

A FRAMEWORK FOR GENERATING STOCHASTIC METEOROLOGICAL YEARS FOR RISK-CONSCIOUS DESIGN OF BUILDINGS

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ABSTRACT

Current performance-based design of buildings is predominantly based on deterministic simulation, but it is being increasingly recognized that the analysis of uncertainty and risk is important for project success, especially in the design of ultra-low energy buildings. As they represent the boundary conditions in energy simulation, weather data significantly affect model outcomes, so the uncertainty of the meteorological conditions should be taken into account in a risk-conscious design process. In the United States, Typical Meteorological Years are used extensively in the analysis of building energy performance, though they fail to account for any variation from typical weather conditions.

This paper seeks to address this issue through the stochastic modeling of meteorological data as a Vector Auto-Regressive (VAR) process with seasonal non-stationarity. We present a framework that characterizes the VAR process using historical meteorological data for any given location. Once defined, the VAR process is able to generate any number of Stochastic Meteorological Years (SMY) for use in simulation packages. The framework is validated with a case study examining predictions of the energy-performance of a solar decathlon competition home.

INTRODUCTION

Risk assessment and management has gained significant attention during the last several decades, spanning many disciplines and a variety of decision-making processes. However, risk assessment of the energy performance is rarely conducted during the process of building design, operation interventions, or retrofit design. As a result, there is no inspection of the probability of underperformance or an assessment of its probable causes. For example, building energy consumption is projected to reduce by 35% over the next 20 years, but the level of confidence of this projection lacks rigorous validation. In practice, it has

been demonstrated that buildings consume more energy than predicted by current deterministic models by an average of 30% and in some cases by up to 100%. Many studies have shown the significance of risk analysis in the process of building design (de Wilde, et al., 2002, Hu, 2009), operation (Moon, 2005), and retrofit (Heo, 2011). The major obstacles that hamper the broad scale application of risk assessment in this area can be summarized as follows:

- The decision context in which risk assessments are to be developed are not well defined.
- The sources of uncertainties that underlie risk assessments are not well understood.

Among various uncertain sources, meteorological variability has been shown as an influential impact on building performance (Bhandari, et al., 2012, Hassan, 2009). For example, Hu's research found that the risk in the weather pattern dominated the risk level of off-grid houses (Hu, 2009).

In general, building simulations are conducted using reference years, such as the Typical Meteorological Year (TMY) in the United States, and Test Reference Year (TRY) in the United Kingdom. These reference years, developed from multi-year historical data may be adequate to calculate the average energy consumption, its variation, however, cannot be revealed. Hence, they are not adequate for risk assessment. More importantly, for other performance indicators such as thermal discomfort hours reference years may even fail to predict the averages accurately.

A recent study compared building energy consumption between using multi-years (1971-2000) and TMY's in different climates in China (Yang, et al., 2008). They found that monthly heating load and cooling loads calculated from 30-year simulations differ from those using TMY's by about 10% to 100% and 10% to 20%, respectively. A study in the UK demonstrated that reference years did not always represent the average energy use for certain architectural types and gave no indication of the expected range of energy use



(Kershaw, et al., 2010). In some cases they also found that TRY-based predictions of heating energy consumption, a dominant percentage of building energy usage in the UK, were off by as much as 40%.

In response to the limitation of reference years in the application of uncertainty quantification and risk assessment, some stochastic weather models have been developed to capture the random behavior of meteorological conditions.

A primary investigator in the field, Van Paassen (Van Paassen and De Jong, 1979) developed the Synthetical Reference Year to reduce the amount of simulation days required for analysis of building performance. The Synthetic Reference Year relies on derived correlation structures and Monte Carlo sampling to predict daily means of meteorological phenomena. These stochastically generated means are then applied to shape functions to determine hourly values.

Multiple authors have developed similar Auto-Regressive processes, attempting to predict one particular phenomena, such as solar radiation for use in analyzing photovoltaic panel sizing (Aguar and Collares-Pereira, 1992, B.J, 1977, Goh and Tan, 1977, Gordon and Reddy, 1988, 1988) or wind speed for analyzing turbine sizing (Blanchard and Desrochers, 1984, Chou and Corotis, 1981, McWilliams and Sprevak, 1982).

Knight et. al. developed a more complex series of Auto-Regressive processes in which Temperature and Radiation are progressed simultaneously. However, cross correlations between the two phenomena are not considered (Knight, et al., 1991).

Hong and Jiang (Hong and Jiang, 1995) took a more complex approach, in which several meteorological phenomena are considered in a Vector Auto-Regressive process. In addition to daily means, measures of the daily variance of each phenomenon are predicted as well, such that the shape function used to develop hourly values is also stochastically generated. To make the model tractable, they made a particularly strong assumption of stationarity and separated the year into summer and winter seasons, treating all days, and therefore hours, identically.

Of the models developed, few allow for consideration of more than one meteorological phenomena concurrently. Even less include cross-correlations between phenomena, none having done so at an hourly level. Rather, they rely upon shape functions.

The remainder of the paper is outlined as follows. The next section briefly introduces the field of time series analysis and Vector Auto-Regression as a method for modeling the behavior and variability of meteorological phenomena in a given location. Then, the authors present a framework for generating a set of

Stochastic Meteorological Years (SMY), which serve to characterize variation of meteorological conditions at the location specified. The framework is validated on the simulation case study of an off-grid, zero-energy home. The differences between evaluations of the zero-energy home using TMY3, historical meteorological data, and SMY are investigated, and concluding remarks are offered.

BACKGROUND

As defined by (Chatfield, 2004), a time series is "a collection of observations made sequentially through time." The analysis of time series, is then an attempt to better understand the relationships between observations for some purpose. Generally, the purpose is to encode these relationships into a model of some sort, such that future values can be predicted. An important, and quite beneficial property of time series models is that they are not purely deterministic. Rather, they also include a characterization of the apparent uncertainty or variability of the process as well. In addition to the ability to estimate the meteorological state at a given time, the ability to characterize the uncertainty in that estimate is of principal interest in this work. By modeling the meteorological state using time series analysis, different possible years can be generated to evaluate the effects of variability in the weather on the performance of a particular building.

Auto-Regressive Processes

A simple example of a model developed using principles from time series analysis is a Auto-Regressive (AR) model. AR models take the form of Equation 1.

$$Y_i = \sum_{j \in J} (\phi_{i,j} \cdot Y_{i-j}) + \varepsilon_i \quad (1)$$

As implied by the name, an AR model is developed by performing a regression in which the indicator variables are the same variable's previous values. The fit produced by an AR model is linear in nature, as the $\phi_{i,j}$ are not functions of Y_{i-j} . When solving for the values of $\phi_{i,j}$, it is convenient to restructure Equation 1 into the form of Equation 2, where Φ_i is the row vector of $\phi_{i,j}$ with L entries.

$$Y_i = \Phi_i \cdot \begin{bmatrix} Y_{i-j(1)} \\ \vdots \\ Y_{i-j(L)} \end{bmatrix} + \varepsilon_i \quad (2)$$

For the special case that $\Phi_n = \Phi_p$ for all n and p , the correlation between the state at two different times is defined only by the amount of time between them. This property, which is known as stationarity, enables modelers to greatly reduce the complexity of the model. However, many time series cannot be adequately modeled as stationary. Such is the case for meteorological data, which tend to have significantly

different statistical properties throughout the day and year.

When stationarity cannot be exploited, then it may be possible for the weaker assumption of seasonality to be utilized instead. Seasonal data exhibit repetitive patterns of behavior, such as those arising from daily or annual cycles. For M seasonal observations of Y_i , each complete with observations of $Y_{i-j}, \forall j \in J$, Equation 2 takes the matrix form of Equation 3.

$$\begin{aligned} [Y_{i,1}, \dots, Y_{i,M}] &= \Phi_i \cdot \begin{bmatrix} Y_{i-j(1),1}, \dots, Y_{i-j(1),M} \\ \vdots \quad \ddots \quad \vdots \\ Y_{i-j(L),1}, \dots, Y_{i-j(L),M} \end{bmatrix} \\ &+ [\varepsilon_{i,1}, \dots, \varepsilon_{i,M}] \quad (3) \\ &= \Phi_i \cdot \mathbf{Y}_i + [\varepsilon_{i,1}, \dots, \varepsilon_{i,M}] \end{aligned}$$

Using the linear least squares approach (Equation 4), it is possible to solve for the values of Φ_i such that the sum of the square residuals, ε_i , is minimized.

$$\Phi_i = [Y_{i,1}, \dots, Y_{i,M}] \cdot \mathbf{Y}_i^T \cdot (\mathbf{Y}_i \cdot \mathbf{Y}_i^T)^{-1} \quad (4)$$

Once the values of Φ_i have been determined, it is possible to then determine the vector of residuals as:

$$[\varepsilon_{i,1}, \dots, \varepsilon_{i,M}] = [Y_{i,1}, \dots, Y_{i,M}] - \Phi_i \cdot \mathbf{Y}_i \quad (5)$$

Once the vector of residuals have been determined, a statistical characterization can be made. If it is assumed that the residuals are normally distributed, then the mean and variance of ε_i can be estimated. Thus, with the regression parameters and the corresponding uncertainty defined, the model of the AR process is complete and ready for prediction.

Vector Auto-Regression

A simple extrapolation of AR process arises when the state at a given time is specified by more than one value. For example, the weather at a given time is not fully specified by the Dry Bulb Temperature, but must include information regarding the Wind Speed, Humidity, Barometric Pressure, etc. In these cases, AR models fail to capture the interdependencies between phenomena, and a Vector Auto-Regressive (VAR) model is required. For VAR processes, a similar progression is followed to determine the relationships between the current and previous states, and results in a similar structure for the regression coefficients and statistical properties of the residuals. The major changes include the notion that the regression coefficients now form a matrix Φ_i that reflect the relationships between current values of a state and previous values of all phenomena, not each phenomenon independently. Further, the covariance between the residuals in a given hour is also considered, rather than simply the variance of each individual phenomenon. These principles are further

expanded in the next section, in which a framework for generating Stochastic Meteorological Years (SMY) is presented.

GENERATING A STOCHASTIC METEOROLOGICAL YEAR (SMY)

The framework for generating SMY (as shown in Figure 1) consists of three stages: Obtain Data for Location, Calibrate Model for Location, and Generate SMY for Location. The next sections will further describe the specifics of each stage.

Obtain Data for Location

The first stage in developing a SMY is to gather the required meteorological data. Strictly speaking, the minimum number of years of data required for a statistical fit is quite small. However, the model fit produced by a smaller sample size is not likely to be accurate. As such, it is recommended that longer datasets be used, similar to the 30 year dataset used to develop the Typical Meteorological Year (TMY) datasets. For reference, the dataset used in the case study introduced later contains 39 years of data for most phenomena, and at least 33 for all phenomena. This data can be obtained for several cities from several sources, including the National Climatic Data Center (NCDC, 2012) and National Renewable Energy Laboratory (NREL, 2012). Unfortunately, most datasets will not be serially complete. Often, data may be unavailable for one or more consecutive hours. It is important that each such occurrences be flagged, and not be used for model calibration.¹

The next step is to take advantage of the seasonality in the data, and gather a sufficient number of samples. This is done in two steps. First, the annual seasonality is exploited, such that if N_{year} years of data are available, N_{year} samples of each hourly phenomena are gathered. Next, the daily seasonality is exploited, such that for each hour in the year, the data from preceding and following N_{day} days is also included, resulting in $M = (N_{\text{year}} - 2) \cdot (2 \cdot N_{\text{day}} + 1)$ available data points.

As stated in the discussion of VAR processes, in order for the residuals of a linear process to be Gaussian, the measured values themselves should be Gaussian as well. In some rare situations, the M data points gathered in the last step may closely approximate samples from a Gaussian (normal) distribution. However, this is not generally the case, and the distributions tend to be skewed. For this reason, a Rosenblatt Transform is used to 'normalize' the data. In

¹ Data sets found via the databases mentioned include flags signaling the quality of data provided.

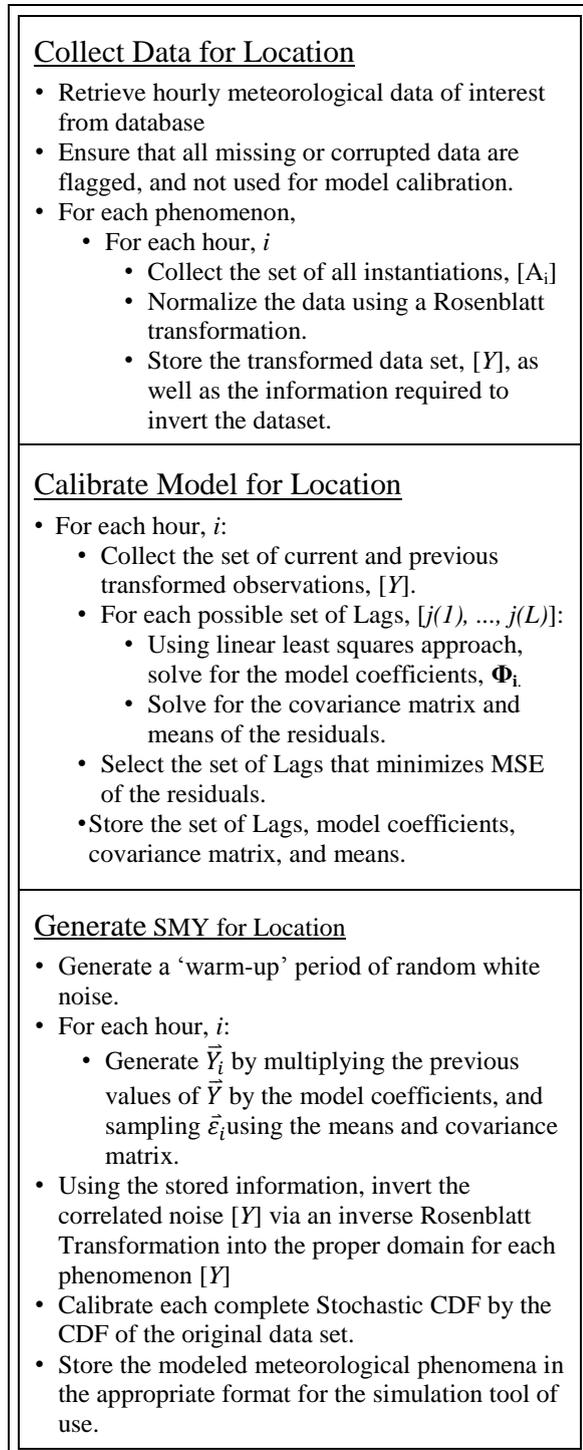


Figure 1. A Framework for the Generation of SMY

a Rosenblatt Transformation, sampled data are inverted through an approximate Cumulative Distribution Function (CDF), and then through the inverse standard normal CDF to obtain a set of samples that more

closely approximate samples from a normal distribution (Rosenblatt, 1952). Once the data have been normalized for each hour and for each phenomenon, the data and information required to invert the data are stored in preparation for model calibration.

Calibrate Model for Location

A Vector Auto-Regressive (VAR) model can be specified in the form of Equation (6).

$$\begin{bmatrix} Y_1 \\ \vdots \\ Y_P \end{bmatrix}_i = \Phi_i \cdot \begin{bmatrix} Y_{1,i-j(1)} \\ \vdots \\ Y_{P,i-j(1)} \\ \vdots \\ Y_{1,i-j(L)} \\ \vdots \\ Y_{P,i-j(L)} \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_P \end{bmatrix}_i \quad (6)$$

Where $\begin{bmatrix} Y_1 \\ \vdots \\ Y_P \end{bmatrix}_i$ correspond to the P different phenomena

of interest at a given hour², Φ_i is the $P \times LP$ matrix of coefficients defining the VAR model, multiplied by the vector of lagged values of the phenomena. For the model calibration to be complete, the modeler must define the matrix Φ_i , as well as the values of the means and covariance used to sample the residuals.

The first step in calibrating the model is to determine the set of lags of interest. In this context, a set of lags is defined as the values $[j(1), \dots, j(L)]$ that define which previous hours the current state is regressed upon. While this step may appear trivial, it is quite important to the proper calibration of the model. Because only a limited amount of data will be available at each hour, only a limited number of lags can be included. Using too many previous coefficients as predictors can lead to over-fitting, resulting in poor predictive capability. Before defining how a set of lags is chosen, we will first briefly digress to introduce how the model is calibrated given a set of defined lags. The reasoning will become clear later in this section.

Once a particular set of lags has been chosen, the modeler creates a set of equations of the form shown in Equation (7).

² The authors chose to include Dry Bulb Temperature, Humidity, Wind Speed Magnitude along the East-West direction, Wind Speed along the North-South direction, Cloud Cover (in fourths), Barometric Pressure, Direct Solar Radiation, and Diffuse Solar Radiation. However, the inclusion of fewer or additional phenomena is allowed.

$$\begin{aligned} [\bar{Y}_{i,1}, \dots, \bar{Y}_{i,M}] &= \Phi_i \cdot \begin{bmatrix} \bar{Y}_{i-j(1),1} & \dots & \bar{Y}_{i-j(L),1} \\ \vdots & \ddots & \vdots \\ \bar{Y}_{i-j(L),1} & \dots & \bar{Y}_{i-j(L),M} \end{bmatrix} \quad (7) \\ &+ [\bar{\varepsilon}_{i,1}, \dots, \bar{\varepsilon}_{i,M}] \\ &= \Phi_i \cdot \bar{Y}_i + [\bar{\varepsilon}_{i,1}, \dots, \bar{\varepsilon}_{i,M}] \end{aligned}$$

where the $\bar{\cdot}$ operator denotes the vector defining the complete set of phenomena or residuals for each phenomenon, and there are M observations of the process where $M = (N_{\text{year}} - 2) \cdot (2 \cdot N_{\text{day}} + 1)$ as previously discussed. Once the set of equations have been thusly defined, Φ_i can be defined via linear least squares using Equation 8.

$$\Phi_i = [\bar{Y}_{i,1}, \dots, \bar{Y}_{i,M}] \cdot \bar{Y}_i^T \cdot (\bar{Y}_i \cdot \bar{Y}_i^T)^{-1} \quad (8)$$

The next step is to define the residuals in the fashion of Equation (9) and then to capture the vector of means and covariance matrix for each hour using standard statistical methods.

$$[\bar{\varepsilon}_{i,1}, \dots, \bar{\varepsilon}_{i,M}] = [\bar{Y}_{i,1}, \dots, \bar{Y}_{i,M}] - \Phi_i \cdot \bar{Y}_i \quad (9)$$

Based on the amount of data available to the authors, a set of seven lags was chosen. The specific lags were selected based upon an algorithm considering iterative improvement. For each hour, each of the 48 preceding hours are considered as the sole predictor, and compared against each other based upon the Mean Square Error of the prediction residuals. After the single best predictor is chosen as the first lag, the process is repeated to find the second lag, third lag, and so on. It should be noted that the algorithm followed may not produce the truly optimal set of lags, since it follows an iterative, rather than all-at-once, optimization process. However, it was deemed that the difference in regression quality was not significant enough to merit the additional computational effort required for exhaustive search (~ 300 vs. $\sim 1.2 \times 10^{10}$ function evaluations). Once performed for each hour of the year, the model is fully specified, and is ready to be implemented.

Generate SMY for Location

The final step in the process of creating an SMY is the generation of a time series of correlated noise using the model developed in the previous stage. First, a "warm-up" period of uncorrelated white noise is generated. The uncorrelated white noise serves as the values of the previous states, and as such should be as long as the largest lag considered. Then, for each hour, \bar{Y}_i is determined by multiplying the linear model coefficients by the previous values and adding $\bar{\varepsilon}_i$, which is generated by sampling a multivariate normal distribution with means and covariance matrix specified by the model. The model should be allowed to "warm-up" by repeating this process for at least 10

days, and then continued until the desired number of SMY years have been created. With the time series thusly generated, an inverse Rosenblatt Transform is used to convert the "normalized" time series into the original domain of the measured data.

The final step is to calibrate the generated time series by the original historical CDF. In this step, a kernel-smoothed approximate CDF is determined for each stochastically generated time series, and then transformed, via a Rosenblatt Transform, into the form of the CDF of the historical data. This ensures that particularly difficult to model phenomena, like direct radiation, have a distribution similar to that found in nature. When completed, the generated time series need only be stored into the correct formatting for the analysis tool of choice. In the next section, a case study is presented in which a set of 100 SMY's are generated, and then compared to TMY3 data and a historical dataset for the city of Atlanta, GA, USA.

CASE STUDY - ANALYSIS OF AN OFF-GRID HOME IN ATLANTA, GA, USA

This section introduces a case study to demonstrate the impact of weather dataset selection on predicted building performance, especially in cases where occurrence of rare events, such as insufficient power to service the home, is of more concern than average performance.

The case study building is an off-grid solar house designed and built by the Georgia Tech Solar Decathlon (GTSD) team as their entry to the Solar Decathlon competition 2007 (Way, 2007). The GTSD house features a single family house, and is powered entirely by 39 photovoltaic (PV) modules with storage provided by 8 battery modules. Further details of the GTSD design and resulting performance have been reported previously (Choudhary et al., 2008).

As the GTSD house is designed to be a zero energy home and completely powered by the installed PV system, power adequacy is one of the most critical performance aspects in design evaluations. There are three basic power adequacy performance indicators: failure rate, outage duration, and annual power unavailability (Billinton and Li, 1994). Failure rate refers to the frequency of power interruptions, which occur when insufficient power is available to perform a house function (such as cooking, shower, etc). This case study does not differentiate between different house functions and counts any time that the total house energy demand is not met as a power interruption. Outage Duration refers to the length of time a power interruption lasts. Specifically, this study will use the mean Outage Duration as the performance indicator for comparison. Annual power unavailability is an aggregated measure of total power outages within



a year, namely the percentage time of a year during which power is insufficient to meet the demand. In addition to the basic power adequacy indices, two other indices are also included to measure the energy performance of the GTSD house: Wasted Energy (due to finite energy storage capacity) and Energy Needed. The remaining performance indicator chosen for this study is the annual power production, considering the high correlation between PV production and available solar radiation in a location. Table 1 lists all performance indicators used in this research.

Three weather datasets are compared in this study: TMY3, historical weather, and the SMY generated based on the approach described in previous sections. The historical meteorological data as obtained from the database includes several gaps when data are not available. These gaps must be filled in order for it to be possible to execute the simulation of the GTSD home. The process followed to fill the gaps in data is similar to that specified in the National Solar Radiation Database 1991-2005 Update (NREL, 2012). If three or less sequential data points are missing, they are filled using linear interpolation of the immediately preceding and following hours. For gaps of four or more, the data is linearly interpolated between the same times at the preceding and following days. In the few cases that remained, interpolation between already-interpolated values was allowed. While the techniques utilized allow for the possibility of discontinuities, they do not significantly affect the statistical properties of the meteorological data over the course of a year, and were deemed sufficient for this analysis.

One hundred SMY were generated for the city of Atlanta using the 39 years of un-edited meteorological data from the Hartsfield-Jackson International airport (ISH ID# 722190). Seven lags were selected at each hour using the simple algorithm described previously. Results of the analyses using TMY3, historical, and SMY are presented in the next section.

Table 1. Summary of Performance Indicators

PERFORMANCE INDEX	DESCRIPTION	UNITS
λ	Failure rate	# /yr
\bar{r}	Mean outage duration	hr
U	Annual power unavailability	%
EN	Energy needed	kWh/yr
EW	Energy wasted	kWh/yr
EP	Electricity production	kWh/yr

RESULTS AND DISCUSSION

Table 2 compares the expected values of the performance indicators of the GTSD house for the three weather datasets. From Table 2, SMY seems to predict slightly more failures per year, but of lesser duration, such that the average percentage of time in which power is unavailable to meet supply is quite similar to the historical average. The TMY3, historical, and SMY-based predictions of average energy needed, produced, and wasted are also similar.

While the averages are somewhat useful for making initial comparisons between the historical data set and SMY, they are less useful for comparisons against TMY3 or the occurrence of extreme events. Especially in the context of a risk-conscious decision making process, the mean of a performance indicator is not sufficient to describe acceptability. Rather, the variation away from the mean should also be captured, such that a proper risk analysis can be performed. To better analyze the effect of different types of meteorological years, the distributions of the various performance metrics are investigated as well.

As shown in Figures 2a and 2b, empirical CDFs can be generated to visualize the spread of data around the average value. In figure 2a, note how even though all three meteorological year types result in similar averages, TMY3 fails to account for any variation away from mean. In figure 2b, note how the TMY-based simulation fails to capture the Mean Outage Duration as predicted by historical or SMY. In order to make statistical comparisons, Kolmogorov-Smirnov hypothesis testing (Kolmogorov, 1933, Smirnov, 1948) can be applied to the CDFs to determine whether the two sets of samples could have been sampled from the same distribution. For a given confidence level $\alpha=0.05$, the maximum vertical difference between the two CDFs is the only factor which determines whether the hypothesis is accepted (the samples come from the same distribution) or rejected (they do not).

For the metrics considered in the case study, the results of the Kolmogorov-Smirnov hypothesis tests are shown in Table 3. When the p value is less than 0.05, the null hypothesis is rejected, else it is accepted. As seen in the hypothesis testing of the given samples, the null hypothesis is rejected for the Failure Rate and Mean Outage Duration in a given year. However, for the remaining factors, namely the Annual Power Unavailability, as well as the Energies Needed, Wasted, and Produced, the null hypothesis is accepted. A possible explanation as to why these particular attributes appear to match historical data closely, while the duration of failure (and therefore mean and frequency of occurrence) do not, concerns the nature of a stochastic prediction.

Table 2. Average Performance attributes Using Different Meteorological Year Types

	E(λ)	E(\bar{r})	E(U)	E(EW)	E(EN)	E(EP)
Hist	41.5	8.91	4.20%	1911	236	9370
SMY	50.4	8.01	4.70%	1894	270	9301
TMY3	57	6.71	4.40%	1364	250	9531

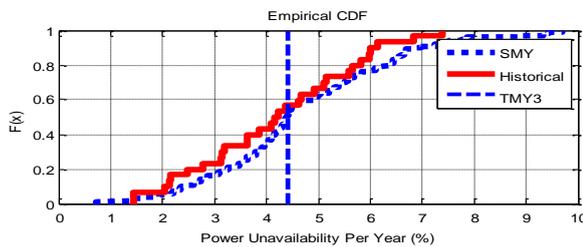


Figure 2a. Comparison of Power Unavailability Predicted by Three Types of Meteorological Years

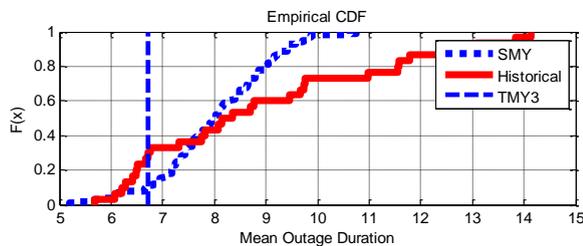


Figure 2b. Comparison of Mean Duration of Failure Predicted by Three Types of Meteorological Years

Table 3. Kolmogorov-Smirnov Hypothesis Testing of Similarity Between SMY and historic data sets

	λ	E(r)	U	EW	EN	EP
p Value	0.015	0.010	0.696	0.174	0.383	0.320
Test Value	Reject	Reject	Accept	Accept	Accept	Accept

When calibrating the model, the modeler assumes that any behavior not captured by the indicator variables is stochastic, and captures it using the residuals, $\bar{\epsilon}$. In reality, there are some phenomena that could better explain these residuals, but are not considered in the model. When using a VAR model, such as that used by the authors, any phenomenon not captured is assumed to be completely stochastic, such that correlations between residuals at subsequent hours are not considered. As such, a stochastic replication of a natural process may appear 'noisy' in comparison. In the context of the meteorological data captured in the model, this is relevant to Temperature, which appears to not maintain sustained levels in the same manner as in reality. Future work to reduce and possibly eliminate this error could include: the incorporation of additional meteorological phenomena to serve as indicator variables (for example: Precipitation); the inclusion of

additional lags, tailored to each phenomenon, or the inclusion of a Moving Average (Chatfield, 2004) process to consider correlations between sequential residuals.

In light of the hypothesis test results, it is not advisable that the model, in its current state, be used for decision-making when the duration of outages is of concern. However, when bulk annual percentage of power unavailability is of primary concern, especially when uncertainties beyond those regarding the meteorological surroundings are of interest as well, the use of SMY as the meteorological basis would allow the modeler to perform Monte-Carlo sampling without relying upon a finite set of historical years. Rare weather events, as generated in the production of SMY, could then be included. Future work should also further investigate the effect of uncertainty in meteorological phenomena relative to other uncertainties prevalent in the design of building systems. Such a comparison could identify scenarios in which the benefit gained by consideration of meteorological uncertainty does not fully offset the cost of doing so.

CONCLUSION

In this paper, the authors have motivated the consideration of uncertainty in the meteorological conditions surrounding a building in the design process. The Stochastic Meteorological Year (SMY) was introduced as a tool for quantifying the variability in the meteorological surroundings of a building, and a framework for its development was developed. Evaluations of an off-grid net zero energy solar decathlon house using three different meteorological year formats were performed as a case study. Relative to historically and TMY-based predictions, SMY-based predictions accurately represented the performance of the house with respect to power unavailability, among other design attributes.

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NOMENCLATURE

- Y - Regressed phenomenon
- Y_i - Value of Y , at current time, i
- Y_{i-j} - Value of Y , at lag, j , of time, i
- \mathbf{Y}_1 - Matrix of M observations of Y_{i-j} for all j
- $\bar{\mathbf{Y}}_1$ - Matrix of M observations of \bar{Y}_{i-j} for all j

- $\phi_{i,j}$ - Coefficient relating Y_i to Y_{i-j} in a model
 Φ_i - Vector of Coefficients ϕ_{i-j} for all j
 Φ_i - Matrix of coefficients ϕ_{i-j} for all j , for all phenomena
 ε_i - Residual between prediction and measured value of Y_i
 $\vec{\cdot}$ - Operator denoting vector referencing all phenomena

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