DEVELOPMENT OF A CLIMATE PATTERN FOR DESIGN AND ANALYSIS OF MULTIPLE-STAGE EVAPORATIVE COOLING SYSTEMS

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ABSTRACT

The concept of climate pattern is introduced in this paper. The climate pattern is a representative of climatic conditions of a specific region. This could be used for design of energy-effective schemes of buildings cooling and heating systems as well as comparison of different strategies through the simulation of system performance under the climatic conditions specified by the climatic pattern. This paper describes the statistical methodology used for development of such a climate pattern for Tehran. Metrological data of last five decades of Tehran has been used for this purpose. Not only the methodology is discussed but also it is analyzed to demonstrate existing limitations. Applicability of the climate patterns in the design and analysis of multiple-stage evaporative cooling systems is also explored.

INTRODUCTION

Energy crisis and development of energy-effective systems has become one of the most important engineering challenges of the current century. Energy that is consumed for heating and cooling of buildings has a considerable contribution to the annually consumed energy of the world, for example about 16% of Iran yearly energy consumption. Thus, it is necessary to develop appropriate strategies for optimization of energy consumption in the buildings. During the recent years, such efforts have led to development, evaluation, simulation, production and test of several energy-effective systems. Solar energy based systems, multiple-stage evaporative cooling systems [1] and desiccant cooling systems [2] are all examples of existing approaches to the problem.

Among energy-effective schemes of building thermal conditioning, evaporative cooling is of a special interest. It is because of the refrigerating process that is replaced by an evaporative cooling process. From thermodynamics point of view, in evaporative cooling moisture is added to the air and evaporation enthalpy of added moisture causes dry bulb temperature of the air to decrease. However, there are times that wet bulb temperature of the outdoor air is close to its dry bulb temperature. During these periods of time, which may be limited in duration, evaporative cooling is not capable of providing comfort conditions of building occupants. To overcome this deficiency, evaporative cooling system is integrated into a multiple-stage cooling system in which some additional air-conditioning stages are available to assist the system during the times of a high wet bulb temperature. Since arrangement of the stages as well as the stages themselves could be different, it is important to select appropriate stages and an appropriate arrangement to arrive at the best design of an energy-effective multiple-stage evaporative cooling system. Climate of the building site affects selection and arrangement of the stages. Thus, some type of climate indicator should be used for the simulation of different alternatives' performance. Then, according to the simulations the best system could be designed.

As previously stated, the fact that performance of a particular energy-effective scheme is dependent on the climatic conditions of the building site makes it necessary to study climate of building site before proposing a particular system. Due to existence of a huge amount of meteorological data one could hardly make a conclusion without applying a suitable statistical method. In the other hand, this problem is completely similar to problem of vehicles performance simulation. There is, evidently, some type of uncertainty in actual conditions that a vehicle may encounter during a real-world trip. However, there are similarities between real-world trips of vehicles traveling in a geographic region comparing with those of another region. It is important to use a statistical approach to capture the main features of a region vehicles trips. These pattern are widely used in simulation of vehicles and are called driving cycles, see e.g. [3]-[5]. Commercially available softwares for simulation of vehicles performance, e.g. ADvanced Vehicle SImulatOR: ADVISOR, use standard driving cycles such as Supplemental Federal Test Procedure: US06 to simulate real-world conditions that vehicle may encounter in its servicing time. Some similar concepts such as Test Reference Year: TRY has previously used for description of geographic areas' climatic conditions. For description of these methods see e.g. [6] and [7]. But, these data are not available for all of geographic areas. Furthermore, the statistical approach used for extraction of sample weather conditions needs to be investigated in order to discover its limitations and deficiencies. Derived climate pattern must, in the other hand, be suitable for simulation purposes. It means that computational cost should be minimized. Due to comparatively small computational cost of buildings energy simulation tasks, this issue may seem not so critical. But, for optimization problems it is (often) necessary to simulate the building energy consumption several times to allow the optimization algorithm arrive at optimal parameter values. A very interesting example is the optimal sizing of multiple-stage evaporative cooling systems. In this optimization problem, one tries to find the size of, say, direct evaporative cooling plant and size of the refrigerating plant. The required successive simulations of building energy performance corresponding to each parameter value calls for a high computational cost. The developed climate pattern of this paper could significantly reduce this computational cost. Novelty in this paper comes from several sources. First, a novel weather sampling methodology is introduced. Second, a climate pattern has been developed for Tehran city and details of applied statistical procedure are given. This climate pattern is based on Tehran's five last decades meteorological data. Third, a discussion is included for validation of this climate pattern in which the phenomenon of climate change has been taken into account. Finally, the relation between climate pattern and multiple-stage evaporative cooling systems is explored.

METHODOLOGY

There are several important climatic parameters upon which the climate pattern could be built. It includes dry bulb temperature, wet bulb temperature, solar heat gain, relative humidity, dew point, and yearly raining rate for example. Among these parameters, two parameters dry bulb temperature and wet bulb temperature has been chosen for development of our climate pattern. Some other thermodynamic parameters such as relative humidity and dew point could be easily computed by using of these two parameters and classic psychometric relations. Remaining parameters are not of a first degree of importance for design and analysis of evaporative cooling systems. But, these parameters could be completely critical when dealing with other technologies. For example solar heat gain parameter is completely important for design and analysis of solar based systems. Thus, hereafter our concentration will be on dry bulb and wet bulb temperature profiles of Tehran.

City of Tehran, capital of Iran, is placed in the center of Iran. Like the other central areas of Iran, this city experiences fairly cold winters and hot-dry summers. National Building Code gives the value -6.7 C (20 F) as winter design dry bulb temperature. Dry bulb and coincident wet bulb design temperatures for the summer are given as 37.7 C (100 F) and 21.1 C (70 F), respectively. These values demonstrate potential of the climate for use of evaporative cooling systems. However, the dry bulb temperature or wet bulb temperature or both occasionally exceed these values and evaporative cooling becomes unlikely to be successful. This deficiency motivates us to introduce multiple-stage evaporative cooling systems for cooling of the spaces. The need for intelligently designed and analyzed evaporative cooling systems calls for some meteorological data of this geographic region. Meteorological parameters of the city have been measured and recorded since 1951. A digital database stores meteorological parameters of this period. Due to some loss of data in the first years and existing delay for newly measured data to be included in the database, only data of 1956 to 1999 period are used in our analysis. Hourly measurements are recorded eight times a day with a three hours gap between records. The first phase of the project was to make the data ready for analysis. It was consisting of converting the data into the form of our computational software, eliminating undesired records of data, validating the new set of data with data of other geographically close meteorology stations and filtering out-of-curve data. After completion of the first phase, dry bulb and wet bulb temperatures profiles for hot months were ready. Figures 1 to 3 depict typical temperature profiles for the July 1980. Figure 1 depicts dry bulb temperature in different days of this month. Figure 2 depicts wet bulb temperature for days of this month. Finally, Figure 3 is a representation of average dry bulb and wet bulb temperature values. The most important concluding point from these three pictures is the effect of this simple statistical process, averaging, on the smoothness of temperature profile. This smoothness is especially important when the data are to be used in a computational simulation program.

The second phase is to build climate pattern upon data of first phase. Definitely, it is not possible to give a single 24-hour pattern as a representative of the whole hot months. It is because of the weather change during the time of hot months. In the beginning of hot months, days become hot and hotter until they reach a day of maximum temperature. After this day the days become, gradually, cool and cooler until the summer is gone. To overcome this difficulty, there is, at least, two alternatives. First alternative is to give our climate pattern as a multi-day temperature profile. The independent variable in this map, i.e. time, is no longer limited to 24 hours of a day. Instead, a very long time period beginning from first day of hot month and continuing to last day of hot months is used as temperature profile of whole summer. Figure 4 and 5 show a *typical* multi-day temperature profile. The data are those of summer 1980. Independent axis, i.e. time axis, shows the hours passed from the beginning of summer and dependent axes show dry bulb and wet bulb temperatures, respectively. As one can easily see, the maximum daily temperature is increasing in the first half time of both maps reaching to a maximum but decreasing in the second half time. Temperature variations in the whole hot months' period are completely comparable with the absolute values of the temperatures. Indeed extension of y-axis values exceeds 0.9 of average temperature values. Thus it is critical to take the summer temperature variations into account. Following this first alternative, one finds out that there are only a limited number of cycles to be treated in the statistical procedure. It is because of our limited number of meteorological measurements. In our study the number of samples is less than fifty simply because of after 1951 meteorological database.

The second alternative is based on division of summer, hot months period, to some sub-seasons. It is much like classifying of traffic conditions in the development of driving cycles. Traffic conditions of a city could be classified as congested urban conditions, urban conditions, extra urban conditions, and highways [8]. In analogy with this classification, weather conditions of a geographic region, during the summer, could be classified into some sub-season conditions. According to this idea, hot months are classified as groups of different climatic conditions. This classification causes the number of available samples that are to be used in the statistical process of climate pattern extraction, be multiplied by number of days in each sub-season. Thus, one concludes that the broader the sub-season period, the greater the number of samples. But, broadening of sub-season period causes a sacrifice in accuracy. It is because of the fact that the broader the sub-season the less the similarities between an individual sub-season days. Hence, it is necessary to construct a balance between number of samples and accuracy of temperature profiles. Albeit sufficiently important to be covered in a separate study, it is not our main objective to study the effect of classification on accuracy and validity of climate pattern. Instead, we simply consider each month as a sub-season. It begins from May and continues to the September. The sub-seasons, which are corresponding to these five months, are called: *pre-summer, lead-summer, hot-summer, trail-summer, and post-summer*.

Once the data are collected and are classified as appropriate sub-season conditions, a representative day should be selected for each sub-season. A selection criterion should be developed to enable us select a suitable day as a representative of each sub-season. Two selection parameters are defined as follows

$$\bar{d}_{rel,i} = \frac{\bar{d}_i}{\bar{d}_{total}} \tag{1}$$

$$\bar{w}_{rel,i} = \frac{\bar{w}_i}{\bar{w}_{total}} \tag{2}$$

where

$$\begin{aligned} \bar{d}_i &= \frac{\sum_k d_{i,k}}{8} \\ \bar{w}_i &= \frac{\sum_k \bar{w}_{i,k}}{8} \end{aligned} \tag{3}$$

Equation 1 and 2 define relations for computation of relative dry bulb and wet bulb of *i*-th day in each sub-season. Over-line denotes average values of involving parameters. Index *total* stands for whole data of a sub-season. Number 8 in Equation (3) is the number of measurements in a day. Representative Day for a sub-season is suggested, by authors, to be defined as

A representative day is a day that minimizes difference between its parameters, day relative dry bulb and wet bulb temperatures, and those of the entire statistical society.

The ideal value for relative dry bulb and wet bulb temperatures of a representative day is unity, like parameters micro-trip average speed and idle time percentage in the driving cycle development process [9]. But, one could hardly find such a day. Therefore, it is important to define a measure of appropriateness to be used as selection criterion. Below-defined parameter, called *Z*-parameter, is used for this purpose

$$Z_i = \left|\bar{d}_{rel,i} - 1\right| + \left|\bar{w}_{rel,i} - 1\right| \tag{4}$$

Day with minimum *Z*-parameter, in each sub-season, is chosen as sub-season's representative day.

The above mentioned analysis, namely Z-analysis hereafter, is applied to meteorological data of Tehran. Results of this analysis are given in Table 1. This table summarizes statistical values of Z-analysis for all of sub-seasons. Average dry bulb and wet bulb temperatures for each sub-season are given in columns one and two. Then, characteristics of selected day in each sub-season are given in four following columns. These are average dry bulb and wet bulb temperatures, day computed Z-parameter and date of the day. Finally, standard deviation of computed Z-parameter all-over of each sub-season is given in the last column. Figures 6 to 10 demonstrate distribution of Z-parameter over the statistical societies of sub-seasons.

As clear from Figures 6 to 10 and Z-parameter standard deviations given in the Table 1, diversity of Z-parameters is greater in the beginning and end of hot months and smaller in the middles. Indeed, it decreases from pre-summer to the lead-summer and reaches its minimum in the hot-summer. Again it increases from hot-summer to trail-summer and from trail-summer to post-summer. One concludes that in the beginning and end of hot months' period the weather is much more unstable and sub-seasons should be shorter comparing with middles of these months.

Once the representative day is selected, it is necessary to fit a curve to data. Since the number of samples per day is limited to eight, the temperature profile is not so smooth. The main reason of curve fitting is to increase smoothness of representative day temperature profile. Smoothness of temperature profile is especially important when it is aimed to be used in a simulation program. Furthermore, equation of fitted curve could be used instead of data themselves. Figures 11 to 15 show the sub-seasons representative days and the fitted curves. Matrices K, C, and D, which are referred in these figures, contain representative day dry bulb and representative day wet bulb temperatures, respectively.

Different Curve fitting techniques were examined and it was founded out that among available curve fitting techniques, polynomials, sinusoidal, exponential, and so many other examined techniques, could hardly give a good fit to data. Thus, cubic spline interpolation technique was used for smoothing of temperature profiles.

Although the first alternative, i.e. multi-day temperature profile, has less potential of statistical accuracy; it, instead, has advantage of a real year hot months temperature variation during the summer. It is not the case for multi-sub-season alternative; because in the latter approach a sub-season is represented by only one day and variation of temperature profiles over an individual sub-season is omitted. Nevertheless, Z-analysis remains valid for selection of representative year. The only thing that changes is the daily average of dry bulb temperature and wet bulb temperature that is replaced by yearly average in the Equations (1) and (2). This analysis is applied to the case of Tehran meteorological data and representative year was selected according to the Z-analysis. The result of Z-analysis show that the year 1981 has minimum Z-parameter, i.e. 0.0102. Total dry bulb and wet bulb average temperatures are 27.0191 and 13.5334 while representative year average dry bulb and wet bulb temperatures are 26.8300 and 13.4900, respectively. Z-parameter distribution standard deviation is 0.0523. A smoothing procedure like that applied to the multi-sub-season approach should be applied to data guaranteeing a sufficient smoothness of temperature profiles. Temperature profiles of this year are not given there due to space constraints. However, one may consult Figure 16 for distribution of Z-parameter over available samples of multi-day approach.

A huge number of intelligently structured simulation tasks are necessary to determine which approach really leads to more accurate results. These simulations are ongoing and are expected to appear in a following paper.

CLIMATE ANALYSIS

Nearly all of existing climate indicators including climate patterns is built upon an important assumption. This assumption implies that climate is not changing during years of study. It does not mean that there is no change of climate in consecutive years of study. But, it implies that there is no changing *pattern* in climate variations and, subsequently, climate variations are on a random basis. In the words of signal processing community, this assumption guarantees that there is no hidden signal in climatic signals. Validity of this assumption should be examined for any climate. Indeed, during the recent years it has been shown that there is considerable variation in many regions climates. Hence, it is necessary to do a climate change analysis not only for validating of this assumption but also to ensure that climate has enough potential for use of evaporative cooling systems. Toward these ends, two analyses are included in this section. The former is a statistical analysis for validation of above-mentioned assumption while the latter examines Tehran climate potential for use of evaporative cooling systems.

From elementary statistics one knows that correlation between two signals demonstrate linear dependency of these two different signals. The correlation coefficient varies between -1 and 1. The correlation coefficient of 1 implies that there is a positive linear dependency between these two signals while the correlation coefficient of -1 denotes that there is a reverse linear dependency between two examining signals. When correlation of a signal with itself is computed, one arrives ate autocorrelation signal of original signal. The autocorrelation signal could be used for identification of signal's historical memory. It means that from autocorrelation analysis it becomes apparent that if the current value of discrete signal depends on the previous values of this signal or not. For a completely random signal, one expects to see an autocorrelation signal fluctuating about zero. But for a periodic signal, for example, it is likely to see a periodic autocorrelation signal. Thus, autocorrelation signals of dry bulb and wet bulb temperatures signals could give a picture of these signals randomness over consecutive years of meteorological measurements. Figure 17 and 18 depict autocorrelation signals for dry bulb and wet bulb temperatures, respectively. Average yearly dry bulb and wet bulb peak temperatures are used as original signals and autocorrelation signals are computed for these two original signals.

Neglecting side-effects in the beginning of autocorrelation signals following conclusions could be made.

- Roughly speaking, wet bulb signal has more historical memory than dry bulb temperature.
- Autocorrelation signals absolute values become greater in the recent years.

These conclusions could be also certified by looking at Figures 19 and 20 that demonstrate original signals versus time. One may notice that level of wet bulb temperature is increasing. Dry bulb temperature is also increasing but its increment is not as clear as wet bulb temperature. Furthermore, these increments are more correlated during the recent years. These facts along with observation of other climatic indicators show that climate of Tehran is, probably, changing. Greater absolute values of autocorrelation signals if accompanied by a specific pattern could be a sign of a separable hidden signal in the temperature signals. However, there is still not enough data for identification of this potentially available hidden signal. From evaporative cooling point of view, it is important to monitor effect of this climatic change in the effectiveness of evaporative cooling process. A parameter called Evaporative Cooling Desirability (ECD) is defined to give a measure of climate's potential for use of evaporative cooling systems. Although in a multiple-stage evaporative cooling system evaporative cooling process is integrated into a multiple-stage thermodynamic process, but energy effectiveness of whole system is dependent on effectiveness of evaporative cooling systems. The above-mentioned parameter is defined as

$$ECD = \frac{\overline{d}_i - \overline{w}_i}{\overline{d}_i - d_{comfort}} \qquad (5)$$

Where d_i and w_i are i-th year's dry bulb and wet bulb temperatures. Subscript *comfort* stands for optimal summer thermal comfort conditions' dry bulb, see [10]. Over-line stands for average value. Figure 21 depicts this parameter over the years of Tehran climate study. Two facts are concluded from this figure. First, the *ECD* value is fairly large comparing with the values of many other climates. Second, the *ECD* value is decreasing during the years of study. It is another sign of Tehran climate change and highlights the fact that climate change should be considered in development of climate patterns which are designed for use in study of multiple-stage evaporative cooling systems.

CONCLUSIONS

The problem of climate pattern development for Tehran city was addressed in this paper. An analogy was constructed between vehicles driving cycles and climatic pattern of a region. According to this analogy, hot months' period was divided to five sub-seasons. For each sub-season a representative day was selected. This representative day minimizes the Z-parameter that is a measure of existing difference between parameters of selected day and those of the whole sub-season. Statistical analysis shows that standard deviation of Z-parameter in middles of summer is smaller than beginning and end of the summer. The method described in this paper could be easily used for construction of annual weather files and it allows use of readily-accessible simulation programs for simulation of evaporative cooling systems. Furthermore, it was shown that the climate of the Tehran is changing and autocorrelation analysis shows greater historical memory of temperature signals during the recent years. The parameter Evaporative Cooling Desirability was also defined and it was shown that albeit still remaining in a high level of desirability, the evaporative cooling desirability is decreasing in Tehran.

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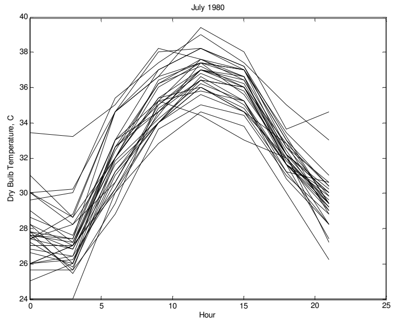

Figure 1. Dry-Bulb Temp. vs. Day Hour

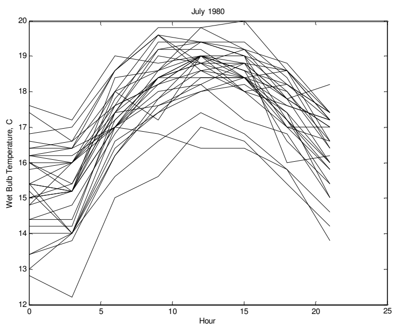

Figure 2. Wet-Bulb Temp. vs. Day Hour

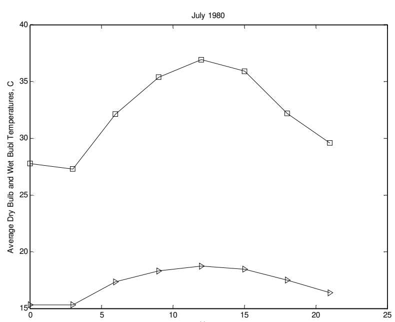

Figure 3. Average Wet-Bulb and Dry-Bulb Temps. vs. Day Hour

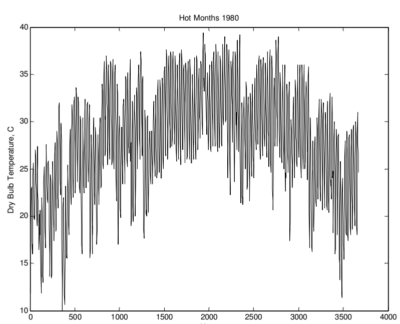

Figure 4. Dry-Bulb Temp. vs. Hour for 1980 Summer

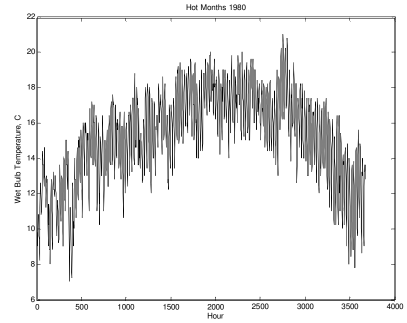

Figure 5. Wet-Bulb Temp. vs. Hour for 1980 Summer

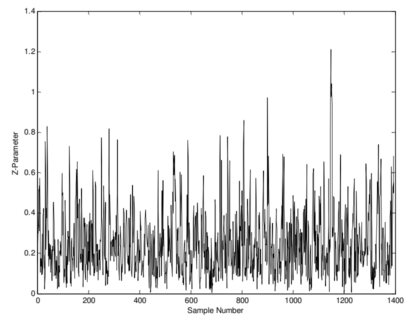

Figure 6. Z-Parameter over Pre-Summer

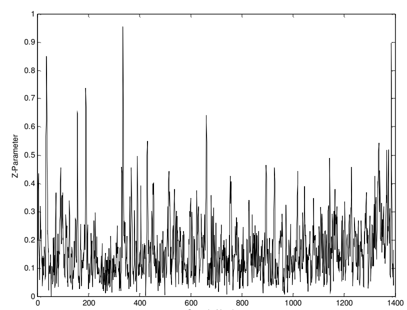

Figure 7. Z-Parameter over Lead-Summer

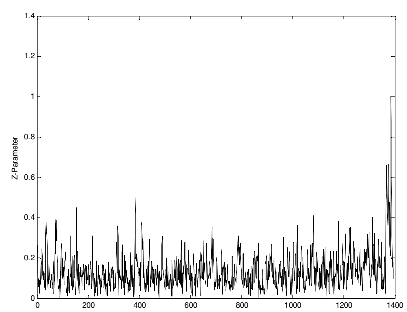

Figure 8. Z-Parameter over Hot-Summer

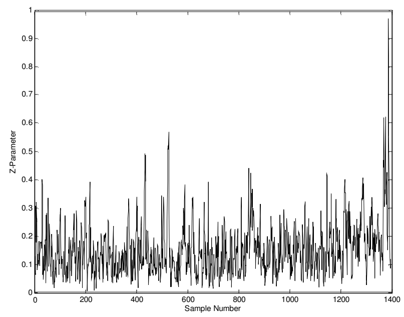

Figure 9. Z-Parameter over Trail-Summer

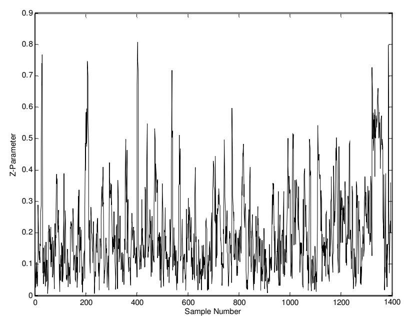

Figure 10. Z-Parameter over Post-Summer

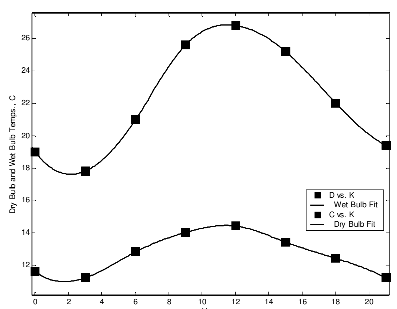

Figure 11. Temperature Profiles for Pre-Summer Sub-Season

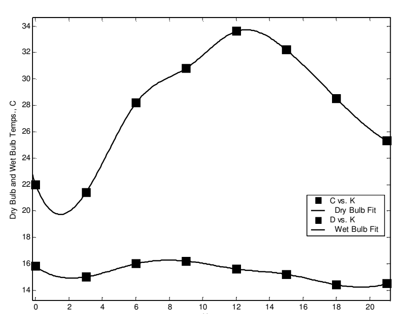

Figure 12. Temperature Profiles for Lead-Summer Sub-Season

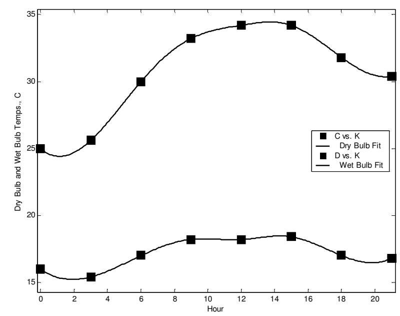

Figure 13. Dry Bulb and Wet Bulb Temperature Profiles for Hot-Summer Sub-Season

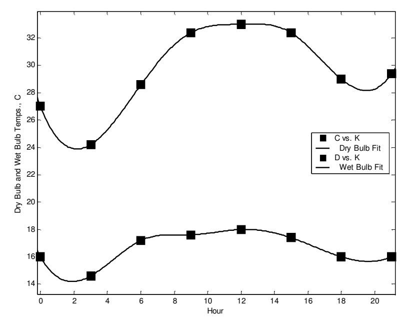

Figure 14. Temperature Profiles for Trail-Summer Sub-Season

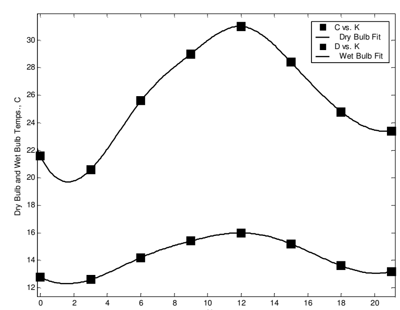

Figure 15. Temperature Profiles for Post-Summer Sub-Season

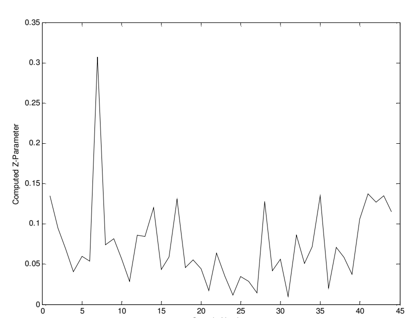

Figure 16. Z-Parameter in the Multi-Day Approach

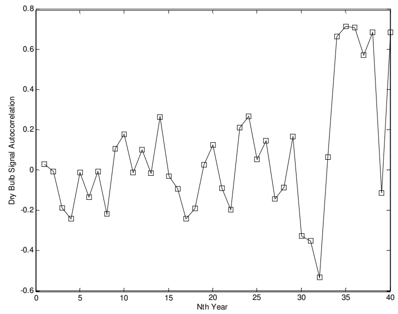

Figure 17. Dry Bulb Autocorrelation Signal

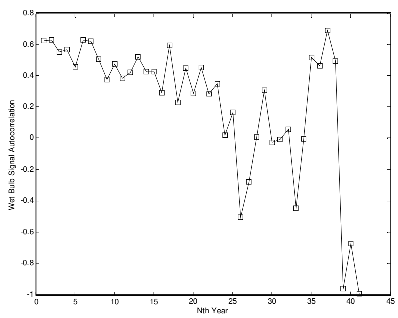

Figure 18. Wet Bulb Autocorrelation Signal

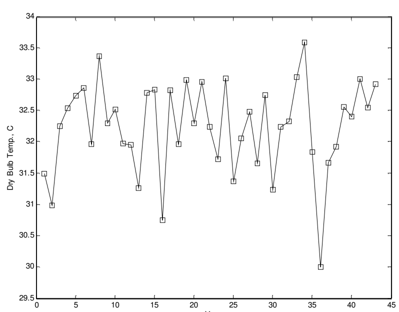

Figure 19. Avg. Yearly Peak Dry Bulb Temps.

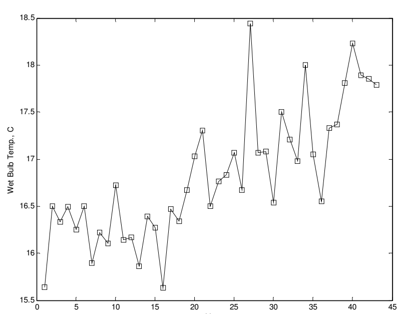

Figure 20. Avg. Yearly Peak Wet Bulb Temps.

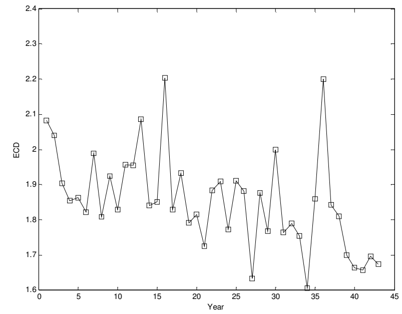

Figure 21. Evaporative Cooling Desirability

	Pre-Summer	**Lead-Summer**	**Hot-Summer**	**Trail-Summer**	**Post-Summer**
Sub-Season's Avg. Dry Bulb Temp., C	22.0657	27.7926	30.5181	29.5455	25.5501
Sub-Season's Avg. Wet Bulb Temp., C	12.5946	15.3400	17.1658	16.5580	14.0498
Representative Day's Avg. Dry. Bulb Temp., C	22.1000	27.7500	30.5500	29.5000	25.5500
Representative Day's Avg. Wet Bulb Temp., C	12.6250	15.3375	17.1250	16.6000	14.1250
Representative Day Computed Z-Parameter	0.0040	0.0017	0.0034	0.0041	0.0054
Representative Day Date	May 2nd, 1977	June 25th, 1957	July 1st, 1984	Aug. 21st, 1962	Sep. 25th, 1963
Z-Parameter Distribution Standard Deviation	0.1635	0.1126	0.0912	0.0946	0.1399

Table 1. Z-Analysis Results