with conventional regression methods. Some early GMDH weather applications are also outlined. The AIM tool is then introduced and compared with the alternative ANN approach. AIM models for predicting the maximum temperature from knowledge of the other 17 weather parameters on the same day are described. A number of models are presented for forecasting the maximum temperature up to three days ahead of the present day, and the results are compared with official forecasts issued for the region as well as with simple persistence and climatology forecasts. The effect of increasing the AIM model complexity for both modeling and forecasting is investigated. Finally, the structures and performance of the resulting models are compared with those previously obtained for the minimum temperature.

2. GMDH-type modeling techniques

a. The classical GMDH approach

In quest of optimal objective models that look only at collected data representing system behavior, Ivakhnenko proposed the GMDH algorithm in 1966 (Ivakhnenko 1971). He observed that physical models often require information that is not readily available, and are therefore subject to many assumptions and simplifications that degrade the quality of the resulting model. Other techniques for quantitative modeling include time series analysis using various linear statistical methods and multivariate regression (Malone 1984). These techniques have difficulties in handling nonlinearities in the modeled phenomena and in dealing with small datasets found in many environmental, ecological, and social applications (Ikeda 1984). Attempts to incorporate nonlinear relationships in such models require the nonlinearity forms to be presumed a priori, rather than being naturally and automatically derived from the data. Inclusion of postulated nonlinearities in this way also increases the possibility of the model curve-fitting noise in the data (Scott and Hutchinson 1984). GMDH-type algorithms solve these problems since they automatically determine the inherent structure of complex and highly nonlinear systems and can synthesize adequate models with relatively few data points. The automation of model synthesis not only lessens the burden on the analyst but also safeguards the model generated from being influenced by human biases and misjudgments.

The GMDH approach is a formalized paradigm for iterated (multiphase) polynomial regression capable of producing a high-degree polynomial in effective predictors. The process is "evolutionary" in nature, using initially simple (myopic) regression relationships to derive more accurate representations in the next phase (iteration). To prevent exponential growth and limit model complexity, the algorithm selects relationships that have good predicting powers and discards all the others within each phase. Iteration is stopped when the new generation of regression equations start to have poorer prediction performance than those of the previous generation, at which point the model starts to become overspecialized and therefore unlikely to perform well with new data. This shows that the algorithm has three main elements: representation (estimation), selection, and stopping. The algorithm applies appropriate heuristics for making decisions concerning some or all of these three aspects.

To illustrate these steps for the classical GMDH approach (Farlow 1984), consider an estimation database of n_e observations (rows) and $m + 1$ columns [for m independent variables $(x_1, x_2, \ldots, x_m)$ and one dependent variable y]. In the first iteration we assume that our predictors are the actual independent input variables. The initial rough prediction equations are derived by taking each possible pair of input variables $(x_i, x_j; i, j = 1, 2, \cdots, m)$ together with the dependent variable y and computing the quadratic regression polynomial:

$$y = A + Bx_i + Cx_j + Dx_i^2 + Ex_j^2 + Fx_i x_j. \quad (1)$$

Each of the resulting $m(m-1)/2$ polynomials is evaluated using data for the pair of x variables used to generate it, thus producing new estimation variables $[z_1, z_2, \ldots, z_{m(m-1)/2}]$. The resulting z variables are screened according to some selection criterion and only those having good predicting power are kept. The original GMDH algorithm employs an additional and independent "selection set" of n_s observations for this purpose and uses the regularity selection criterion based on the root-mean-square error r_k over the selection dataset, where

$$r_k^2 = \frac{\sum_{l=1}^{n_s} (y_l - z_{kl})^2}{\sum_{l=1}^{n_s} y_l^2}; \quad k = 1, 2, \cdots, m(m-1)/2. \quad (2)$$

Only those polynomials (and associated z variables) that have r_k below a prescribed limit are kept, and the minimum value, $r_{\min}$, obtained for r_k is also saved. The selected z variables are more effective in describing and predicting y than the original input variables, and their corresponding columns represent a new database for repeating the estimation and selection steps in the next iteration to derive a set of higher-level variables. At each iteration, $r_{\min}$ is compared with its previous value and the process is continued as long as $r_{\min}$ decreases or until a given degree of complexity is reached. An increasing $r_{\min}$ is an indication of the model becoming overly complex, thus overfitting the estimation data and performing poorly in predicting the new selection data. Keeping model complexity checked is an important aspect of GMDH algorithms, which keep an eye on the final objective of constructing the model, that is using it with new data previously unseen during training. The best model for this purpose is one that provides the shortest description for the data available (Barron 1984). Computationally, the resulting GMDH model can be seen as a layered network of partial quadratic descriptor polynomials, with each layer representing the results of an iteration in the algorithm. The single polynomial in the final layer predicts the independent variable y in two intermediate variables, which are themselves quadratics in two lower-level variables, etc. The lowest-level polynomials in the first layer operate directly on the m independent input x variables. Each layer produces a polynomial having double the degree of the polynomial of the preceding layer. Making necessary substitutions for the complete model, we can reach a highly complex polynomial of the following form (known as the Ivakhnenko polynomial):

$$y = a + \sum_{i=1}^{m} b_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} c_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} d_{ijk} x_i x_j x_k + \cdots. \quad (3)$$

It is worth pointing out a number of advantages of the GMDH approach compared to conventional regression analysis, particularly for modeling large and complex systems. For the modest case of $m = 10$ variables and order $p = 8$, obtaining the coefficients of the regression polynomial directly requires solving 43 758 ill-conditioned linear equations simultaneously, while a 3-layer GMDH model obtains the equivalent Ivakhnenko polynomial by repetitively solving regression equations in only six variables [Eq. (1)]. This reduces ill-conditioning effects (smaller matrices) and allows GMDH to model complex relationships using only a small number of data points, while with conventional regression we need at least as many observations as coefficients. GMDH also keeps generating new variables by intermixing lower-level variables, thus reducing linear dependence (Farlow 1984).

b. *GMDH variations and the ALN approach*

The original GMDH algorithm has been subject to many variations in the methods used for estimating the partial descriptor functions and in the choice of decision rules for descriptor selection and criteria for stopping the iterations. Optimized polynomials as well as different descriptor functions have been used. The external regularity criterion for selection and stopping required the splitting of the training data available into two sets, which reduces the amount of data available for estimation. Moreover, results depend on the way the data was divided and some splitting heuristics and cluster analysis were often required (Barron et al. 1984). A number of methods have been proposed that operate on the whole training dataset for estimation, selection, and stopping, thus avoiding these limitations. GMDH-related activities in the United States have been generally identified as the adaptive learning network (ALN) approach (AIM being an example), which emphasized the use of the predicted squared error (PSE) criterion for selection and preventing model overfitting. The PSE criterion minimizes the expected error that would be obtained when the network is used for predicting new data, which are different from those used during training (Barron 1984). For example, AIM expresses the PSE as

$$\mathrm{PSE} = \mathrm{FSE} + \mathrm{CPM}\left(\frac{2k}{n}\right)\sigma_p^2, \quad (4)$$

where FSE is the fitting squared error for the model on the training data, CPM is a complexity penalty multiplier selected by the user, k is the number of model coefficients, n is the number of samples in the training dataset, and σ_p^2 is a prior estimate for the variance for the error obtained with the true (unknown) model. This estimate does not depend on the model being evaluated and is usually taken as half the variance of the independent variable y (Barron et al. 1984). It is noted that as the model becomes more complex, relative to the size of the training set, the second term increases linearly while the first term decreases. Therefore, the PSE goes through a minimum at the optimum model size which strikes a balance between accuracy and simplicity (or exactness and generality). CPM has a default value of 1 in AIM. Lower values allow the synthesis of more complex models, while higher values allow simpler ones.

c. *Weather applications of GMDH-type algorithms*

Various forms of GMDH and ALN models have been used in a wide range of applications, including signal and image processing (Barron et al. 1984), economics and financial modeling (Nomura 1984 and Scott and Hutchinson 1984), environmental and ecological studies (Fujita and Koi 1984), as well as weather forecasting. GMDH was used for modeling seasonal

(May–September) precipitation for four regions in Canada over the period 1948–1976, and the results were compared with a linear regression model based on seasonal persistence (Lebow et al. 1984). While the regression model tended to track about the mean, GMDH was shown to identify some structure, which is different from seasonal persistence, thus giving improved tracking performance. Both models were used to estimate the 1977 data. Taken as the average for the four regions, GMDH error for this estimate was 7%, while that for the regression model was 18%. The latter error was not much different from that for an estimate based on the climatic mean. The same authors used GMDH for the more global problem of forecasting monthly and seasonal averages of 700-mbar geopotential height fields over the Northern Hemisphere. It was found that both the regression and GMDH models were inferior to persistence in this case. However, the poor GMDH performance reported was attributed to the data reduction technique used, rather than to GMDH shortcomings (Lebow et al. 1984). A GMDH-type algorithm was used to model and predict typhoon rainfall, and the results were compared with those of a physical model (Ikeda 1984). GMDH had the advantages of simplicity, short computation times, and applicability to limited data sizes, though the physical model more effectively explained the physical properties of the modeled phenomenon.

d. The AIM modeling tool

AIM is a supervised inductive machine-learning tool for automatically synthesizing abductive network models from a database of input and output values that represent a training set of example situations. It draws on developments in neural networks, abductive networks (Montgomery and Drake 1990), and algebraic modeling techniques. However, its use of the PSE modeling criterion makes it closely associated with the ALN approach, which, in turn, has its roots in GMDH. A typical AIM network is shown in Fig. 1. The network is a layered structure of functional elements (nodes) represented by rectangles in the figure. There is no feedback within or between the various layers—that is, the network is of the feed-forward type. Elements in the first layer operate on various combinations of the independent input variables (x's) and the single element in the final layer produces the predicted output for the dependent variable y. In addition to the functional elements in the main layers of the network, there is an input layer of normalizers, which convert the input variables into an internal representation with zero mean and unity variance (Abtech 1990), and an output layer of unitizers for restoring the results to the original problem space. Each layer can be considered as the result of a main iteration in the GMDH algorithm, and the various types of functional elements are forms of optimized polynomials. Both the element type and

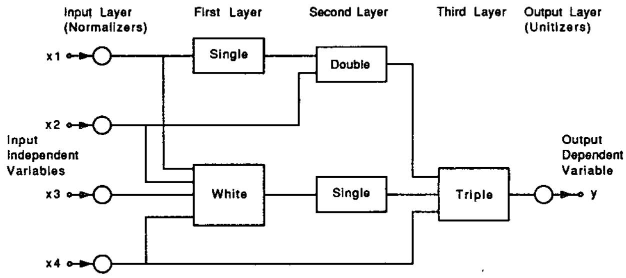

FIG. 1. A typical AIM network structure showing the various types of functional elements.

the combination of inputs to it from all the previous layers are selected for best prediction performance according to the PSE criterion. Currently, AIM supports the following types of elements.

(i) A white element, which consists of a constant plus the linear weighted sum of all outputs of the previous layer; that is,

$$\text{“White” Output} = W_0 + W_1x_1 + W_2x_2 + W_3x_3 + \cdots + W_nx_n, \quad (5)$$

where $x_1, x_2, \ldots, x_n$ are the inputs to the element and $W_0, W_1, \ldots, W_n$ are the element coefficients.

(ii) Single, double, and triple elements, which implement a third-degree polynomial expression with all possible cross-terms for one, two, and three inputs, respectively; for example,

$$\text{“Double” Output} = W_0 + W_1x_1 + W_2x_2 + W_3x_1^2 + W_4x_2^2 + W_5x_1x_2 + W_6x_1^3 + W_7x_2^3. \quad (6)$$

AIM synthesizes networks layer by layer until no further improvement in performance is possible or a preset limit on the number of layers is reached. Within each layer, every element is computed and its performance scored for all combinations of allowed inputs. The best network structure, element types and coefficients, and connectivity are all determined automatically by minimizing the PSE modeling criterion [Eq. (4)]. This selects the most accurate model that does not overfit the training data, and therefore strikes a balance between the accuracy of the model in representing the training data and its generality, which allows it to fit yet unseen future data. In this way we optimize the model for the actual use for which it is developed, rather than simply at the training stage. The user may optionally control this trade-off between accuracy and generality using the CPM parameter. Larger values than the default value of 1 lead to simpler models that are less accurate but are more likely to generalize well with unseen data, whereas lower values produce more complex networks that overfit the training data and can therefore degrade prediction performance with noise.

Compared with the alternative self-organizing approach based on neural networks, AIM has the advantage that model synthesis is highly automated through the use of well-proven optimization criteria, and therefore requires little or no user intervention. This makes AIM much easier to use and considerably reduces the learning/development time and effort compared to neural networks. With the neural network approach the user has to experiment with various architectures. For example, there are no hard and fast design rules to determine the optimum number of hidden layers or the number of neurons in each layer. These parameters strongly influence network performance, and often a number of possibilities have to be tried in search of the best combination. In forecasting minimum temperature with a back propagation neural network, Schizas et al. (1991) report results from 13 models with different network architectures and different input weather parameters, for which the ±3°C forecasting yield varied over the range 42%–68%. A first-shot AIM network with the *default* values for the AIM parameters and automatic selection of the relevant weather parameters achieved a yield of 93% (Abdel-Aal and Elhadidy 1994). A comparison between the performance of an AIM model developed for a given problem using default settings and that of the best back propagation network reveals that AIM is more accurate (giving about one-fourth the average error) and is also much faster (Montgomery and Drake 1990). Whereas the processing elements in neural networks are restricted by the neuron analogy, AIM builds networks of various types of functional numerical elements based on utility. Because it is not limited by the binary nature of the neuron output, AIM is more comfortable in handling applications accurately. For example, in the ANN application by Schizas et al. (1991), each value for the output temperature is represented by a neuron in the output layer. For the temperature range of −5°C to +15°C, the resolution is limited to 0.5°C to restrict the number of output neurons to 40, since larger networks for improved resolution or wider range would increase the training time. It is obvious that the AIM modeling approach does not suffer from such limitations. The large speed improvement over neural networks, as well as the ability of AIM to encode networks as C subroutines, make it more appropriate for applications where prediction/forecasting needs to be performed in real time.

Databases of training/evaluation examples can be entered into AIM manually or imported as ASCII text files produced by other applications. A network is then synthesized automatically using the training data, with the possibility of some fine tuning by the user, if so desired, through the choice of the CPM and a few other parameters (Abtech 1990). Once generated, the network may be evaluated using an independent set of data. To obtain good AIM models, it is important to ensure that the training set is a good representation of the problem space. For instance, training examples of meteorological data derived from only one season would not produce an adequate module for use over the whole year. Uniform random splitting of a database into two separate sets for training and evaluation is a common practice. AIM's learning task is simplified by breaking the problem into smaller and more manageable assignments and by imparting any human knowledge on relationships underlying the problem being considered in the choice of input parameters presented to AIM as training data (AbTech 1990). For example, if the underlying relationship being modeled is known to depend on the ratio of two input parameters, then it helps to use this ratio explicitly as an input parameter during training.

3. AIM modeling of the maximum temperature

AIM was used to model the relationship between the maximum daily temperature on a given day and the other 17 daily meteorological and radiation parameters measured at the RI Meteorological Station on the same day. Generally, this is a useful approach for identifying weather parameters that are most influential in determining a given parameter. Another area of application is the filling-in of data missing for some weather parameters—for example, as a result of instrument failure—by using data available for other parameters. The 18 daily parameters recorded by the RI station are listed in Table 1. Physical quantities required for deriving these parameters are recorded once per minute and, where applicable, the hourly minimum, maximum, and mean values for the measured quantity are computed and recorded. The daily parameters, for example, TAN, TAX, and TA for the air temperature, are derived from the hourly data. The

TABLE 1. List of the 18 daily weather parameters recorded at the RI meteorological station.

Serial number	Symbol	Description	Unit
1	TAX	Maximum air temperature	°C
2	TA	Mean air temperature	°C
3	TAN	Minimum air temperature	°C
4	WSX	Maximum wind speed	m s^{-1}
5	WS	Mean wind speed	m s^{-1}
6	WSN	Minimum wind speed	m s^{-1}
7	WSV	Wind speed vector	m s^{-1}
8	WD	Wind direction	°
9	BPX	Maximum barometric pressure	mmHG
10	BP	Mean barometric pressure	mmHG
11	BPN	Minimum barometric pressure	mmHG
12	RHX	Maximum relative humidity	%
13	RH	Mean relative humidity	%
14	RHN	Minimum relative humidity	%
15	PWD	Prevailing wind direction	see text
16	NHP	Number of hours in PWD	hours
17	DMW	Direction of maximum wind	°
18	THR	Mean global solar radiation	W-day m^{-2}

mean air temperature TA is calculated as the average of the 24 h mean values. The PWD parameter was encoded as an integer (1–16), indicating 1 of 16 22.5°-sectors with sector 1 centered on the north direction. The predicted value of the maximum temperature is designated TX, while TAX is the measured maximum temperature. The prediction error E is the difference (TAX − TX). For quantitative evaluation of the AIM models, we use a set of seven statistical parameters defined in Table 2.

The 365 daily observations in 1987 were randomly split into 300 observations used to train the AIM network and 65 observations, which served as an independent dataset for evaluating the resulting model. Evaluations were also performed using 1988 data. Throughout this paper, NT and NE designate the numbers of the training and evaluation observations, respectively. The TAX column in the training database was designated as output, while those for all the other 17 parameters were declared as inputs. The 1-layer 5-input network obtained using the default value CPM = 1.0, with no restrictions imposed on AIM in the selection of relevant model parameters, is shown at the top of Fig. 2a. Network synthesis took about 30 min on a Macintosh II computer. Substituting into the expressions for the various functional elements of the network using the symbolic processor of Mathcad 3.1 produces the following model relationship:

$$\mathrm{TX} = 2.247 + 1.856\mathrm{TA} - 0.833\mathrm{TAN} - 6.909 \times 10^{-2}\mathrm{WS} + 4.788 \times 10^{-2}\mathrm{RH} - 6.617 \times 10^{-2}\mathrm{RHN}. \quad (7)$$

Using a smaller value for the CPM parameter allows AIM to synthesize more complex models if this can lead to improvements in the estimated prediction performance. For a given training dataset, increased model complexity with lower CPM values generally indicates that the modeling process could do with more training examples than those currently available. AIM attempts to compensate for the shortage in the number of training examples by resorting to more complex relationships. Using CPM = 0.5 with NT = 300 produces the 2-layer 9-input network shown at the bottom of Fig. 2a. In addition to 4 new input parameters, the triple element introduced as the second layer produces third-order nonlinearities in the new model. Models were also constructed using the complete set of 365 observations for 1987. The resulting models are shown in Fig. 2b for CPM = 1.0 and CPM = 0.5. With the larger training dataset, the reduction in the value of the CPM parameter had only the minor effect of introducing one additional input parameter, with no change in the network structure. The model relationship with NT = 365 and CPM = 1.0 is

TABLE 2. List of the statistical parameters used for evaluating the prediction and forecasting performance of the AIM daily temperature models.

Symbol	Description	Unit
MAE	Mean of the absolute error |TAX − TX|	°C
ESD	Standard deviation of the absolute error |TAX − TX|	°C
MGE	Mean of the algebraic error (TAX − TX)	°C
MXE	Signed maximum of the absolute error |TAX − TX|	°C
H_d	Percentage hit number with |TAX − TX| ≤ 1.5 °C	%
H_c	Percentage hit number with |TAX − TX| ≤ 3 °C	%
LE	Percentage number of large errors with |TAX − TX| ≥ 6 °C	%

$$\mathrm{TX} = -43.953 + 1.860\mathrm{TA} - 0.801\mathrm{TAN} - 6.024 \times 10^{-2}\mathrm{WS} + 6.044 \times 10^{-2}\mathrm{BP} + 4.921 \times 10^{-2}\mathrm{RH} - 6.695 \times 10^{-2}\mathrm{RHN}. \quad (8)$$

The resulting networks were evaluated using independent observations (i.e., different data from those used for synthesis). AIM runs the network through the evaluation data and generates a report listing the individual expected and estimated values and the corresponding error, as well as a statistical summary. These data were exported to Mathcad 3.1 for further analysis and plotting. The values of the statistical error parameters MAE, ESD, MGE, and MXE were computed, and histograms for the prediction errors at 0.5°C error intervals were used to determine the values of H_d, H_c, and LE. Models constructed with NT = 365 (1987 data) using CPM = 1.0 and CPM = 0.5 were evaluated using NE = 364 of 1988 data. Figure 3 is a plot of the measured and predicted values (CPM = 1.0) for the maximum temperature over the year 1988. Table 3 lists the statistical parameters for the results, together with the data obtained for the corresponding minimum temperature models. In all cases listed in the table, no errors were observed in the large errors category of ±6°C; that is, LE = 0 and is not listed in the table. The table shows that the prediction error in the maxima is within ±3°C for 97% of the evaluation dataset. Bearing in mind the definition of the error E, figures for both the MGE and the MXE errors suggest that, on average, maxima tend to be overestimated by the AIM models while minima tend to be underestimated. The results show a small improvement in performance with the lower CPM value, but the gain may be too little to justify the added model complexity. However, the adequate performance with the more complex models is an indication of the good quality of the training weather data. This is because complex networks, being more closely attached to the training data, could model large error or noise components, leading to large prediction errors when used with independent evaluation data.

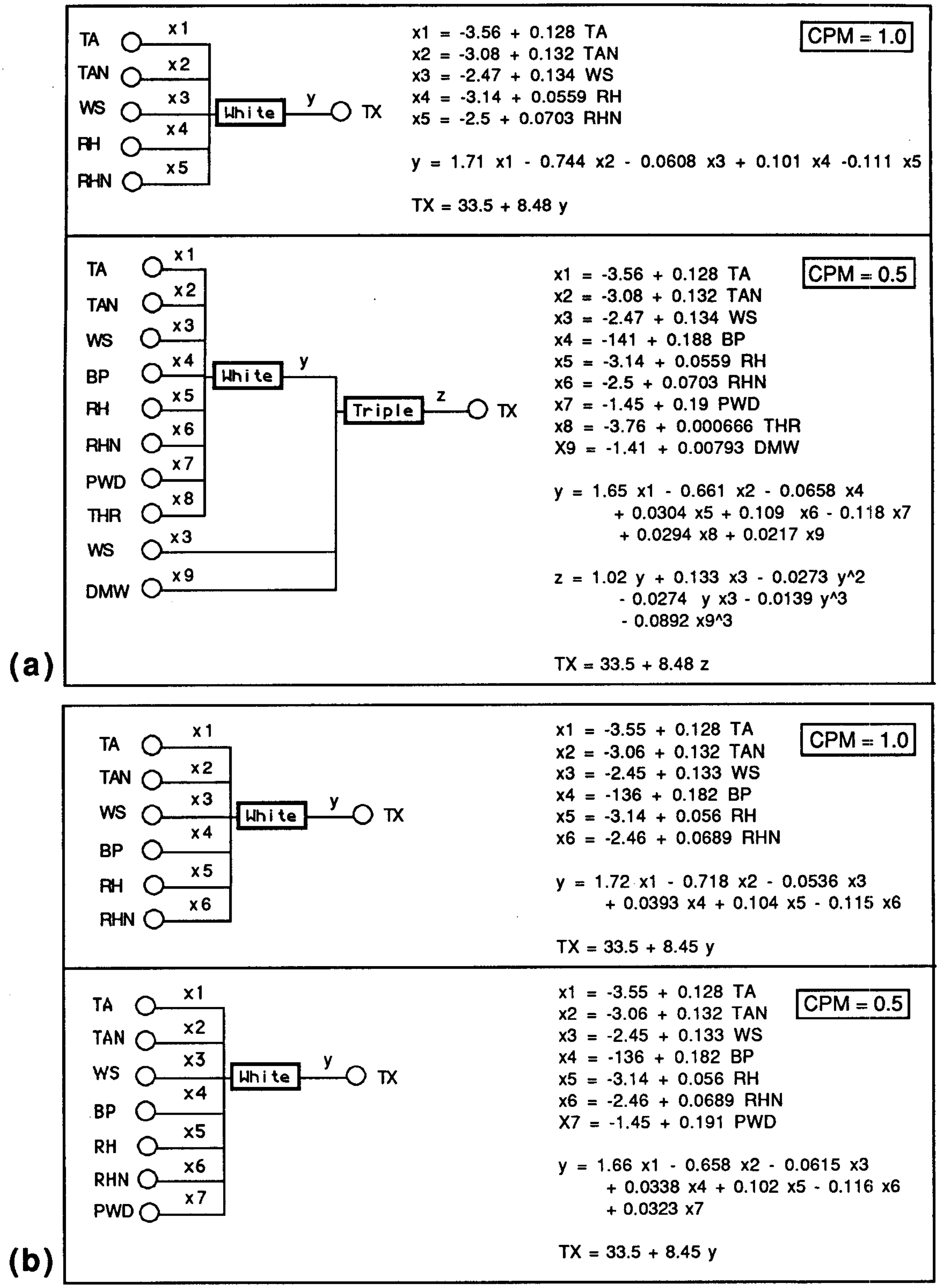

FIG. 2. AIM networks synthesized for modeling the maximum temperature in terms of other weather parameters on the same day for two values of CPM. Training on 1987 data with no restrictions on the selection of model parameters by AIM: (a) NT = 300, (b) NT = 365.

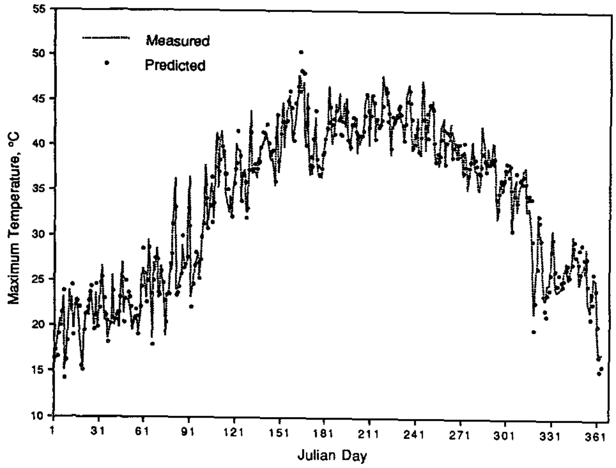

FIG. 3. Predicted and measured maximum temperatures vs the Julian day in 1988. The model is generated with NT = 365 (1987 data) and CPM = 1.0.

Therefore, the small errors obtained with complex models suggest low noise and error components in the data used. The table also indicates that minimum temperature models are superior to those for the maximum temperature on almost all scores. For example, with CPM = 1.0 the H_d value (percentage of errors $\leq$1.5°C) for the minima forecasts is 87% versus 79% for the maxima.

It is noted that TAX models synthesized by AIM are more complex than is suggested by the basic relationship TX = 2TA − TAN, which holds if TA was determined as the simple average of TAX and TAN for each record in the training dataset. Because TA is determined differently, as described at the beginning of this section, the model contains other weather parameters, though still dominated largely by TA and TAN. AIM allows the exclusion of any of the input variables from contributing to model synthesis by simply declaring it as "ignored" in the training database. If TA and TAN are the only parameters allowed to take part in model synthesis, the prediction accuracy of TX to ±1.5°C experiences a large drop from 79.4% to 64.8% with CPM = 1.0. If only the minimum temperature TAN is excluded, other parameters come into play and an accuracy as high as 77.7% is maintained. This shows the usefulness of the technique in filling up missing data records for parameters such as TAX using available data for other parameters even if critical temperature data, such as TAN, are also missing. An AIM model was also developed for predicting TX with all the 3 temperature parameters (TAX, TA, and TAN) barred from contributing to the model. Under such conditions with CPM = 1, AIM produced a 7-input 3-layer model with a triple element in each layer. The input parameters selected by AIM are BP, BPN, THR, WS, RHN, PWD, and NHP. This model predicts TX with an average absolute error of 2.8°C and a ±3°C yield of 66%.

Table 4 compares the model structures obtained for both the maximum and minimum temperatures using two values of NT and CPM values of 1.0 and 0.5. Using NT = 300, the reduction in CPM leads to a two-layer nonlinear model for the maximum temperature (Fig. 2a), while this does not change the one-layer linear structure of the minimum temperature model, where only the number of input parameters is increased from 3 to 6. Using NT = 365, the linear model for the maximum temperature is preserved with the reduction in CPM. It is seen that maximum temperature models are relatively more complex and require somewhat larger training datasets and, as seen from Table 3, their performance is slightly inferior to models derived for the minimum temperature. This supports the comment by Klein and Hammons (1975) that maxima tend to be more sensitive to broadscale circulation and less sensitive to local conditions than minima, and therefore would generally be more difficult to model accurately with only local weather parameters.

4. Forecasting the maximum temperature

A number of AIM models were developed for forecasting future values of the daily maximum temperature over a period of three days following the present day. This section describes these forecasting models and presents results on their performance.

a. *The 1-day-to-3-days model*

With this model, all 18 weather parameters available for the present day (d), are inputs to

TABLE 3. Performance comparison between two AIM models of different complexity for the maximum and minimum temperatures. Models synthesized on full data for 1987 are evaluated on full data for 1988.

AIM Model NT = 365 (1987) NE = 364 (1988)	CPM value	Mean absolute error MAE, °C	Standard deviation of absolute error ESD, °C	Mean algebraic error MGE, °C	Percentage of hits $\lvert E\rvert \leq 1.5$ °C H_d, %	Percentage of hits $\lvert E\rvert \leq 3$ °C H_c, %	Maximum error MXE, °C
Maximum temperature	1.0	0.97	1.26	−0.093	79.4	97.0	−5.39
(TAX)	0.5	0.93	1.22	−0.080	79.9	97.8	−5.80
Minimum temperature	1.0	0.79	1.00	0.130	86.8	99.2	4.43
(TAN)	0.5	0.77	0.98	0.044	88.7	99.5	4.25

TABLE 4. Comparison of the structures of AIM model obtained for the maximum and minimum temperatures using two values for NT and CPM, with no restrictions on the selection of model parameters by AIM.

		Maximum temperature (TAX) models			Minimum temperature (TAN) models		
Number of training examples, NT (1987)	CPM value	Number of layers	Number of input parameters selected	Overall model relationship	Number of layers	Number of input parameters selected	Overall model relationship
300	1.0	1	5	linear	1	3	linear
	0.5	2	9	third order	1	6	linear
365	1.0	1	6	linear	1	4	linear
	0.5	1	7	linear	1	6	linear

the network synthesis procedure. Outputs are the maximum temperature recorded on the following three successive days. Shown below is a representation of a data record for one training observation:

Inputs	Outputs
TAX(d) TA(d)	TAX(d + 1) TAX(d + 2)
TAN(d) WSX(d)	TAX(d + 3);
. . . . NHP(d)	d = 1, 2, · · ·, 362.
DMW(d) THR(d)	

This arrangement allows a maximum of 362 training examples to be derived from the full dataset for 1987. AIM synthesizes a network for each variable declared as output in the training database. Figure 4 shows the networks generated for the three forecast outputs using the default value of CPM = 1.0. It is noted that model complexity increases for forecasting beyond the first day. Using CPM = 1.0, the eight-term model relationship for the first day is given by

$$\begin{aligned} \mathrm{TX}(\mathrm{d}+1)|_{1-3} &= 7.592 + 1.063\mathrm{TA}(\mathrm{d}) \\ &- 0.181\mathrm{TAN}(\mathrm{d}) - 4.959 \times 10^{-2}\mathrm{WSX}(\mathrm{d}) \\ &- 4.453 \times 10^{-2}\mathrm{WS}(\mathrm{d}) - 3.909 \times 10^{-2}\mathrm{RH}(\mathrm{d}) \\ &+ 3.958 \times 10^{-2}\mathrm{RHN}(\mathrm{d}) + 7.642 \times 10^{-4}\mathrm{THR}(\mathrm{d}). \end{aligned} \tag{9}$$

One-day forecasts using the MOS approach have also employed eight-variable MOS equations (seven predictors plus a constant) (Woodcock 1984), though not necessarily using the same AIM predictors of Eq. (9). As seen from Fig. 4, the complete model for 3-day forecasting requires knowledge of 9 weather parameters including the global solar radiation and the prevailing wind direction. To minimize the number of weather parameters needed for forecasting, we investigated the use of models that require only one parameter but use history data for that parameter to achieve adequate forecasting accuracy. When forecasting the maximum temperature TX, an obvious contender for the input parameter is the maximum temperature itself (TAX). With the strong correlation between the maximum and mean temperatures on the same day, as indicated by Eqs. (7) and (8), TA also appears to be a good choice. Models were developed that forecast future values of TAX for three consecutive days following the present day from values of the input parameter on a number of days (including the present day). These are described in the following two sections.

b. The 3-days-to-3-days models

These models forecast future values of TX for three consecutive days following the present day (d) from values of the input parameter (TAX or TA) on the three days (d − 2), (d − 1), and (d); that is, two preceding days plus the present day. Therefore, the database of training examples contains six columns as shown below for the model using TA:

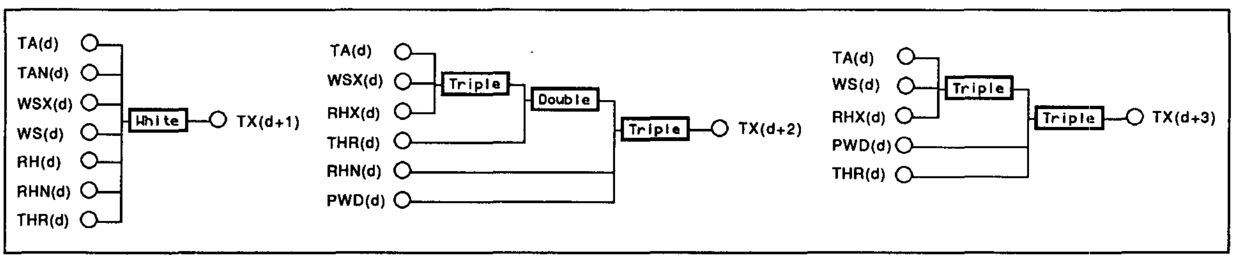

FIG. 4. AIM networks synthesized for 3-day forecasting of the maximum temperature using the 1-day-to-3-days model. Training on 1987 data: CPM = 1.0. NT = 362.

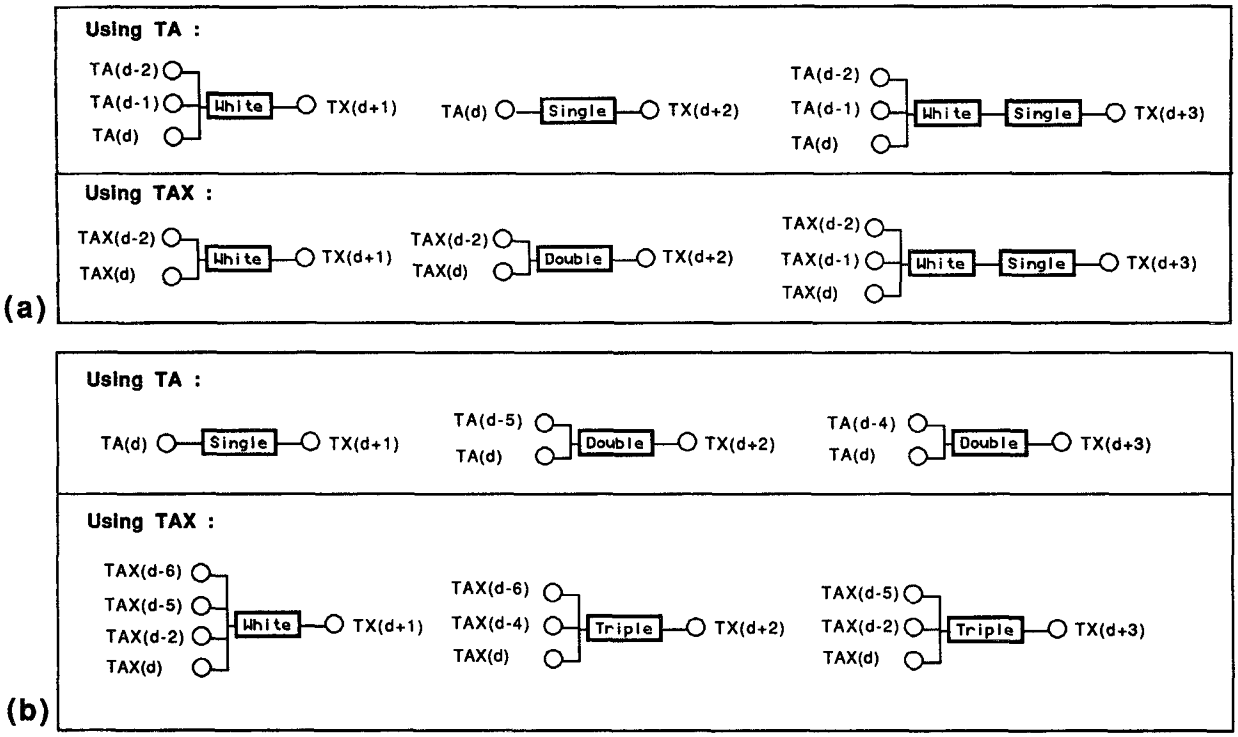

FIG. 5. AIM networks synthesized for 3-day forecasting of the maximum temperature using models based on the past history of TA and TAX. Training on 1987 data, CPM = 1.0, NT = 360: (a) The 3-days-to-3-days model, (b) the 7-days-to-3-days model.

Inputs	Outputs
TA(d − 2) TA(d − 1)	TAX(d + 1) TAX(d + 2)
TA(d)	TAX(d + 3);
	d = 3, 4, · · ·, 362.

This arrangement allows a maximum of 360 training examples from the 1987 data. The networks generated

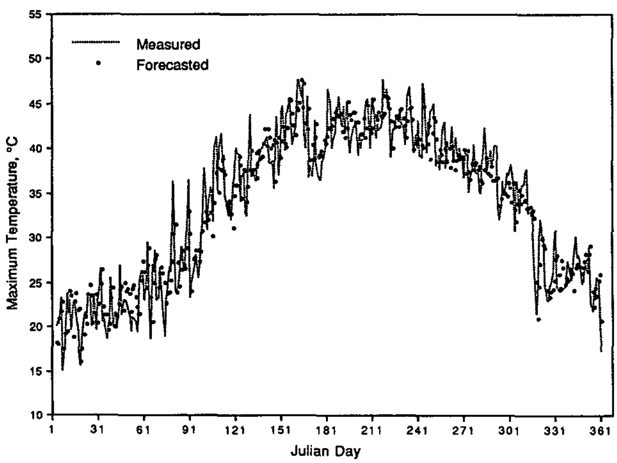

FIG. 6. Forecasted and measured maximum temperatures for the first forecasting day vs the Julian day in 1988. Forecasting model: 3-days-to-3-days using TA. The evaluation uses 359 examples of 1988 data.

for the three outputs TX(d + 1), TX(d + 2), and TX(d + 3) are shown in Fig. 5a for the models based on TA and TAX. For both model types, the forecast for the first day is simply a linear function of the input parameters, but model complexity increases for forecasting further into the future. Model relationships for the first forecasting day are

$$\mathrm{TX}(d+1)|_{3-3(\mathrm{TA})} = 5.243 + 0.272\mathrm{TA}(d-2) - 0.589\mathrm{TA}(d-1) + 1.339\mathrm{TA}(d) \quad (10)$$

$$\mathrm{TX}(d+1)|_{3-3(\mathrm{TAX})} = 1.457 + 0.215\mathrm{TAX}(d-2) + 0.743\mathrm{TAX}(d). \quad (11)$$

c. The 7-days-to-3-days models

These models forecast future values of TX for three consecutive days following the present day (d) from values of the input parameter (TAX or TA) on the seven days (d − 6), (d − 5), . . . , (d − 1), and (d); that is, six preceding days plus the present day. Therefore, the database of training examples contains 10 columns as shown below for the model using TA:

Inputs	Outputs
TA(d − 6) TA(d − 5)	TAX(d + 1)
TA(d − 4) TA(d − 3)	TAX(d + 2)
TA(d − 2) TA(d − 1)	TAX(d + 3);
TA(d)	d = 7, 8, · · ·, 362.

TABLE 5. Performance comparison of the five forecasting models using two values for the CPM parameter for each of the three forecasting days.

Forecasting day	Model type	NT (1987)	NE (1988)	CPM value	Mean absolute error MAE, °C	Standard deviation of absolute error ESD, °C	Mean algebraic error MGE, °C	Percentage of hits $\lvert E\rvert \leqslant 1.5$ °C H_d, %	Percentage of hits $\lvert E\rvert \leqslant 3$ °C H_c, %	Percentage of large errors $\lvert E\rvert \geqslant 6$ °C LE, %
Day d + 1	1-day-to-3-days	362	361	1.0	2.07	2.58	−0.361	44.3	75.9	2.8
				0.5	2.04	2.60	0.007	44.0	78.1	1.7
	3-days-to-3-days									
	Using TA	360	359	1.0	2.10	2.65	0.08	42.9	76.6	3.3
				0.5	2.06	2.61	0.054	44.3	75.8	3.1
	Using TAX	360	359	1.0	2.16	2.83	0.008	44.0	73.5	3.1
				0.5	2.11	2.76	0.041	46.0	76.0	3.9
	7-days-to-3-days									
	Using TA	356	355	1.0	2.19	2.77	0.20	43.1	69.3	3.4
				0.5	2.15	2.70	0.12	42.0	72.1	3.1
	Using TAX	356	355	1.0	2.11	2.76	0.028	46.8	74.4	3.4
				0.5	2.18	2.84	0.078	41.7	73.2	4.2
Day d + 2	1-day-to-3-days	362	361	1.0	2.77	3.45	0.238	32.4	60.9	8.0
				0.5	2.81	3.52	0.206	33.8	60.7	8.6
	3-days-to-3-days									
	Using TA	360	359	1.0	2.61	3.34	0.245	37.9	64.3	7.0
				0.5	2.52	3.22	0.058	37.6	65.8	6.1
	Using TAX	360	359	1.0	2.65	3.38	0.05	36.5	63.8	7.3
				0.5	2.69	3.44	0.123	36.8	64.1	8.1
	7-days-to-3-days									
	Using TA	356	355	1.0	2.43	3.15	0.075	38.3	67.3	7.6
				0.5	2.53	3.28	0.144	37.7	67.6	7.0
	Using TAX	356	355	1.0	2.51	3.30	0.074	41.1	68.7	6.0
				0.5	2.61	3.42	0.088	39.2	65.9	8.7
Day d + 3	1-days-to-3-days	362	361	1.0	2.83	3.52	0.482	31.3	61.5	10.2
				0.5	2.80	3.53	0.136	30.2	62.0	8.0
	3-days-to-3-days									
	Using TA	360	359	1.0	2.55	3.33	0.248	39.0	67.4	7.5
				0.5	2.65	3.41	0.054	35.4	63.2	5.6
	Using TAX	360	359	1.0	2.75	3.50	0.281	34.0	63.2	11.1
				0.5	2.85	3.59	0.234	31.5	60.7	9.7
	7-days-to-3-days									
	Using TA	356	355	1.0	2.46	3.22	0.117	42.5	67.6	6.8
				0.5	2.63	3.41	0.167	36.9	64.5	6.8
	Using TAX	356	355	1.0	2.56	3.39	0.085	40.3	66.8	7.9
				0.5	2.62	3.39	0.068	38.0	65.6	7.9

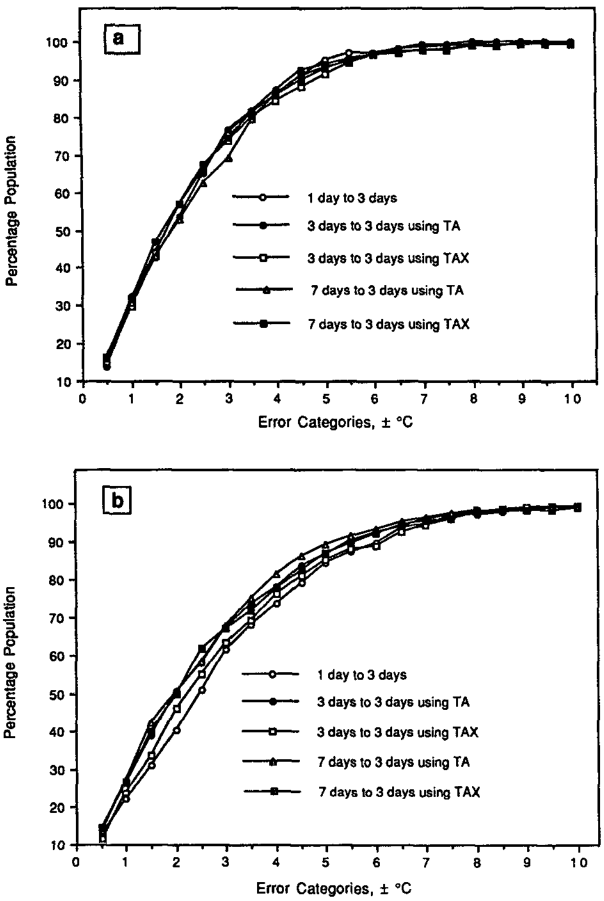

FIG. 7. Comparison of the performance of the five models for maximum temperature forecasting (shown in Figs. 4 and 5). (a) For the first forecasting day. (b) For the third forecasting day. The evaluation uses maximum possible number of examples of 1988 data.

This arrangement allows a maximum of 356 training examples from the 1987 data. The networks generated for the three outputs TX(d + 1), TX(d + 2), and TX(d + 3) are shown in Fig. 5b for the models based on TA and TAX. The model using TA is nonlinear for all three forecasting days, while that using TAX introduces nonlinearities only on the second day. Model complexity increases as the forecasting lead time increases, with a change in the model structure after the first day. Although models for the last two days have the same structure, inspection of relationships for the functional elements shows that the significance of nonlinear terms increases with increased lead time. The value of the input parameter at the present day (d) appears in all the resulting models and has the largest linear coefficient. As the lead time increases, the effect of more recent days increases. With CPM = 1.0, model relationships for the first forecasting day are

$$\mathrm{TX}(d+1)|_{7-3(\mathrm{TA})} = 18.688 - 0.547\mathrm{TA}(d) + 5.833 \times 10^{-2}[\mathrm{TA}(d)]^2 - 6.936 \times 10^{-4}[\mathrm{TA}(d)]^3, \quad (12)$$

$$\mathrm{TX}(d+1)|_{7-3(\mathrm{TAX})} = 1.062 + 0.102\mathrm{TAX}(d-6) + 9.690 \times 10^{-2}\mathrm{TAX}(d-5) + 0.111\mathrm{TAX}(d-2) + 0.662\mathrm{TAX}(d). \quad (13)$$

d. Performance of the forecasting models

Forecasting models synthesized with 1987 data were evaluated using the maximum number of observations that can be derived from 1988 data for each model type. Figure 6 is a plot of both the measured and forecasted maximum temperature on the first forecasting day for the 3-days-to-3-days model using TA. The plot shows inferior accuracy compared with that of Fig. 3 for modeling TAX using other parameters on the same day. Table 5 lists values for some of the statistical parameters introduced in section 3 (Table 2) for the three forecasting days d + 1, d + 2, and d + 3 using the five forecasting models described above, each with two values for the CPM parameter. For the first forecasting day (d + 1), the 3-days-to-3-days model using TA gives a mean absolute error of 2.1°C, an H_c hit number of about 77%, and an LE number of 3.3%. The corresponding values obtained for the minimum tempera-

TABLE 6. List of the statistical parameters used to compare AIM forecasts with official MEPA forecasts.

Symbol	Description	Unit
B	Mean bias, B = Mean of forecasts (TX) − mean of observed (TAX) = −MGE in Table 2	°C
SDD	Standard deviation difference, SSD = standard deviation of observed (σ_0) − standard deviation of forecasts (σ_f)	°C
MAE	Mean absolute error, as in Table 2	°C
MSE	Mean of the squared error $(\mathrm{TAX} - \mathrm{TX})^2$	$°\mathrm{C}^2$
—	Percentage number with absolute error $\lvert\mathrm{TAX} - \mathrm{TX}\rvert \geq 3$ °C	%
—	Percentage number with absolute error $\lvert\mathrm{TAX} - \mathrm{TX}\rvert \geq 6$ °C	%
r	Correlation between forecasts and observed (Woodcock 1984) Larger for better forecasts $r = (\sigma_0^2 + \sigma_f^2 + B^2 - \mathrm{MSE})/2\sigma_0\sigma_f$	—
P	Priestley skill score (Priestley 1945)—Larger for better forecasts $P = 1 - (\mathrm{MSE}/\sigma_0^2)$	—

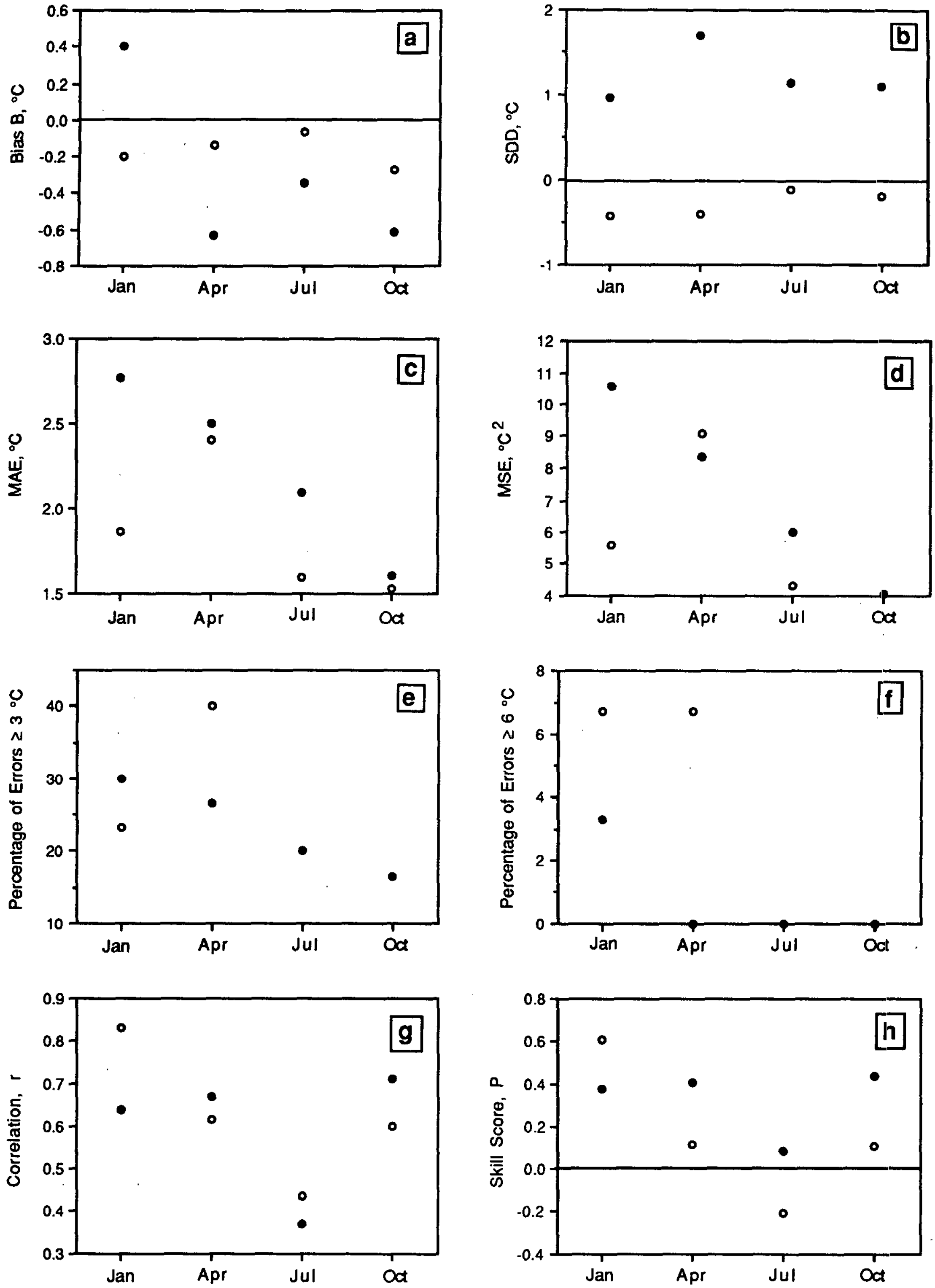

FIG. 8. Comparison between AIM (●) and official MEPA (○) forecasts for the four midseason months of 1993. AIM model: 3-days-to-3-days using TA, NT = 365 (1987), CPM = 1.0: (a) bias, (b) standard deviation difference, (c) mean absolute error, (d) mean square error, (e) percentage of errors ⩾ 3°C, (f) percentage of errors ⩾ 6°C, (g) correlation, and (h) Priestley skill score.

TABLE 7. Comparison of 3-day forecasts over the full year of 1988 using an AIM model and a simple persistence model. The AIM model: 3-days-to-3-days using TA, CPM = 1, based on 1987 data. The persistence model assumes that temperature on a given day persists for the following 3 forecast days.

Forecasting day	Forecasting model	Mean absolute error MAE, °C	Maximum error MXE, °C	Percentage of hits $\|E\| \leq 3$ °C H_c, %	Percentage of large errors $\|E\| \geq 6$ °C LE %
$d+1$	AIM	2.10	7.8	76.6	3.3
	Persistence	2.23	13.3	74.2	5.2
$d+2$	AIM	2.61	10.8	64.3	7.0
	Persistence	2.95	12.2	61.1	11.8
$d+3$	AIM	2.55	11.7	67.4	7.5
	Persistence	3.14	11.8	55.9	14.5

ture were 1.3°C, 92%, and 0.3%, respectively (Abdel-Aal and Elhadidy 1994). The inferior performance with the maximum temperature models again agrees with the suggestion that maxima are less amenable to modeling with local weather parameters than minima (Klein and Hammons 1975).

Table 5 shows that the five models give similar performance on the first forecasting day, with accuracy dropping sharply on the second day and very little difference between the second and third days. Variations in the performance of the models with CPM = 1.0 for different lead times is better illustrated in Fig. 7, which plots the cumulative percentage population of the 1-yr evaluation dataset versus the error category, for the first and the third forecasting days. For the first day, the model shows only small variations in performance with the 1-day-to-3-days model giving the best performance. On the third day, wider variations are visible. Having the largest amount of historical data, the 7-days-to-3-days model (using TA) gives the best performance. The 1-day-to-3-days model severely lacks in historical data, and therefore gives the poorest forecasting performance for this extended lead time.

1) COMPARISON WITH OFFICIAL FORECASTS

The quality of AIM forecasts made on the first day with the 3-days-to-3-days model using TA (synthesized using 1987 data) were compared with official forecasts issued for the Dhahran region by the Meteorology and Environmental Protection Administration (MEPA) for each of the midseason months (January, April, July, and October) of 1993. Eight statistical parameters were used, 7 of which have been used in a similar comparison between MOS and official forecasts for a number of Australian cities (Woodcock 1984). These parameters are listed in Table 6. MEPA bulletins are based on a day that starts at 0800 (local time), while that for the RI station starts at 0000 (local time). This can lead to differences between the observed temperature maxima. To avoid introducing these errors in the comparison, MEPA parameters were computed using the observed MEPA values and AIM parameters using the observed RI values. Other sources of error remain, since both the observed and forecasted MEPA maxima are given approximated to the nearest °C. Figure 8 plots the above 8 parameters for both AIM and MEPA forecasts. For the month of January, the official MEPA forecasts are better than AIM forecasts on almost all scores, the percentage of errors ≥6°C being the only exception. It is interesting to note that this has also been the case for the 7 parameters used to compare official forecasts with MOS forecasts by Woodcock (1984). The MEPA forecasts are generally better over all the four midseason months for the bias B, the standard deviation difference SDD, the mean algebraic error MAE, and the mean-squared error MSE. However, with the exception of the month of January, linear differences in the performance parameters for the two types of forecast are small and may be partially attributed to the approximate values issued in the MEPA bulletin and the different day definition in the two forecasting schemes. As indicated in Figs. 8e–h, AIM forecasts are better during the hotter seasons (April, July, and October) for the two percentage of errors parameters, the correlation r, and the Priestley skill score P, with the exception of July for r. For both the two forecasts, r and P exhibit a minimum at the hottest season, at which point the P parameter for the MEPA forecasts has a negative value.

2) COMPARISON WITH PERSISTENCE AND CLIMATOLOGY

AIM forecasts were also compared with forecasts based on persistence. Table 7 compares 1988 daily

TABLE 8. Comparison of monthly averages for TAX during 1988 based on measured data, AIM forecasts for the first forecasting day, and 27-year climatology data. Errors with measured averages are shown for both AIM and climatology. AIM model: 3-days-to-3-days model using TA, CPM = 1, based on 1987 data.

	Monthly average of daily maximum temperature, °C			Absolute error in monthly average, °C	
Month	Measured data	AIM forecast	Climatology data	AIM	Climatology
January	20.6	21	21	0.4	0.4
February	22	22.9	22	0.9	0.0
March	26.1	26.4	26	0.3	0.1
April	33.3	32.6	31	0.7	2.3
May	38.5	38.7	37	0.2	1.5
June	41.5	42.3	42	0.8	0.5
July	42.8	42.8	42	0.0	0.8
August	43	43.1	42	0.1	1.0
September	40.8	40	40	0.8	0.8
October	37.3	36.7	35	0.6	2.3
November	29.8	29.4	29	0.4	0.8
December	25.2	25.6	23	0.4	2.2
Average absolute error over the twelve months of 1988				0.5	1.1

forecasts made by the 3-days-to-3-days forecasting model using TA, based on 1987 data, with those of a simple persistence model that assumes that TAX on a given day remains unchanged for the following three consecutive days. AIM scores better on all the main statistical parameters as shown in the table. For the first forecasting day, AIM's maximum error is about 0.6 that of persistence and the number of days with large errors ($\geqslant 6°C$) over the year is only 12 days versus 19 days for persistence. As the forecasting lead time increases, AIM proves even better on the frequency of large errors and on the $\pm 3°C$ yield, while its advantage on the maximum error gradually decreases.

The performance of AIM forecasts for the same year and using the same model was also compared with simple forecasts that could be based on climatology data for the Dhahran region. Monthly averages for TAX based on measured data for 27 yr (1950 to 1976) (Williams 1979) were compared with the monthly averages measured for 1988 as well as the corresponding monthly averages obtained from the AIM forecasts for the first forecasting day. The results of the comparison are shown in Table 8. While the absolute error between monthly averages for measured and AIM-forecasted data does not exceed 0.9°C, it can be as high as 2.3°C for the climatology averages. On average for the 12 months of 1988, the error for the AIM model is approximately 0.5°C as opposed to 1.1°C for climatology.

5. Conclusions

AIM provides a fast, convenient, and accurate approach to the modeling and forecasting of weather data as judged by the present application to the daily maximum temperature at Dhahran. Optimum models are configured and their parameters determined automatically without the user having to experiment with various architectures and structures as in the case of the neural network approach. AIM network training is also much faster. These factors considerably reduce development time and effort and makes it feasible to implement both model synthesis and query in real time. Predictions with AIM models for the maximum temperature from other parameters on the same day give a 97% yield in the $\pm 3.0°C$ error category, whereas 1-day forecasts give a 77% yield. The latter value is considerably lower than the figure of 92% for the minimum temperature, which is believed to be more amenable to modeling with local conditions. It was found that more complex AIM models (CPM $<$ 1.0) give a slight improvement in the prediction/forecasting accuracy. This is a sign of the good quality of the weather data used, but the gain in accuracy may be too small to warrant the use of the more complex models in practical situations. The AIM forecasts described compare favorably with official, persistence, and climatology forecasts, and it is expected that the forecasting accuracy could be further improved using dedicated seasonal or even monthly models, at the expense of requiring more training data. Results with the minimum and maximum temperatures are encouraging, and we plan to extend the use of AIM to other weather parameters such as wind speed and direction. Earlier GMDH-type algorithms proved useful with precipitation, and AIM would therefore be expected to perform at least equally well.

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