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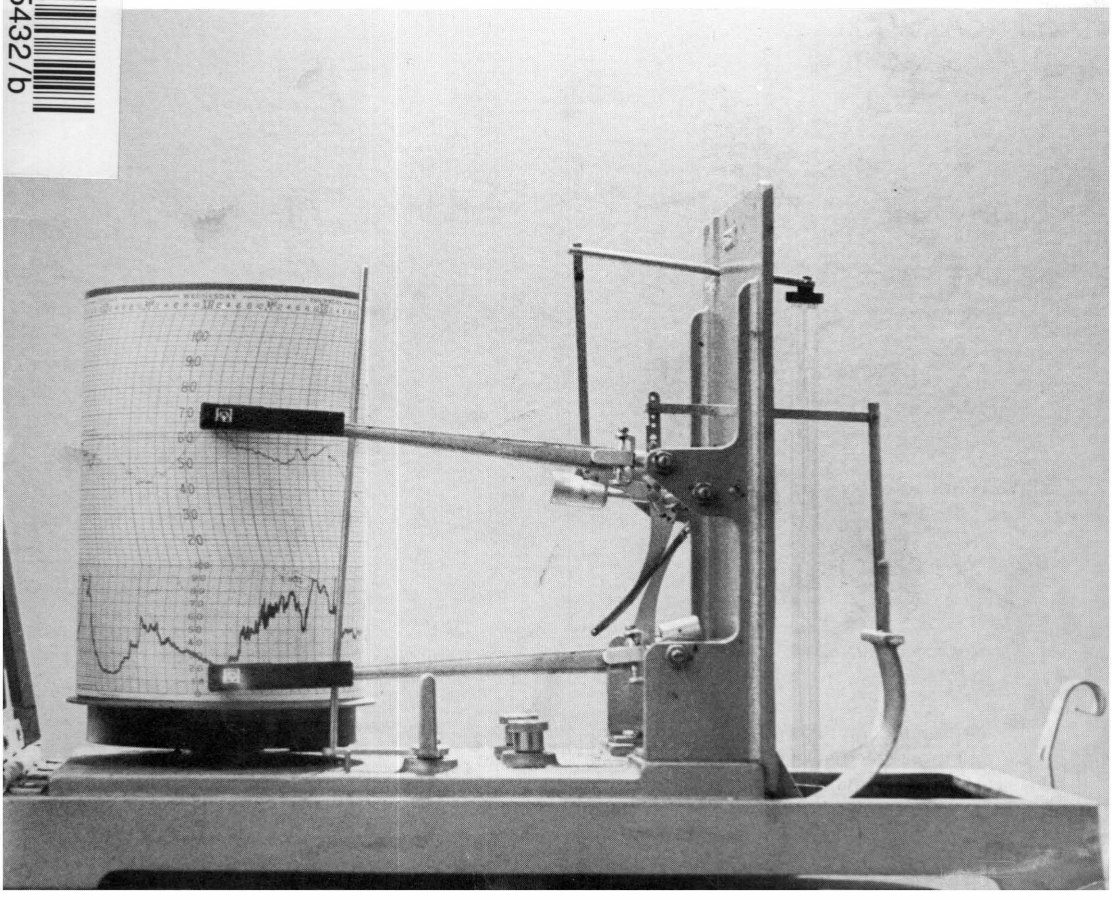

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The Virginia Agricultural and Mechanical College came into being in 1972 upon acceptance by the Commonwealth of the provisions of the Morrill Act of 1862 "to promote the liberal and practical education of the industrial classes in the several pursuits and professions of life." Research and investigations were first authorized at Virginia's land-grant college when the Virginia Agricultural Experiment Station was established by the Virginia General Assembly in 1886.

The Virginia Agricultural Experiment Station received its first allotment upon passage of the Hatch Act by the United States Congress in 1887. Other related Acts followed, and all were consolidated in 1955 under the Amended Hatch Act which states "It shall be the object and duty of the State agricultural experiment stations . . . to conduct original and other researches, investigations and experiments bearing directly on and contributing to the establishment and maintenance of a permanent and effective agricultural industry of the United States, including the researches basic to the problems of agriculture and its broadest aspects and such investigations as have for their purpose the development and improvement of the rural home and rural life and the maximum contributions by agriculture to the welfare of the consumer . . . ."

In 1962, Congress passed the McIntire-Stennis Cooperative Forestry Research Act to encourage and assist the states in carrying on a program of forestry research, including reforestation, land management, watershed management, rangeland management, wildlife habitat improvement, outdoor recreation, harvesting and marketing of forest products, and "such other studies as may be necessary to obtain the fullest and most effective use of forest resources."

In 1966, the Virginia General Assembly "established within the Virginia Polytechnic Institute a division to be known as the Research Division . . . which shall encompass the now existing Virginia Agricultural Experiment Station . . . ."

Computer Simulation of Hourly Dry-Bulb Temperatures

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Abstract

A computer model of hourly dry-bulb temperatures was developed for Blacksburg, Virginia, from a 9-year sample of hourly dry-bulb temperature data. The periodic variations over the course of a year were estimated by least-square approximation. A first order Markov chain model was used to simulate the stochastic nature of temperature. These two models were combined to simulate years of hourly dry-bulb temperatures.

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INTRODUCTION

Ambient air temperature is a fundamental requirement for many agricultural models. The characteristics of temperature have often been obtained, usually with considerable difficulty, from historical climatic records. Climatic records are often incomplete and hard to manipulate and incorporate into a model.

A procedure for estimating fan system duty factors was developed by Albright and Cole (1980). The yearly duty factor was dependent on the probability distribution of the ambient dry-bulb temperature. The frequency of occurrence for each possible temperature was determined. These frequencies acted as weighting factors to determine the contribution of each temperature to the total fan system duty factor. A dry-bulb temperature simulator would be useful for predicting the probability of occurrence of a high or low duty factor, which determines an economical fan design.

Hydrologic models that simulate the response of a watershed system include an algorithm to describe the soil-water balance of the area. Most mathematical descriptions of the soil-water balance require dry-bulb temperature to estimate potential evapotranspiration, which provides an upper limit to soil-water loss due to meteorological factors. A model for dry-bulb temperature can be used to generate repeated realizations of the potential evapotranspiration for a specified growing season and crop. By coupling the stochastic nature of evapotranspiration with the stochastic nature of rainfall, probability statements can be made with regard to the need for irrigation, allocation, and quantity.

The development of an hourly dry-bulb temperature simulator by regression and statistical techniques can provide an accurate and more versatile means for modeling agricultural systems. With the addition of a wet-bulb temperature model, the dry-bulb model may be applied to crop-drying simulations. Bunn (1982) developed a computer drying model for corn such that the drying front in the grain mass was animated on a cathode ray terminal (CRT), providing a continuous visual display of the state of the drying process. Each drying sequence required actual hourly pairs of dry-bulb temperature and relative humidity. With the addition of a humidity component to the dry-bulb model, a stand-alone graphic grain-drying simulation would be possible. Many possible drying realizations could then be viewed to assess the likelihood of various levels of damage due to different drying strategies.

LITERATURE REVIEW

Gringorton (1966) described the frequency and duration of temperature as well as other weather elements with a Markov chain model

$$y_{i+1} = \rho y_i + t_{i+1} \sqrt{1 - \rho^2} \tag{1}$$

where t_{i+1} is a standard normal deviate and ρ is the hour-to-hour correlation. The model assumes that the hourly values were standard normal, denoted by N(0,1), and that the correlation coefficients were constant with time. Monte Carlo simulation techniques were used to generate probability distributions of duration of the weather variations. Sharon (1967) showed that Gringorton's model tended to overestimate the duration of weather events.

Hansen and Driscoll (1977) developed a model that simulated mean hourly temperatures. A Fourier analysis was used to determine the parameters of the periodic variations associated with mean hourly temperature. The data base used for this analysis was the mean of 11 years of temperatures.

From the Fourier analysis, Hansen and Driscoll (1977) found that the first, 365th, 730th, and 1095th (yearly, daily, 12-hour, and 8-hour variations, respectively) harmonics accounted for 97 percent of the variance of the mean of the hourly temperatures. It should be noted, at this point, that most of the year-to-year hourly variation in temperature is removed by averaging, and hence a least-squares analysis of averaged data will, in general, produce different results than least-squares on the data itself. All other associated deterministic harmonics could be neglected while retaining a reasonably accurate model.

After modeling the deterministic course of the data, Hansen and Driscoll (1977) simulated the aperiodic (i.e., the residual temperatures) course with a Markov chain model. The same Markov chain model was employed by Gringorton (1966) in Equation 1. Assuming normality in the data, a stand-alone Markov chain model was found to insufficiently estimate the behavior of the residuals.

In order to adjust the stochastic model, Hansen and Driscoll (1977) investigated the time variation of the variance, skew, and serial correlation. The first order serial correlation was found to vary seasonally. The serial correlations ρ, used in Equation 1, were interpolated from serial correlation coefficients calculated for each month of the 11-year sample. The time dependence of the skew and variance was modeled by Fourier analysis. Thus, the total model could then be generated by transforming normally distributed temperatures into appropriately skewed distributions, taking into account the time dependence of variance and serial correlation.

METHODS

A dry-bulb temperature model was developed from hourly temperatures for Blacksburg, Virginia. A 9-year (1971-1979) developmental sample was used to derive the parameters for an equation which was subsequently used to generate hourly dry-bulb temperatures. A two-year period (1969-1970) not included in the developmental sample was used for an independent "check" of the model. The hourly temperatures were obtained by digitizing recorded charts* onto a cassette tape. Several short periods of data were missing as a result of a recorder malfunction. These missing periods were obtained from Crab Creek, near Christiansburg, Virginia, a site approximately eight miles from the Blacksburg recording site.

Temperature can be represented as a time series that is composed of deterministic and stochastic events. The deterministic event is composed of periodic components. The procedure in the development of this model was to extract these periodic components and consider them independently of the stochastic events.

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*The charts were recorded on a Belfont Hygrothermograph Model No. 5-594.

The simulated temperatures were generated by superimposing the stochastic model onto the deterministic model.

Spectral analysis was used to determine the periodic components of the deterministic part of the sample. Haan (1977) suggests that periodicities in data can be determined by analyzing the time series in the frequency domain. A spectral analysis partitions the variance of the sample time series into a number of intervals or bands of frequency. The quantity of variance per interval of frequency is the spectral density.

The spectral density function S(f) is given by Haan (1977) as

$$S(f)=2\int_{-\infty}^{\infty} \rho(\tau)\cos(2\pi f\tau)d\tau \qquad (2)$$

where $\rho(\tau)$ is the serial correlation with lag τ. A sample spectral density function $\hat{S}'(f)$ can be computed by numerical integration of Equation 2 using the rectangular rule, and it is given by

$$\hat{S}'(f)=\Delta t\{r(0)+2E\sum_{k=1}^{m-1} r(k)\cos(2\pi kf\Delta t)+r(m)\cos(2\pi kf\Delta t)\} \qquad (3)$$

where

Δt = time between equally spaced observations

r(k) = estimated serial correlation with lag k

m = number of correlation lags

Haan (1977) recommends that m should not exceed 10 to 25 percent of the sample size. He also recommends that the final estimates of S(f) be smoothed such that

$$\hat{S}(0) = 1/2(S'(0)+\hat{S}'(f_N/m) \quad (4)$$

$$\hat{S}(f_N/m) = 1/4(\hat{S}'((k-1)f_N/m) + 1/4\hat{S}'((k=1)f_N/m) \quad (5)$$

$$\hat{S}(f_N) = 1/2(\hat{S}'((m-1)f_N/m)+\hat{S}'(f_N)) \quad (6)$$

where $f_N = 1/2\Delta t$ and $k=1,2,3,\ldots,m-1$.

The spectral density for 4 years of the 9-year sample is illustrated in Figure 1. In this case, m was chosen to be 3504 or 10 percent of the 4 years of hourly data. As expected, the one-year and 24-hour periods (first and 365th harmonics) greatly influenced the variation of temperatures. The spectral density also shows less obvious 12-hour and 8-hour periods (730th and 1095th harmonics). From these periodic components, the deterministic event $T_d(t)$ is written as

$$\begin{aligned} T_d(t)=\bar{T} &+ A_1\sin(2\pi t/N) + B_1\cos(2\pi t/N) \quad (7) \\ &+ A_{365}\sin(2\pi(365t)/N) + B_{365}\cos(2\pi(365t)/N) \\ &+ A_{730}\sin(2\pi(730t)/N) + B_{730}\cos(2\pi(730t)/N) \\ &+ A_{1095}\sin(2\pi(1095t)/N) + B_{1095}\cos(2\pi(1095t)/N) \end{aligned}$$

where $\bar{T}$ is the mean of the sample and N is the number of discrete intervals in one year (8760 hours). Junkins (1978) describes a regression model which can be used to

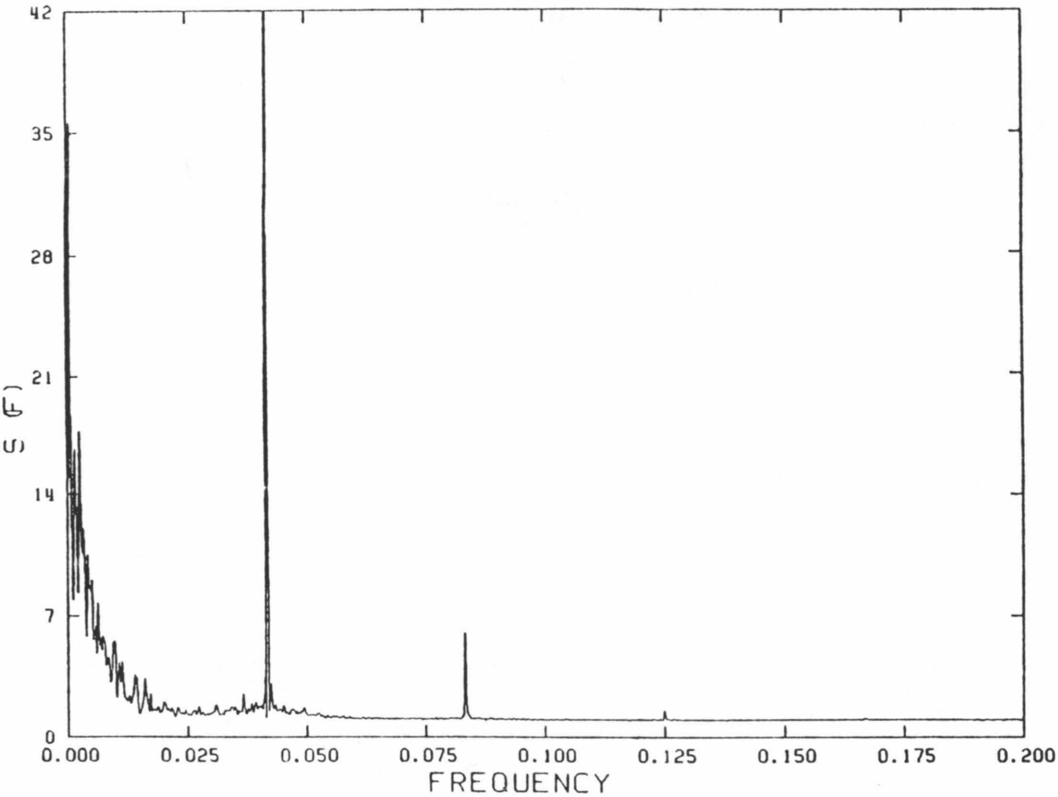

Figure 1. The spectral density function S(f) shows yearly, 24-hr., 12-hr., and 8-hr. periodic variations which are evidenced by spikes in the spectral density.

estimate coefficients A and B (denoted by their corresponding harmonics). Gauss principle of least-squares selects an optimum choice for the unknown coefficients by minimizing the sum of the squares of the residual errors.

Equation 7 can be rewritten in matrix form as

$$Y = A\hat{X} \tag{8}$$

where Y is the temperature realization and $\hat{X}$ is the estimation of the coefficients. A is an independent set of specified basis functions which were determined by spectral analysis. The actual measured temperatures, $\tilde{Y}$, are described similarly by

$$\tilde{Y} = A\hat{X} + E \qquad (9)$$

where E is the vector of residual errors.

The realization, $\tilde{Y}$, is estimated by minimizing the sum of the squares of the residual errors, ϕ. From Junkins (1978)

$$\phi = \sum_{j=1}^{n} e_j^2 = E^t E \qquad (10)$$

where e_j is the residual at time j and E^t is the matrix transpose of E. By solving for E in Equation 9 and then substituting into Equation 10,

$$\phi = \tilde{Y}^t\tilde{Y} - 2\tilde{Y}^t A\hat{X} + \hat{X}^t A^t A\hat{X} \qquad (11)$$

By using matrix calculus differentiation rules

$$\nabla_x \phi = -2A^t\tilde{Y} + 2A^t A\hat{X} = 0 \qquad (12)$$

and

$$\nabla_x^2 \phi = 2A^t A \qquad (13)$$

$\hat{X}$ can be solved for the necessary condition

$$\hat{X} = (A^t A)\ A^t\tilde{Y} \qquad (14)$$

To find the $\hat{X}$ which minimizes ϕ, Equation 13 must be positive definite. This sufficient condition must be satisfied to prevent a maximum ϕ.

A Fortran computer program was utilized to estimate $\hat{X}$. The nine years or 78,840 hours of temperatures were entered into the program as a column matrix (78840 X 1). The last 24 hours of the leap years (1972 and 1976) were truncated. After matrix manipulation, $\hat{X}$ (9 x 1) resulted and is shown in Table 1. The coefficient of determination, R^2, was 69 percent, indicating that the deterministic model accounts for 69 percent of the total variation in the 78,840 hours of temperature data. Further examination of the deterministic model found that the mean of the residual temperatures was 0.0176°F, which is close to the desired value of zero.

The residuals or the difference between the actual temperatures and the deterministic model are a

Table 1. Values of the parameters used to generate the deterministic part of the model which is $T_d(t)$ in Equation 16.

Parameter	Value
$\bar{T}$	51.30
A_1	-5.52
B_1	-19.56
A_{365}	-6.16
B_{365}	-4.58
A_{730}	1.26
B_{730}	0.82
A_{1095}	0.20
B_{1095}	-0.15

stochastic variable that requires statistical modeling. Figure 2 shows a portion of the hourly residuals. These residual temperatures have a very high hour-to-hour correlation. This high correlation is expected because the temperature at any one hour is generally near the temperature of the preceding hour. With all the major periodicities extracted, it was assumed that the residuals were random and that they had a high first-order serial correlation.

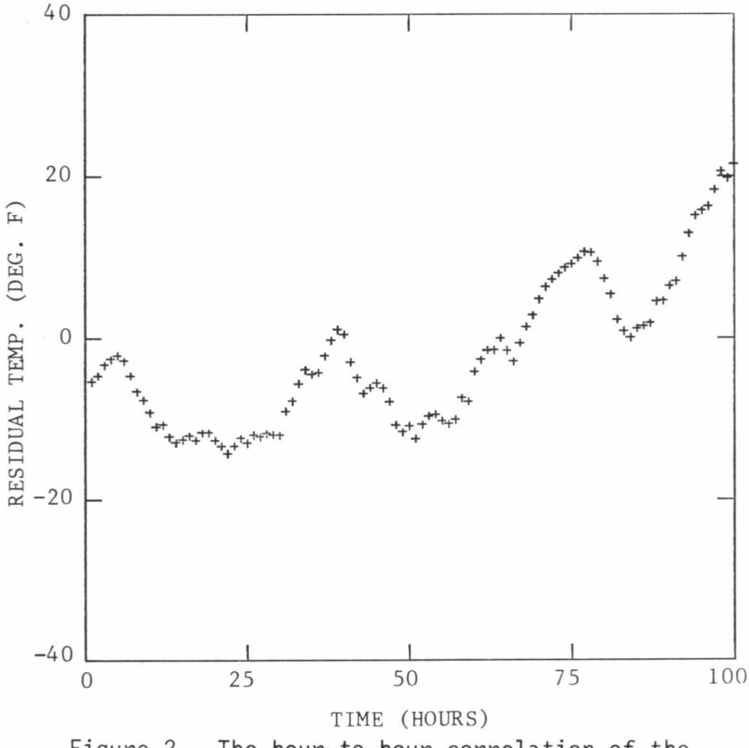

Figure 2. The hour-to-hour correlation of the residual temperatures for a portion of the data is clearly evidenced by the small changes in the residuals from one time period to the next.

Haan (1977) used a first-order Markov chain model for stochastic events having a high first-order serial correlation (i.e. a high correlation for a time lag of 1). The Markov model simulates a stochastic event by adding a random component to a value of a time process that is dependent only on the value of X in the preceding time period. If the distribution of the time value X is $N(\mu_x, \sigma_x^2)$, then the model can be written as

$$X_{i+1} = \mu_x + \rho_x(1)(X_i - \mu_x) + t_{i+1}\ \sigma_x\sqrt{1 - \rho^2(1)} \tag{15}$$

where t_{i+1} is a standard normal deviate and ρ_x (1) is the first order serial correlation.

Figure 3 shows a relative frequency histogram of one year of residual temperatures superimposed with a fitted normal probability function. Similar fits were found with the other years and, because they were close, it was assumed that the distribution of the residuals was "approximately" normal.

The procedure according to Haan (1977) for generating X_{i+1} in Equation 15 is to estimate the mean μ_x, the standard deviation σ_x, and the first order serial correlation $\rho(1)$ and then select a t_{i+1} at random from the standard normal distribution. Parameters μ_x, σ_x and $\rho(1)$ were estimated from the 78,840 residual temperatures and found to be 0.0176, 10.120 and 0.9821,

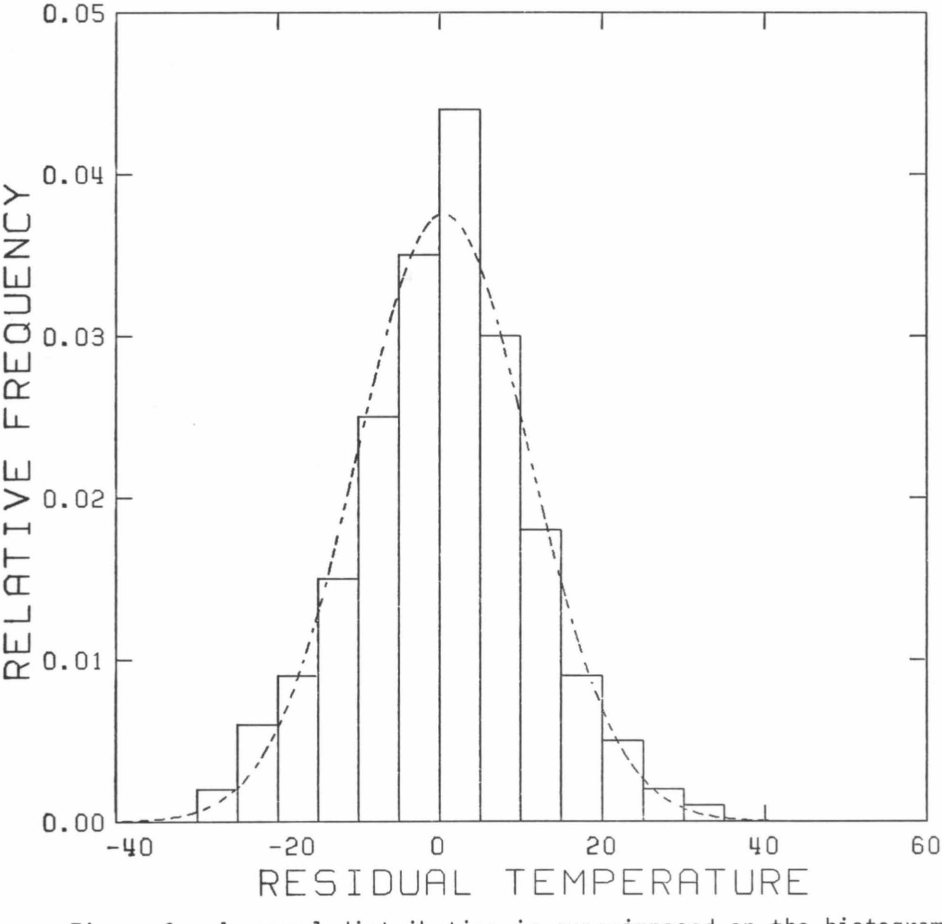

Figure 3. A normal distribution is superimposed on the histogram of the residual temperatures for one year of dry-bulb temperature data.

respectively. The complete model for simulating hourly dry-bulb temperatures is completed by adding Equation 7 to Equation 15 or

$$T(t) = T_d(t) + X_{i+1} \tag{16}$$

Testing of the Model

A comparison of an actual hourly temperature realization to a model-predicted realization is shown in Figure 4. The deterministic or periodic part of the simulation followed the trends of the actual data. Although the two curves do not exactly match, the simulated curve "appears" to closely mimic a possible realization.

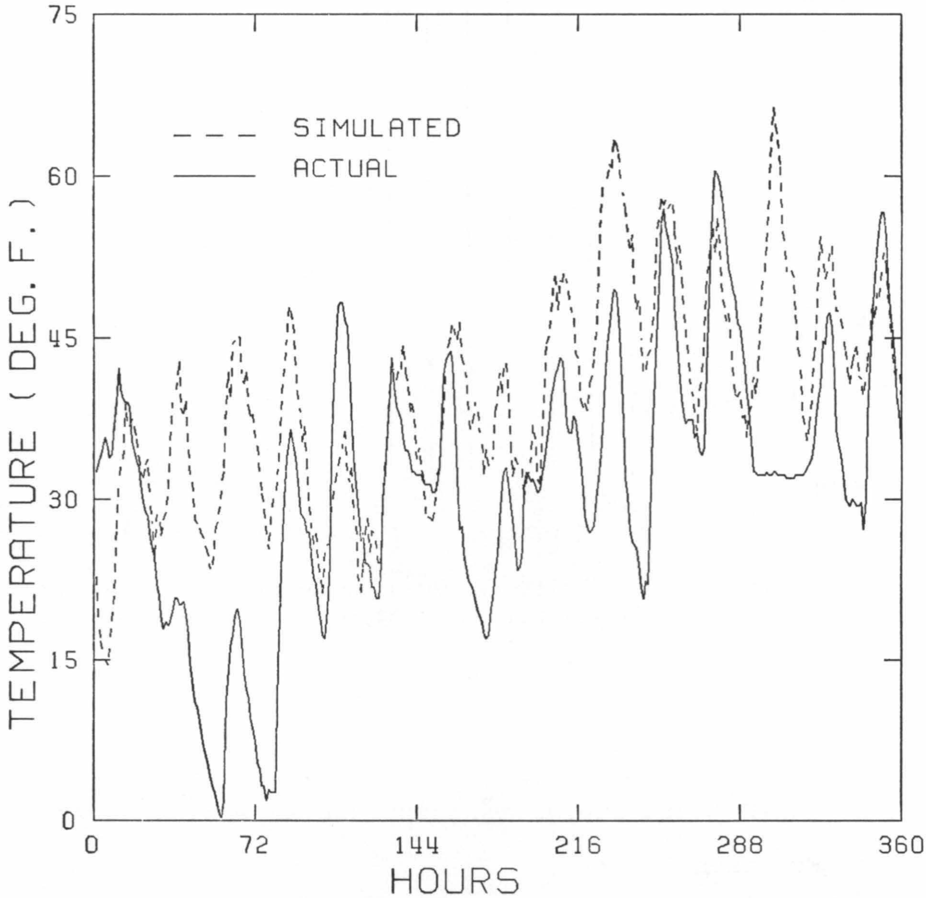

Figure 4. A portion of the dry bulb temperature model is simulated and compared to actual recorded data of the same time period starting midnight February 15, 1971.

In order to statistically test the model, the 1st, 2.5, 50th, 97.5, and 99th percentiles were estimated for each of the 11 individual years of the actual data. These percentiles were also estimated for one trial of eleven simulated years and compared in Tables 2, 3, 4, 5 and 6. Years 1969 and 1970 demonstrate how the model predicts years independent from those years used to develop the model. The model is expected to accurately simulate temperature realizations if the difference between the predicted and actual temperatures varies randomly about zero and the sum total of the differences is close to zero.

The lower percentile comparisons of Tables 2 and 3 show that the model overestimated the actual

TABLE 2. The first percentile of 11 years of simulated hourly dry-bulb temperatures are compared to that of the actual data. Equation 16 was used to simulate the dry-bulb temperatures.

Year	Actual 1% °F	Simulated 1% °F	Difference °F
1969*	14.9	8.7	- 6.2
1970*	4.7	9.4	+ 4.7
1971	8.6	13.5	+ 4.9
1972	11.7	13.6	+ 1.9
1973	12.2	3.3	- 8.9
1974	15.7	15.1	- 0.6
1975	16.3	14.7	- 1.6
1976	9.0	11.6	+ 2.6
1977	-1.3	10.0	+11.3
1978	8.5	12.0	+ 3.5
1979	8.0	13.6	+ 5.6

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

TABLE 3. The 2.5 percentile of 11 years of simulated hourly dry-bulb temperatures are compared to that of the actual data. Equation 16 was used to simulate the dry bulb temperatures.

Year	Actual 2.5% °F	Simulated 2.5% °F	Difference °F
1969*	18.6	15.6	- 3.0
1970*	15.4	15.8	+ 0.4
1971	13.8	17.2	+ 3.4
1972	18.2	17.5	- 0.7
1973	16.3	12.0	- 4.3
1974	21.4	20.2	- 1.2
1975	22.1	18.9	- 3.2
1976	14.7	16.9	+ 2.2
1977	6.1	15.0	+ 8.9
1978	12.8	17.5	+ 4.7
1979	13.1	17.7	+ 4.6

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

TABLE 4. The 50th percentile of 11 years of simulated hourly dry-bulb temperatures are compared to that of the actual data. Equation 16 was used to simulate the dry-bulb temperatures.

Year	Actual 50% °F	Simulated 50% °F	Difference °F
1969*	50.9	50.5	- 0.4
1970*	51.8	50.7	- 1.1
1971	55.4	51.7	- 3.7
1972	51.8	51.3	- 0.5
1973	54.7	53.1	- 1.6
1974	54.4	48.6	- 5.8
1975	54.1	51.5	- 2.6
1976	52.8	49.4	- 3.4
1977	54.1	50.7	- 3.4
1978	52.5	50.8	- 1.7
1979	51.8	48.7	- 3.1

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

TABLE 5. The 97.5 percentile of 11 years of simulated hourly dry-bulb temperatures are compared to that of the actual data. Equation 16 was used to simulate the dry-bulb temperatures.

Year	Actual 97.5%	Simulated 97.5%	Difference
1969*	84.2	84.1	- 0.1
1970*	83.2	79.8	- 3.4
1971	81.6	86.2	+ 4.6
1972	80.3	84.7	+ 4.4
1973	81.9	88.7	+ 6.8
1974	82.2	84.4	+ 2.2
1975	82.9	87.8	+ 4.9
1976	82.6	85.9	+ 3.3
1977	83.2	86.9	+ 3.7
1978	85.1	87.1	+ 2.0
1979	80.3	83.9	+ 3.6

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

TABLE 6. The 99th percentile of 11 years of simulated hourly dry-bulb temperatures are compared to that of the actual data. Equation 16 was used to simulate the dry-bulb temperatures.

Year	Actual 99% °F	Simulated 99% °F	Difference °F
1969*	88.6	89.0	- 0.4
1970*	86.1	84.0	- 2.1
1971	84.5	90.7	+ 6.2
1972	83.8	88.8	+ 5.0
1973	85.1	93.4	+ 8.3
1974	85.1	89.5	+ 4.4
1975	85.8	94.0	+ 8.2
1976	85.8	89.6	+ 3.8
1977	86.7	90.8	+ 4.1
1978	87.0	91.8	+ 4.8
1979	82.9	89.2	+ 6.3

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

temperatures in these regions. The 50th percentile comparison in Table 4 indicated that the model underestimated the temperatures, and the higher percentiles in Tables 5 and 6 show that the model consistently overestimated the percentiles of the actual data. These differences were attributed to the assumptions of the residuals having a normal distribution and a constant first-order serial correlation coefficient.

Model Refinement

Hansen and Driscoll (1977) observed a skewness in the residual temperatures during certain times of the year for their temperature data. Their observations suggested the possibility that the Blacksburg data could follow the same trend or perhaps have a different distribution for each month. If the monthly distributions or the monthly residual variance changes, then modeling the residual variance and serial correlation coefficients monthwise would tend to remove the effects of skew and a time-dependent residual variance.

The first-order serial correlation, mean, and standard deviation for each of the 108 months of the nine-year sample of residual temperatures were estimated. Both the standard deviation and first-order serial correlation coefficients were found to be higher in the winter months than in the summer months, suggesting that a more precise model would be achieved by incorporating the monthly variations of the standard deviation and first-order serial correlation coefficient.

By spectral analysis, the monthly first-order correlation coefficients and standard deviations were found to have a yearly period. The least square regression technique, described earlier, was used to model the variations of these two parameters. The first harmonic coefficients C, D, E, and F and averages for the standard deviations and first-order serial correlation coefficients are shown in Table 7. σ and $\rho(1)$ in the first-order Markov chain now become time-dependent variables where

$$\sigma = \bar{S} + C\sin(2\pi t/N) + D\cos(2\pi t/N) \tag{17}$$

and

$$\rho(1) = \bar{r}(1) + E\sin(2\pi t/N) + F\cos(2\pi t/N) \tag{18}$$

Table 7. The parameters are for the periodic variation of standard deviation and first order serial correlation as given by Equations 17 and 18, respectively.

Parameter	Value
$\bar{S}$	9.010
C	2.069
D	2.348
$\bar{r}(1)$	0.972
E	0.013
F	0.015

The regression curve in Figure 5 is shown with a scatterplot of the 108 standard deviations. A wide range in variance of the standard deviations was observed.

The estimated 1st, 2.5, 50th, 97.5, and 99th percentiles were found as before for the refined dry-bulb temperature model and compared to the actual

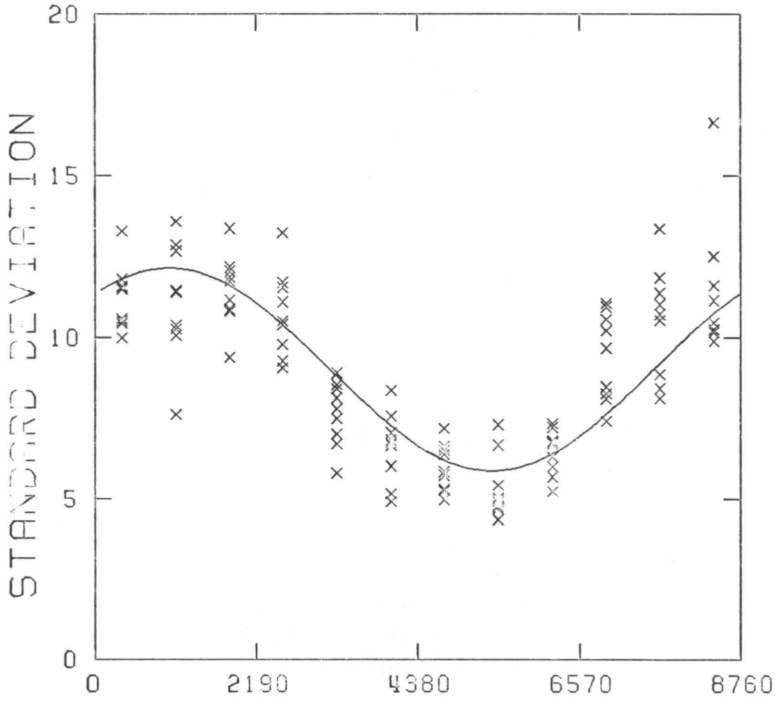

Figure 5. The least square regression curve given by Equation 17 with parameters in Table 7 is shown here for the periodic variation of standard deviation along with a scatter plot of the 108 estimated monthly values of standard deviation. For each month there were nine estimates of the residual standard deviation obtained from the nine years of temperature data.

estimates. Tables 8-12 show that the refined model closely predicts the actual realizations. Trial 1 shows the estimated percentiles with only Equation 17 incorporated whereas Trial 2 incorporates, Equations 17 and 18 into the model. Only a small difference was observed between the two trials; therefore the model can be simplified by using a constant serial correlation coefficient, with only a small loss in accuracy. All percentile comparisons indicated that the model adequately simulated hourly dry-bulb temperature. The differences between the predicted and actual temperatures vary about zero. The model predicts temperatures in the lower and higher percentiles very close to the actual temperature, an important factor in many design considerations.

TABLE 8. The first percentile for the refined hourly dry-bulb temperature model is compared to that of the actual data.

Year	Actual 1%	Simulated 1% Trial 1**	Simulated 1% Trial 2***	Difference Trial 1**	Difference Trial 2***
1969*	14.9	5.7	5.8	- 9.2	- 9.1
1970*	4.7	6.9	7.2	+ 2.2	+ 2.5
1971	8.6	11.7	12.0	+ 3.1	+ 3.4
1972	11.7	11.3	12.4	- 0.4	+ 0.7
1973	12.2	-1.1	-2.6	-13.3	-14.8
1974	15.7	13.9	15.7	- 1.8	0.0
1975	16.3	12.3	11.4	- 4.0	- 4.9
1976	9.0	8.8	11.0	- 0.2	+ 2.0
1977	-1.3	6.5	6.3	+ 7.8	+ 7.6
1978	8.5	11.6	11.5	+ 3.1	+ 3.0
1979	8.0	11.3	11.6	+ 3.3	+ 3.6

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

** Trial 1 incorporates only the standard deviation variations.

*** Trial 2 incorporates both the standard deviation and first order serial correlation variations.

TABLE 9. The 2.5 percentile for the refined hourly dry-bulb temperature model is compared to that of the actual data.

Year	Actual	Simulated 2.5% Trial 1**	Simulated 2.5% Trial***	Difference Trial 1**	Difference Trial 2***
1969*	18.6	13.2	12.4	- 5.4	- 6.2
1970*	15.4	14.0	13.7	- 1.4	- 1.7
1971	13.8	15.7	15.5	+ 1.9	+ 1.7
1972	18.2	15.8	16.2	- 2.4	- 2.0
1973	16.3	8.8	5.6	- 7.5	-10.7
1974	21.4	19.5	20.6	- 1.9	- 0.8
1975	22.1	17.3	16.2	- 4.8	- 5.9
1976	14.7	15.6	15.8	+ 0.9	+ 1.1
1977	6.1	14.5	13.3	+ 8.4	+ 7.2
1978	12.8	16.0	16.1	+ 3.2	+ 3.3
1979	13.1	16.1	16.2	+ 3.0	+ 3.1

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

** Trial 1 incorporates only the standard deviation variations.

*** Trial 2 incorporates both the standard deviation and first order serial correlation variations.

TABLE 10. The 50th percentile for the refined hourly dry-bulb temperature model is compared to that of the actual data.

Year	Actual 50%	Simulated 50% Trial 1**	Simulated 50% Trial 2***	Difference Trial 1**	Difference Trial 2***
1969*	50.9	51.8	51.6	+ 0.9	+ 0.7
1970*	51.8	52.7	53.2	+ 0.9	+ 1.3
1971	55.4	53.0	52.9	- 2.4	- 2.5
1972	51.8	52.6	52.2	+ 0.8	+ 0.4
1973	54.7	54.3	54.7	- 0.4	0.0
1974	54.4	50.2	50.6	- 4.2	- 3.8
1975	54.1	52.7	52.7	- 1.4	- 1.4
1976	52.8	50.6	50.4	- 2.2	- 2.4
1977	54.1	52.3	52.4	- 1.8	- 1.7
1978	52.5	52.5	52.6	0.0	+ 0.1
1979	51.8	49.9	49.9	- 1.9	- 1.9

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

** Trial 1 incorporates only the standard deviation variations.

*** Trial 2 incorporates both the standard deviation and first order serial correlation variations.

TABLE 11. The 97.5 percentile for the refined hourly dry-bulb temperature model is compared to that of the actual data.

Year	Actual 97.5%	Simulated 97.5% Trial 1**	Simulated 97.5% Trial 2***	Difference Trial 1**	Difference Trial 2***
1969*	84.2	80.8	81.1	- 3.4	- 3.1
1970*	83.2	78.6	78.9	- 4.6	- 4.3
1971	81.6	81.4	81.5	- 0.2	- 0.1
1972	80.3	81.0	81.9	+ 0.7	+ 1.6
1973	81.9	84.3	83.1	+ 2.9	+ 1.2
1974	82.2	80.4	80.6	- 1.8	- 1.6
1975	82.9	83.4	82.4	+ 0.5	- 0.5
1976	82.6	81.6	82.0	- 1.0	- 0.6
1977	83.2	82.9	82.6	- 0.3	- 0.6
1978	85.1	82.9	82.2	- 2.2	- 2.9
1979	80.3	80.4	80.8	+ 0.1	+ 0.5

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

** Trial 1 incorporated only the standard deviation variations.

*** Trial 2 incorporates both the standard deviation and first order serial correlation variations.

TABLE 12. The 99th percentile for the refined hourly dry bulb temperature model is compared to that of the actual data.

Year	Actual 99%	Simulated 99% Trial 1**	Simulated 99% Trial 2***	Difference Trial 1**	Difference Trial 2***
1969*	88.6	84.7	85.4	- 3.9	- 3.2
1970*	86.1	81.4	82.7	- 4.7	- 3.4
1971	84.5	85.0	85.4	+ 0.5	+ 0.9
1972	83.8	84.3	84.9	+ 0.5	+ 1.1
1973	85.1	87.7	87.2	+ 2.6	+ 2.1
1974	85.1	84.0	84.5	- 1.1	- 0.6
1975	84.8	87.6	86.1	+ 1.8	+ 0.3
1976	85.8	84.7	85.1	- 1.1	- 0.8
1977	86.7	85.7	85.8	- 1.0	- 0.9
1978	87.0	86.5	85.6	- 0.5	- 1.4
1979	82.9	84.7	84.6	+ 1.8	+ 1.7

* 1969 and 1970 provide an independent test of the model since the model was built on years 1971 to 1979.

** Trial 1 incorporates only the standard deviation variations.

*** Trial 2 incorporates both the standard deviation and first order serial correlation variations.

CONCLUSIONS

A computer model was developed for Blacksburg, Virginia, for simulating hourly dry-bulb temperatures. By using least-squares regression, the periodic variations over the course of a year were modeled. The aperiodic or stochastic variations were modeled using a first-order Markov chain model. These two models were then combined to simulate hourly temperature realizations.

Extreme temperatures were overestimated significantly when monthly variations of residual standard deviations and first-order serial correlations were neglected. By accounting for these monthly variations, the extreme temperatures are closely estimated.

The residual temperatures were observed to have a higher standard deviation and first-order serial correlation in the winter months than in the summer months. Based on this observation, the first-order Markov chain model was modified to incorporate time-dependent variations in monthly residual standard deviations and first-order serial correlations. With the addition of these time-dependent parameters, an adequate model was developed for simulating hourly dry-bulb temperatures. The model can be simplified, with only a small loss in accuracy, by assuming a constant first-order correlation.

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Virginia's Agricultural Experiment Stations

1—Blacksburg
Virginia Tech

2—Steeles Tavern
Shenandoah Valley Research Station

3—Orange
Piedmont Research Station

4—Winchester
Winchester Fruit Research Laboratory

5—Middleburg
Virginia Forage Research Station

6—Warsaw
Eastern Virginia Research Station

7—Suffolk
Tidewater Research and Continuing Education Center

8—Blackstone
Southern Piedmont Research and Continuing Education Center

9—Critz
Reynolds Homestead Research Center

10—Glade Spring
Southwest Virginia Research Station

11—Hampton
Seafood Processing Research and Extension Unit