First Order Multivariate Markov Chain Model for Generating Synthetic Series of Weather Data to Evaluate the Performance of Open Cycle Solar Desiccant Air Conditioning System

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ABSTRACT

Dehumidification of air conditioning is traditionally accomplished with vapour refrigeration equipment. The disadvantage of this air handling process is that the temperature of the air must be cooled below its dew-point which is deemed to be energy expensive. An open cycle liquid desiccant dehumidification system driven by solar energy was emerged as a potential alternative to conventional vapour refrigeration system for humidity control in air conditioning. This system can utilize solar energy and can possibly provide cooling more efficiently.

As it is an open cycle system, the performance of the proposed system is more sensitive to the ambient conditions. Unlike other types of solar utilization methods which solar radiation is the only dominate weather parameter, the performance of the open cycle solar desiccant dehumidification system is also related to the ambient humidity and temperature significantly. For continuous operation, storage system and auxiliary heat source should be considered in the system in case solar radiation is not available. Thus, sizing represents an important part of the solar desiccant dehumidification system design.

Firstly, this paper presents a stochastic simulation approach to syntactical generate a series of meteorological parameters using 15 years of real weather conditions of Hong Kong (between 1979~1988 and 1996~2000). Specifically, a first-order multivariate Markov chains model is developed to represent ambient temperature, humidity and isolation. The static properties of real weather data, like mean value, standard variance and persistence of certain climate, are well preserved in the syntactically generated weather data. Further more, the inter-dependence of the solar radiation, ambient temperature and humidity are well reflected. The information provide by this series of meteorological parameters is quite useful to the sizing of the solar C/R, storage capacity and capacity of auxiliary heat source.

Secondly, using the synthetic series of weather condition developed in this study, the performance of the open cycle liquid desiccant dehumidification system was simulated. The results reveal that the open cycle desiccant system can meet most of the latent load through out the cooling season if the components are proper sized and the energy saving.

1. INTRODUCTION

The fast growing demand for air conditioning has imposed a significant increase in demand for primary energy. Electric utilities have their peak loads in hot summer days, and are often faced with brown-out situations, barely capable of meeting the demand. These embarrass situations have made planners and policy makers think and search for ways to supplement the energy base with renewable energy sources. With suitable technology, solar cooling can help alleviate the problem. The fact that peak cooling demand in summer is often associated with high solar radiation offers an excellent opportunity to exploit solar thermal technologies that can match heat-driven cooling technologies. Open cycle solar desiccant dehumidification system is one of these promising technologies.

This system can utilize solar energy and can possibly provide cooling more efficiently. Additional advantages are more precise humidity control and possible anti-bacterial effect (Collier R. K., 1979; Yang R. and Yan W. J., 1992; Yang R. and P-L Wang, 2001). The independent liquid desiccant dehumidification system consists of two loops: the air dehumidification loop and the liquid desiccant regeneration loop. Figure 1. shows the schematic diagram of an open cycle solar liquid desiccant air dehumidification system. These two loops are connected by two solution tanks which are specified as strong solution tank and weak solution tank. In the dehumidifier, the strong liquid desiccant solution absorbs water vapour from air at the surface of the packing materials. It is then diluted and pumped from the bottom of the dehumidifier to the weak solution tank waiting for regeneration. The flow rate of the strong desiccant solution varies with the outdoor air humidity ratio to meet the dehumidification task. In the regeneration cycle, the weak solution passes through the regenerative heat exchanger on its way to the solar C/R. As mentioned before, the weak solution slowly flows down the collector's inclined surface where it is heated by solar radiation and releases water vapour to the air. To ensure its continuous operation, a solution storage tank and an auxiliary heater are often involved in the system. As an open cycle system, its performance strongly depends on the ambient conditions such as solar radiation, air temperature and humidity. Designing a proper open cycle solar desiccant dehumidification system requires the prediction of weather statistical parameters. These parameters include the average value, standard deviation, maximum and minimum value of a historical weather data. Especially for the storage system, frequency and persistence of a certain weather condition are also required in this sizing process.

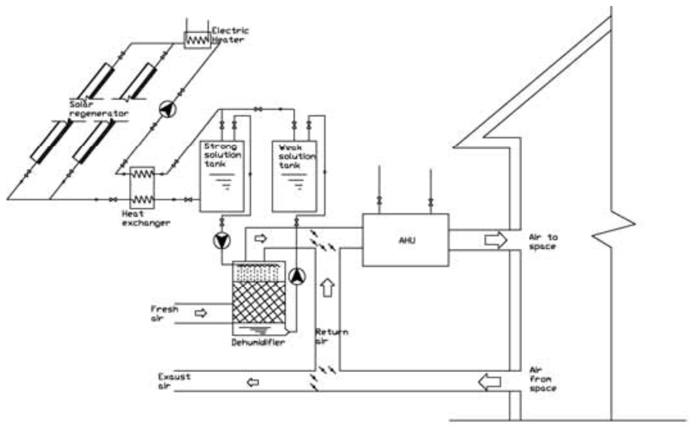


Figure1: Schematic diagram of a solar liquid desiccant dehumidification system

For applications requiring prediction of annual performance and design of solar energy systems, there are two kinds of annual weather data in genera1 use, one is the typical meteorological year (TMY), and another is the standard meteorological year (SMY). TMY and SMY are similarly based on the smallest deviation from the long term historical years' values; By considering the weight factor of the annual and monthly mean values of air temperature, air humidity and solar radiation, the year or month with the smallest deviation from the mean value is taken as a TMY or 'standard' month. The selection of TMY or SMY is highly relays on the weight factors of the different metrological variables. For strict statistical significance, different energy systems will have different TMYs or SMYs. Furthermore, these two types of annual weather data did not take the frequency and persistence of certain kind of weather condition and extreme conditions into consideration, which will also limit their application in the performance evaluation of solar energy utilization system with energy storage.

As descried above, the working fluid is direct contact with the ambient air in both regeneration cycle and dehumidification cycle. Besides solar radiation, the ambient air temperature and humidity are also strongly effect the heat and mass transfer rate between the air and solution film. Unlike those traditional solar thermal utilization systems, such as solar hot water system whose performance is just dominated by the solar radiation, the performance of the open cycle solar desiccant dehumidification system is closely related to the multivariate weather parameters. In this case, those TMY and SMY data are no longer reliable and new set of weather data are needed to fill this gap.

2. Description of the multivariate Markov chain model

W. Ching (2002) proposed a first-order multivariate Markov chain model to model the behavior of multiple categorical sequences generated by similar sources. Assuming that there are s categorical sequences and each has m possible states, they assume that the state probability distribution of the j th sequence at time $t = r + 1$ depends on the state probabilities of all the sequences (including itself) at time $t = r$. In the proposed first-order multivariate Markov chain model, the following relationship is assumed:

$$X_{r+1}^{(j)} = \sum_{k=1}^{s} \lambda_{jk} P^{(jk)} X_r^{(k)} \quad \text{, for } j = 1, 2, \ldots, s \text{ and } r = 0, 1, \ldots, \tag{1}$$

where

$$\lambda_{jk} \geq 0, 1 \leq j,k \leq s \text{ and} \sum_{k=1}^{s} \lambda_{jk} \text{ , for } \mathrm{j} = 1, 2, \ldots, \mathrm{s} \tag{2}$$

and $X_0^{(j)}$ is the initial probability distribution of the j th sequence. The state probability distribution of the j th sequence, $\mathrm{X}_{\mathrm{r}+1}^{(j)}$ at the time $(r+1)$, depends on the weighted average of $P^{(jk)}X_r^{(k)}$. Here $P^{(jk)}$ is the one-step transition probability matrix from the states at time t in the k th sequence to the states in the j th sequence at time $t+1$, and $\mathrm{X}_{\mathrm{r}}^{(k)}$ is the state probability distribution of the k th sequences at the time r. In matrix form we write

$$X_{r+1} = \begin{pmatrix} X_{r+1}^{(1)} \\ X_{r+1}^{(2)} \\ \vdots \\ X_{r+1}^{(s)} \end{pmatrix} = \begin{pmatrix} \lambda_{11}P^{(11)} & \lambda_{12}P^{(12)} & \cdots & \lambda_{1s}P^{(1s)} \\ \lambda_{21}P^{(21)} & \lambda_{22}P^{(22)} & \cdots & \lambda_{2s}P^{(2s)} \\ \vdots & \vdots & \vdots & \vdots \\ \lambda_{s1}P^{(s1)} & \lambda_{s2}P^{(s2)} & \cdots & \lambda_{ss}P^{(ss)} \end{pmatrix} \begin{pmatrix} X_r^{(1)} \\ X_r^{(2)} \\ \vdots \\ X_r^{(s)} \end{pmatrix}. \tag{3}$$

or

$$X_{n+1} = QX_n$$

Again fast numerical algorithms based on linear programming are proposed to solve the model parameters $P^{(jk)}$ and λ_{jk}. In this subsection we propose some methods for the estimations of $P^{(jk)}$ and λ_{jk}. For each data sequence, we estimate the transition probability matrix by the following method. Given the data sequence, we count the transition frequency from the states in the k th sequence to the states in the j th sequence. Hence one can construct the transition frequency matrix for the data sequence. After making normalization, the estimates of the transition probability matrices can also be obtained. We note that one has to estimate $m \times m$ transition frequency matrices for the multivariate Markov chain model. More precisely, we count the transition frequency $f_{\mathrm{i_j\, i_k}}^{(\mathrm{jk})}$ from the state i_{k} in the sequence $\{X(k)\}$ to the state i_{j} in the sequence $\{X(j)\}$ and therefore the transition frequency matrix for the sequences can be constructed as follows:

$$F^{(jk)} = \begin{pmatrix} f_{11}^{(jk)} & \cdots & f_{m1}^{(jk)} \\ f_{12}^{(jk)} & \cdots & f_{m2}^{(jk)} \\ \vdots & \vdots & \vdots \\ f_{1m}^{(jk)} & \cdots & f_{mm}^{(jk)} \end{pmatrix} \tag{4}$$

From $F^{(jk)}$, we get the estimates for $P^{(jk)}$ as follows:

$$P^{(jk)} = \begin{pmatrix} p_{11}^{(jk)} & \cdots & p_{m1}^{(jk)} \\ p_{12}^{(jk)} & \cdots & p_{m2}^{(jk)} \\ \vdots & \vdots & \vdots \\ p_{1m}^{(jk)} & \cdots & p_{mm}^{(jk)} \end{pmatrix} \tag{5}$$

where

$$p_{i_j\, i_k}^{(jk)} = \begin{cases} s\dfrac{f_{i_j\, i_k}^{(jk)}}{\sum_{i_k=1}^{m} f_{i_j\, i_k}^{(jk)}} & if \sum_{i_k=1}^{m} f_{i_j\, i_k}^{(jk)} \neq 0 \\ 0 & otherwise \end{cases} \tag{6}$$

Besides the estimates $P^{(jk)}$, one needs to estimate the parameters λ_{jk}. We assume that the multivariate Markov chain model has a stationary vector $\hat{X}$. The vector $\hat{X}$ can be estimated from the sequences by computing the proportion of the occurrence of each state in each of the sequences, and let us denote it by:

$$\hat{X} = \left(\hat{X}^{(1)}, \hat{X}^{(2)}, \cdots, \hat{X}^{(s)}\right) \tag{7}$$

One would expect that:

$$\hat{X} \approx \begin{pmatrix} \lambda_{11}P^{(11)} & \lambda_{12}P^{(12)} & \cdots & \lambda_{1s}P^{(1s)} \\ \lambda_{21}P^{(21)} & \lambda_{22}P^{(22)} & \cdots & \lambda_{2s}P^{(2s)} \\ \vdots & \vdots & \vdots & \vdots \\ \lambda_{s1}P^{(s1)} & \lambda_{s2}P^{(s2)} & \cdots & \lambda_{ss}P^{(ss)} \end{pmatrix} \hat{X} \tag{8}$$

This equation suggests one possible way to estimate the parameters $\lambda = \{\lambda_{jk}\}$ as follows. In fact, W.Ching proposed the following minimization problem:

$$\begin{cases} \min\limits_{\lambda} \max\limits_{i} \left| \left[\sum_{k=1}^{m} \lambda_{jk} P^{(jk)} \hat{X}^{(k)} - \hat{X}^{(j)} \right]_i \right| \\ \textit{subject to} \\ \sum_{k=1}^{s} \lambda_{jk} = 1, \\ \textit{and} \\ \lambda_{jk} \geq 0, \quad \forall k. \end{cases} \tag{9}$$

This Problem can be further formulated as s linear programming problems see for instance.
For each j:

$$\begin{cases} \min\limits_{\lambda} \omega_j \\ \textit{subject to} \\ \begin{pmatrix} \omega_j \\ \omega_j \\ \vdots \\ \omega_j \end{pmatrix} \geq \hat{X}^{(j)} - B \begin{pmatrix} \lambda_{j1} \\ \lambda_{j2} \\ \vdots \\ \lambda_{js} \end{pmatrix}, \\ \begin{pmatrix} \omega_j \\ \omega_j \\ \vdots \\ \omega_j \end{pmatrix} \geq -\hat{X}^{(j)} + B \begin{pmatrix} \lambda_{j1} \\ \lambda_{j2} \\ \vdots \\ \lambda_{js} \end{pmatrix}, \\ \omega_j \geq 0, \\ \sum_{k=1}^{s} \lambda_{jk} = 1, \quad \lambda_{jk} \geq 0, \quad \forall k. \end{cases} \tag{10}$$

where

$$B = \left[\hat{P}^{(j1)} \hat{X}^{(1)} \mid \hat{P}^{(j2)} \hat{X}^{(2)} \mid \cdots \mid \hat{P}^{(js)} \hat{X}^{(s)} \right]. \tag{11}$$

3. Weather data analysis

The essence of stochastic identification then is a decomposition of weather variables for two elements, namely random and deterministic components. Deterministic components have been found by taking the hourly, within a day, averages of 15 years for every month separately using auto-correlation method. As regards global solar radiation, its hourly amounts have been performed as time series of clearness index. Clearness index is defined as the ratio of hourly global radiation G on the earth's surface to the global extraterrestrial G_0, and G_0 is calculated by the well known empirical equations. The same process is also applied to the ambient air temperature and humidity to remove time dependency of the weather variables. The effectiveness of this process is tested by the following methods.

3.1. Testing of Markov chain properties

The Markov chain properties of the daily global solar irradiation can be tested statistically by checking whether the successive events are independent of each other (the null hypothesis) or dependent (the alternative hypothesis). If dependent, they can form a first order Markov chain. If successive events are independent, then the statistic α, defined as:

$$\alpha = 2\sum_{i,j}^{m} n_{ij} \ln(\frac{p_{ij}}{p_j}), \tag{12}$$

is distributed asymptotically as χ^2 with $(m-1)^2$ degrees of freedom, where m is the total number of states. n_{ij} is the number of transitions and p_j the marginal probabilities for the j th column of the transition probabilities matrix. The results obtained from the statistics α are larger than the χ^2 value of 103 at the 5% level with 81 degrees of freedom, so we can reject the null hypothesis that the successive transitions are independent and conclude that the transition of hourly weather data occurrence possess the first order Markov chain property.

3.2. Testing of Markov chain stationary

A Markov process is stationary if its transition probabilities are independent with respect to time. A convenient way to check the stationary is to divide the whole sequence of events into a few subintervals and then compute and compare the transition probability matrix for each interval. For a stationary process, all these matrices should be approximately equal to each other. The statistic test c is defined as following:

$$\gamma = 2\sum_{t}^{T}\sum_{i,j}^{m} n_{ij}(t) \ln(\frac{p_{ij}(t)}{p_{ij}}) \tag{13}$$

where T is the number of subintervals, and $n_{ij}(t)$ and $p_{ij}(t)$ represent, respectively, the number of transitions and the transition probabilities for each subinterval. If the Markov chain is stationary, the statistics γ has χ^2 distribution with $(T-1)m(m-1)$ degrees of freedom. For this case, these statistics, specifically solar radiation, air temperature and humidity, are smaller than the χ^2 value of 16200 at the 5% level with 16110 degrees of freedom, which means that the Markov chain property of global irradiation typical days occurrence is stationary for the previously cited cases.

4. Synthetic generation

For generating the sequences of weather states, the initial state, say i, was selected randomly. Then, random values between 0 and 1 were produced by a uniform random number generator. For next state in first order Markov process, the value of the random number was compared with the elements of the i th row of the cumulative probability transition matrix. If the random number value was greater than the cumulative probability of the previous state but less than or equal to the cumulative probability of the following state, the following state was adopted. The wind speed states have been converted to the actual wind speed using the following relationship.

$$V = V_l + Z_i(V_h - V_l) \tag{14}$$

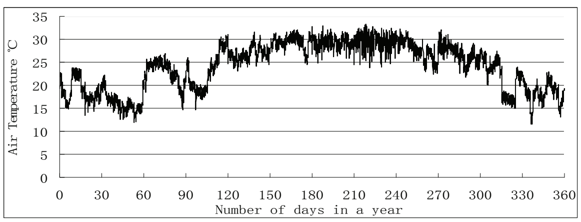
where V_l and V_h are weather states lower boundary and upper boundary of the state and Z_i is the uniform random number between (0, 1). The procedure is repeated for the other hours. However, if two consecutive hours, $t-1$ and t, belong to the same state k, it is considered that sequences of hours with the same state k began at hour $t-1$. Thus, to determine the length of this sequence (hours of state k), the following procedure is used: a random number Z_i, between 0 and 1, is randomly chosen; and elements of persistence probabilities

$(\mathrm{P}\,(t-1:k), \mathrm{P}(t-2:k), \cdots, \mathrm{P}(t-L:k))$ are added until their sum is greater than Z_i. Thus, the length of the sequence is L. In this case, the hours $t-1$ to $t+L-1$ belong to state k.

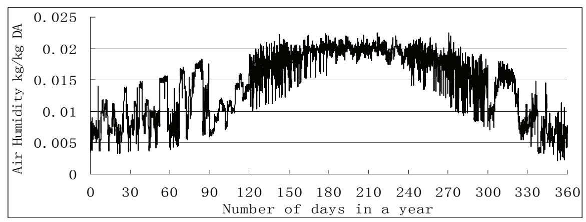
5. Results and vilification

Using this method, one year of hourly total solar radiation, humidity and ambient air temperature were simulated. It was found that the probabilistic properties are the same as the real ones, based on 15 years of data. The synthetically generated data, by the first order multivariate Markov chain model, have been compared qualitatively and quantitatively in terms of probability distribution with those of the observed values. Figure 2.shows one set of simulated weather data. The statistical characteristics of the generated weather are compared with the long-term average value of the real weather data. As listed in table 2, the comparison includes annual average value, standard deviation, yearly maximum value and minimum value. The results reveal that the simulated weather data well preserved the characteristics of the real weather data. All relative errors are within 5% magnitude.

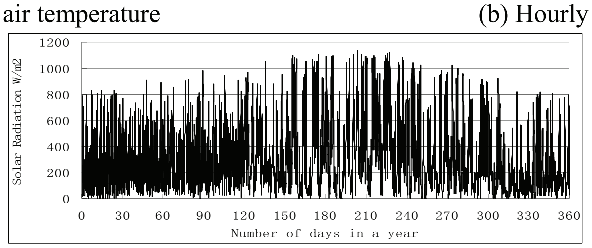
For qualitative assessment, the frequency distributions for the observed weather data and the generated time series have also been examined. The probability distributions of solar radiation, humidity and air temperature are shown in Fig. 3. An examination of this figure reveals that the probability at different states have almost the same values.



(a) Ambient air temperature

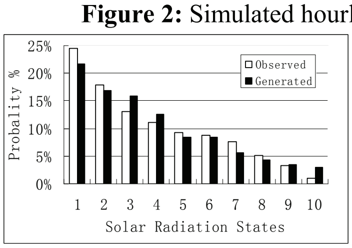


(b) Hourly air humidity

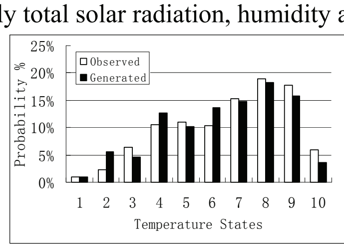


(c) Hourly total solar radiation

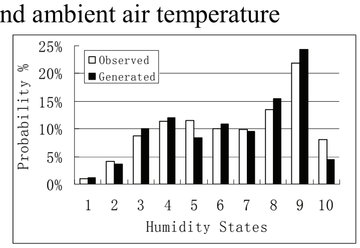
Figure 2: Simulated hourly total solar radiation, humidity and ambient air temperature



(1) solar radiation



(2) air temperature



(3) humidity

Figure 3: Probability distributions of solar radiation, humidity and air temperature

Table 1: The comparison between real weather data and synthetically generated weather data.

Parameter	Observed.			Generated.			Relative Errors		
	Solar Radiation W/m^2	Air Temperature ℃	Air Humidity Kg/kg DA	Solar Radiation W/m^2	Air Temperature ℃	Air Humidity Kg/kg DA	Solar Radiation W/m^2	Air Temperature ℃	Air Humidity Kg/kg DA
AVERAGE	326.17	23.94	0.0144109	336.90	23.42	0.0144096	3.29%	2.19%	0.01%
STDEV	250.31	5.34	0.0049091	258.78	5.50	0.0048847	3.38%	3.02%	0.50%
Max	998.52	33.70	0.0229394	1030.12	33.59	0.0226600	3.16%	0.33%	1.22%
Min	0.00	7.99	0.0028256	0.00	8.32	0.0027200	0.00%	4.17%	3.74%

6. Simulation of the open cycle desiccant dehumidification system

The proposed open cycle solar liquid desiccant dehumidification system is shown in Figure 1. Analysis of this system has been accomplished by using a dynamitic simulation program for synthetically generated weather data of Hong Kong on an hour-by-hour basis. The transient performance of the system was described numerically by applying energy and mass balance of the weak and strong desiccant solution tanks. The simulation time step was set to 1 min to reveal sufficient detailed information.

The effect of the solution flow rate on the system's performance has been proved by earlier researchers that the minimum flow rate which is closely related to the C/R surface flatness and wettability can result in optimum performance. According to the experimental results reported in publications, this optimum flow rate varies within the range of 10~30 kg/m hr with different experimental setup. In this study, the flow rate of the weak solution was controlled at 0.0055kg/m s (about 20kg/m hr), which is the normal flow rate of a solar water heater. Before entering the solar C/R, the weak desiccant solution is further heated by an electric heater to ensure desorption as soon as the weak solution entering the C/R. The model for the desiccant dehumidifier is derived from Tsair-wang Chung's publication (1994) and rashing ring was chosen as the packing material.

In the transient analysis, the heat and mass transfer coefficients between the air and desiccant solution film were calculated for each time step for the assumed solar C/R length. The total electricity consumption and auxiliary heating energy was obtained by summing up the electricity consumption of calculation time step. The related parameters are listed in Table 2.

Table 2: Parameters for system simulation.

Parameter	Value	Unite
Area of air conditioning space	1000	m^2
Solar C/R area	600	m^2
Solar radiation absorbed by the solution/ Solar radiation	0.8	
C/R glazing height	0.05	m
C/R solution flow rate	0.0055	kg/m s
Heat exchanger effectiveness	0.7	
Solution initial temperature	Ambient air temperature	℃
Solution initial concentration	45%	wt%
Room temperature set-point	25	℃
Room relative humidity set-point	55%	%
Operating period	8:00~18:00	hr
Fresh air flow rate	0.0111	m^3/s person
Latent load from human activities	1.39 E-5	kg/s person

7. Results and discussion

Using the syntactically generated weather data, the dynamic performance of the open cycle solar desiccant dehumidification system was studied. Figure.4 shows the solution concentration variation throughout the year. The upper limit of concentration is set at 50% and 25% for the lower boundary. When the concentration of the desiccant solution reaches at 50%, the diluted solution is no longer supplied to the regenerator for re-concentration and the regenerator stops working. While when the concentration of the desiccant solution is lower than 25%, the kind of solution is deemed to be incapable to remove moisture from the fresh air and the dehumidifier stops working. This hour is also deemed as 'failure hour' that means this system cannot meet the demand of the air conditioning task. Figure 4 reveals that during early spring and later autumn the concentration of the desiccant solution stays at relatively high level. While in the summertime, when the humidity of the air is high the concentration of the solution decrease quickly. Figure 4. also shows that the higher initial solution capacity the lower fluctuation. The dark blue line in the figure 4 represents the system performance for 2000 liter initial solution capacity, and the sky blue line is for 600-litre initial solution capacity. The lost of availability, which is defined by the ratio of number of 'failure hour' and total hours that need dehumidification, for 600 liter initial solution capacity condition is 10.2% and 7.3% for 2000 liter initial solution capacity condition.

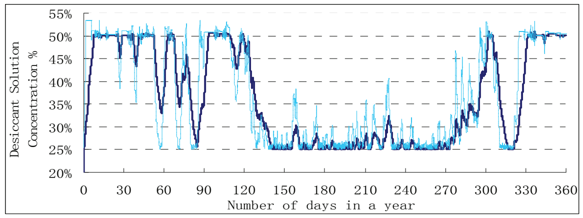
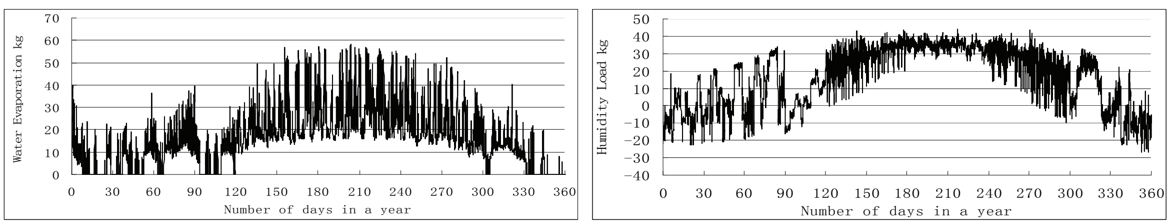


Figure 4: Solution concentration variation for different initial solution capacity (Sky blue: 600 L; Dark blue: 2000 L)

Figure 5. illustrates the water evaporation rate of the open cycle solar C/R and the humidity load of the proposed building. This value dose not significantly affect by the initial solution capacity, so only the water evaporation amount for 2000 liter capacity is illustrated. As an important indicator for the performance of the solar C/R, it seems that the solar C/R performs well in Hong Kong. From January to April, the ambient air humidity is lower than that of the indoor design condition and there is no dehumidification task for most of the time. However, it is worth mentioning that the fluctuation of the humidity is significant, especially in March; and those days that are characterized by high humidity and lower radiation level will persist for several hours, or even several days. The desiccant solution storage tank will 'deplete' quickly in this case. Those fluctuations are clearly shown on the figure 4. Referencing figure 4 and weather data during early spring, just using summer design day condition to sizing such kind of solar utilization system is not enough in Hong Kong climate. It is better to take the variances and spell of certain kind of weather condition into consideration. During the summer period, the proposed system can meet most of the dehumidification task and the water evaporation amount almost always stays above 20 kg/hr. although the concentration of the desiccant solution stays at the lower level, the system still can ensure continuously operation. The 'depleted' solution tank can be refilled quickly due to strong solar radiation during the summer time.



(1) Water evaporation amount, kg/hr; (2) Dehumidification task, kg/hr.

Figure 5: Humidity load and water evaporation throughout the year

8. Conclusion

This paper presents a first-order multivariate Markov chains model to syntactical generate a series of meteorological parameters using 15 years of real weather conditions of Hong Kong (between 1979~1988 and 1996~2000). The results show that the simulated weather data well preserved the characteristics of real weather data. The main benefit of this method is that the synthetic generated weather data can be helpful in the study of energetic system When applying these weather data to the open cycle desiccant dehumidification system, it is more reliable than those design conditions.

NOMENCLATURE

F	Transition frequency matrix;
L	The length of the data sequence;
m	The number of states of a data sequence;
P	One-step transition probability matrix;
s	The number of categorical sequences;
T	The number of subintervals;
V	Value of the state;
X	The state probability distribution;
Z	Uniform random number between (0, 1).

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