Effect of Selected Weather Year for Hygrothermal Analyses

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ABSTRACT

Until recently, the most common use of reference year data has been related to energy calculation. Representative weather data for use in moisture design calculations is as critical as other parameters required for heat, air, moisture (HAM) simulations e.g., material data or indoor climate data. The objective of ASHRAE's research project, RP-1325 (2010), was to develop a method for generating more representative design weather years for use in heat and moisture performance predictions of building enclosure systems. Existing methods for selecting moisture design reference years have been reviewed. A new method was developed that provides an improved approach for selecting the most critical years in terms of hygrothermal performance. During the development of the method, eight U.S. locations were investigated, with 30 years of hourly weather data for each location. Another four locations were used to validate the accuracy of the method. The new method was applied in selecting the hygrothermal weather year for European location.

The performance of six different building enclosure components, 4 walls and 2 roofs, was investigated using existing hygrothermal simulation models. The effect of weather data on the performance of building enclosure components was evaluated. The new method allows for selection of weather years that are among the most severe for the simulated structures. The results show that weather data is an essential component of design criteria.

INTRODUCTION

Advanced hygrothermal simulation models require both indoor and outdoor environmental conditions to calculate heat, air, and moisture transport across building enclosure components. More advanced transient models typically use hourly climate parameters such as temperature, relative humidity, solar radiation, wind speed and orientation, cloud index, and rain. Simplified steady-state models, such as the Dew-Point method or Glazer method (ASHRAE 2009a), use averaged winter and summer conditions to predict hygrothermal response of a construction and do not provide correct building enclosure moisture design guidance. This is particularly true in enclosure systems with high thermal performance. In a moisture design process, the environmental data should impose a more severe stress than the average climate in order to provide a level of safety related to moisture performance and durability. Figure 1 shows differences in predicted moisture contents in exterior sheathing when simulated with 30 years of hourly weather data for the same location. Some years provide net moisture accumulation from initial conditions, and some years allow the wall to dry.

Several attempts have been made in the past (Sanders 1996; Hagentoft and Harderup 1993; Geving 1997; Karagiozis 2003; Cornick et al. 2003) to select representative moisture design years for different locations.

The existing available approaches for generating representative weather data, such as the IEA-Annex 24 approach, the Carsten Rode method, the Geving approach, the π-factor method, the Moisture Index method, and the ANK/ORNL-method are reviewed below.

The Annex 24 approach is a construction-dependent method based on determination of the 10% level of condensation

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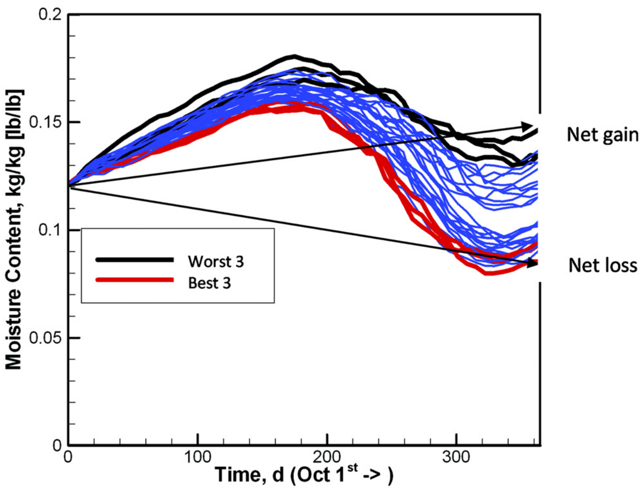

Figure 1 *Moisture content of OSB in a wall predicted in simulations using 30 different weather years for Portland, ME. "Worst" and "Best" years have been selected based on the RHT-index.*

(90th percentile) occurring within the construction using one of three methods: the Glaser method, computer software such as MATCH, or the π-factor method. The procedure is repeated for several different wall constructions and orientations. The mean and standard deviations of the accumulations for each year are determined. These values are subsequently used in calculating the 10% level of accumulation for each construction from the normal distribution function. In this manner, an interstitial condensation due to a ten-year return period is determined for each construction. This might or might not be the same. If different years lead to this level of accumulation for each wall, the monthly values are averaged.

The Carsten Rode (1993) method is a construction-dependent method that requires calculating moisture content integral for as many years as there are available weather data for several different wall constructions and orientations and ranking them in accordance with the severity of moisture conditions—i.e., the higher the moisture content integral, the worse moisture conditions are in the construction.

The Geving approach is based on the method developed by Carsten Rode (1993) and the development within the framework of the IEA Annex 24 HAMTIE. Geving (1997) examined the applicability of this approach for different types of climates, varied construction type, orientation, indoor climate conditions, duration of simulation, and initial moisture content of the construction. The approach requires carrying out a number of simulations with every year of available weather data (10 years minimum). For each preselected construction type, simulations are performed to generate maximum and average moisture contents. From the normal distribution function the 10% level (90th percentile) moisture content is determined for both maximum and average moisture content criteria, and mean and standard deviation is calculated.

The π-factor method uses the drying potential of the wall by relating absolute humidity at the outside wall surface to that in the external air. With the increase in π-factor, the drying out potential likewise increases. The π-factor is determined for each year from the available hourly water vapor concentrations. The 10% percentile of the π-factor corresponds to the 10% year, i.e., the year in which 10% of moisture accumulation would be expected.

The Moisture Index approach, developed in the MEWS project (Cornick et al. 2003), consists of a wetting and a drying function. In this respect, the moisture index can be related to a moisture balance, and it can be visualized as a storage container in which the level of water changes depending on whether wetting or drying takes place. Thus, the wetting and drying functions describe the source and sink components of a moisture balance. Using moisture index, each year can be defined as dry (lowest moisture index), average (mean moisture index), or wet (highest moisture index). In the MEWS project, the average years were defined as being within one standard deviation of the mean, and dry and wet years were defined as remaining years that were more than one standard deviation from the mean moisture-index value.

The ANK-ORNL method was developed by Karagiozis (2003) and is the only method that includes the potential impact of airflow through the structure. The method includes the potential for moisture deposition due to infiltration and exfiltration interactions on an hourly basis. The pressure field due to the wind speed and orientation is calculated and applied to the wall structure. As such, the method is best evaluated when a hygrothermal model that includes the impact of airflow is deployed. The hygric load includes all the hygric contributions available for the structure to accumulate moisture. The method assumes the most absorptive wall system with a very large moisture capacity, maximizing the impact of the various climatic loads, and minimizing the impact of the type of wall structures. The higher the hygric load, the greater potential to cause moisture induced damage. The hygric load provides the net moisture available due to diffusion, capillary transport (wind-driven rain [WDR]), and airflow movement in a particular year. The method has been implemented in the weather file analyzer provided by ORNL (Karagiozis 2002).

The methods were evaluated against simulated performance of walls, and in the end none of the existing methods were deemed satisfactory, as consistent predictions were not achieved, and a new more general method was developed.

Many weather data sets are available in the U.S., such as, for example, Typical Meteorological Years and Weather Years for Energy Calculations. However, these sets are derivations of the same source of measured data and typically only include one year of weather data per location. Typically, the source provider of the raw or base weather data is the National Climatic Data Center.

The available weather data sets for the U.S. are NOAA-NCDC SAMSON data sets (1961–1990) and the NCDC update (1985–2005). For statistically meaningful hygrothermal design years, at least 30 years or more of weather data are typically needed.

The NCDC SAMSON data set, composed of 30 years of hourly weather data for the U.S. from 1961 to 1990, is adequate for this analysis. The update for the NCDC data set, which includes weather data from 1990 to 2005, has recently become available but was not used in this project.

The weather parameters analyzed included outdoor dry bulb temperature, outdoor relative humidity, solar radiation (total, normal, and diffuse), sky radiation (represented by either cloud index or measured long-wave radiation from the sky), wind speed (velocity and direction), and rain.

Generally, two techniques are available for weather year selection (ranking of weather years): construction dependent and construction independent methods. Construction dependent methods can be used for detailed studies of particular climate, while construction independent methods are best used for large-scale parametric studies combining many climates (Cornick 2003).

Based on past research findings, none of the existing methods were found satisfactory, and a new method was developed to rank the years in terms of hygrothermal loading. The objective of RP-1325 (ASHRAE 2010) was to develop a process to select more representative weather year data for moisture design calculations. The research approach involved simulating hygrothermal performance of a typical wall assembly using 30 years of measured hourly weather data and using damage functions or durability criteria to quantify and rank the response of the wall to weather loads.

The research results show that the developed method allows the user to select weather years that are more severe in terms of hygrothermal loading and, therefore, provides a more representative ranking of the weather data. Even though the new method was developed using simulation results for an individual construction, the selected years seem to be common and most severe years for many types of construction.

DESIGN WEATHER YEAR—SELECTION PROCESS

The process of generating a design weather year involves several steps, given that many years of weather data are available for a location under consideration. A series of year-long simulations are carried out with each of the years of available weather data. Performance data must be analyzed using various methods to provide a ranking of the weather years in terms of severity. This ranking is determined by calculating values for different damage functions that use the simulated performance data as input. These damage functions indicate the severity of the weather for the durability and service life of the structure. The damage functions provide a way to quantify change in aspect of moisture performance for the building enclosure. Examples of damage functions are, for example, time of wetness (relates to corrosion) and mold index (indicates conditions favorable for mold growth). The principle of the method is conceptualized in Figure 2.

Rankings Based on Damage Functions

Over the years different *damage functions* have been developed to estimate the deterioration or damage in materials and structures in a way that allows for predicting the durability or service life.

The simulation results were analyzed using damage functions to create the ranking of weather years based on each function. A range of physio-chemical and mechanical processes lead to deterioration of building enclosures. The ability of construction materials to transfer loads depends on the magnitude of the applied stresses, moisture contents, and temperatures. Moisture retained in the building enclosure is a function of both the ambient environmental conditions as well as the microstructure of the materials. Damage functions are used to estimate the hygrothermal damage for materials in building enclosure assemblies. Different damage mechanisms affect different materials: wood grows mold at high moisture content and relative humidity, ice is a typical cause of damage in masonry, steel corrodes in wet environments, and paints and coatings can crack due to various reasons. Damage can be either structural or aesthetic without the expectance of failure or reduced service life. Damage modes

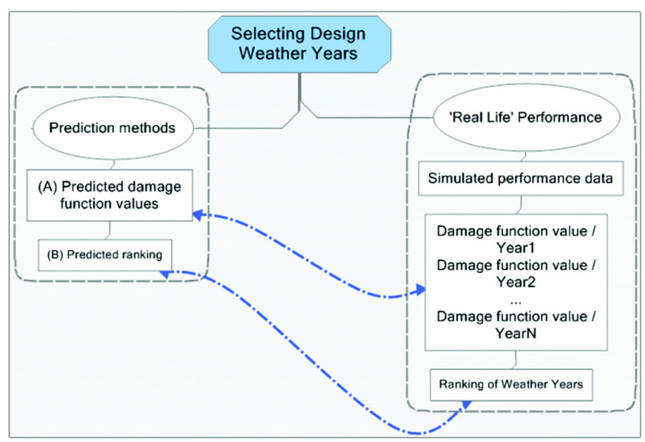

Figure 2 *Principle of selecting weather years: Use prediction methods to match the ranking based on "real-life" performance data generated by simulation models. The methods to select the weather years (prediction methods) can produce either (a) predicted damage function values, which can be used to rank the weather years, or (b) they can directly produce the prediction for ranking without intermediate damage function values.*

can vary depending on the climate. In cold climates, freeze-thaw cycles and winter condensation can cause severe problems; whereas in hot climates, UV-radiation can weaken the structures, allowing for crack formation and subsequent water ingress exacerbated by WDR. In both climates, excessive moisture and temperature fluctuations contribute to undesirable deformations.

In this study, the damage functions used provide criteria for ranking the years in terms of the stresses induced in materials or assemblies. A high damage function value based on the simulated response of the structure indicates a severe year with respect to hygrothermal performance.

For each location under consideration, the damage functions are ranked in decreasing order (i.e., from most to least severe). The critical moisture design year is selected on the basis of this ranking. The damage functions selected for the purpose of this study were Time of Wetness (TOW), RHT-Index, Mold Growth Index, and Maximum Moisture Content. The first three damage functions are of integral type. In many cases, the hygrothermal loading—for example, wetting and drying cycles—lead to permanent changes in the material, allowing additional damage to occur during the subsequent cycles.

The TOW, RHT-Index, Mold Growth Index, and Maximum Moisture Content values were calculated for the critical layer within the wall assembly at any hour of the year. In wall constructions selected for this study, the critical layers are the exterior sheathing (oriented strand board [OSB]) in the stucco-clad wood-frame wall and the outer wythe of the concrete masonry unit (CMU) block in the masonry wall.

Time of Wetness. This is calculated as time in hours when both the temperature and the relative humidity are above prescribed critical levels. Commonly used reference values are 0°C for temperature and 80% for relative humidity. For a full year, the value for TOW can range between 0 and 8760 hours. Alternatively, the TOW can be expressed as a percentage of the potential time of wetness, 50% being wet 50% of the time.

RHT-Index. This is similar to TOW. Instead of only counting the hours when the conditions are met, the actual value of the following integral is calculated (if $T > T_L$ and $RH > RH_L$) as in Equation 1:

$$RHT = \sum(T - T_L) \cdot (RH - RH_L) \qquad (1)$$

The limiting values are typically chosen to be the same as those for the time of wetness: $T_L = 32°F$ (0°C) and $RH_L = 80\%$. The limiting value for the relative humidity was, however, later reduced to 70% for practical reasons. In some climates, the interstitial conditions in the walls were so dry that the resulting damage function value was zero for most of the years, which did not allow for proper ranking of performance. The method has been extensively used by, for example, Mukhopadhyaya et al. (2006).

Mold Growth Index. Presence of mold fungi indicates increased humidity and moisture levels in buildings. Mold fungi are able to grow on any building material with organic content, including wood. The most severe damage includes odor and poor indoor-air quality that could impact the health and well being of the occupants.

During the past decade, different mold-growth models based on laboratory experiments (Sedlbauer 2002; Hukka and Viitanen 1999). Sedlbauer developed a biohygrothermal procedure to predict mold fungus formation. Hukka and Viitanen developed a mathematical model that takes into account the delay in mold growth rate due to unfavorable conditions.

Maximum Moisture Content. Hourly moisture content of the material layers in the simulated wall assemblies are considered. In ASHRAE RP-1325, the above listed damage functions were evaluated, and the results showed that all damage functions provided similar rankings for the weather years. The RH index was used as the criterion in the final method development.

WALL SYSTEMS SELECTED FOR ANALYSIS

Two wall systems were selected for comprehensive analysis:

1. Stucco-clad light-weight wall (LWW) consisting of the following layers listed from outside to inside:
   - conventional stucco with an acrylic finish
   - 60 min asphalt impregnated paper based water-resistive barrier
   - OSB
   - 2×4 fiberglass insulation
   - kraft paper vapor retarder and drywall (gypsum board) with primer and latex paint
2. Heavy-weight wall (HWW) consisting of:
   - 3 5/8 in. brick cladding
   - 1 in. air cavity (nonvented)
   - 8 in. CMU block
   - R-13 fiberglass insulation with metal frame
   - kraft paper
   - drywall
   - one coat of latex primer
   - one coat paint layer

The simulation results for the stucco-clad wood-frame wall and the CMU block wall and the resulting weather year rankings were compared. These results showed similar trends, and further analysis was carried out with only stucco-clad wood-framed walls. This hypothesis was tested afterward by simulating additional wall and roof systems and using additional climate locations to validate the proposed method.

SIMULATION RESULTS

The stucco-clad wood-framed wall was simulated with 30 years of weather data for eight U.S. locations. Since solar radiation and WDR depend heavily on orientation, it was necessary to investigate whether orientation is a critical factor in the selection process.

Analysis of the Orientation Effects

The effects of weather on the performance of building enclosure components can vary depending on the orientation. Orientation affects the hygrothermal loading imposed on the building enclosure components as solar radiation, rain, and wind loads on the north, east, south, and west elevations are different. The influence of orientation on moisture performance of walls is a well-known factor. Solar radiation and WDR provide different loads for north- and south-facing walls. It was necessary to investigate whether a single orientation could be used as a design orientation or whether all orientations always need to be analyzed. The equations used to calculate solar radiations and WDR are contained in ASHRAE Standard 160 (ASHRAE 2009b). A series of simulations were carried out to evaluate orientation effects. The stucco-clad wood-framed wall was simulated facing eight (8) orientations at 45° intervals: north, northeast, east, southeast, south, southwest, west, and northwest. The performance of the wall was then analyzed using damage functions to rank the years in order of worst performance. Figure 3 shows three years of simulated data for each of the four damage functions for New Orleans, LA. It is apparent that for this location, irrespective of the year or damage function selected, that north represents the most severe orientation. In this location, the bulk of the driving rain comes from northeast–southeast (Year 1), south–southeast (Year 2), and northeast–southeast (Year 3) orientations.

The most desirable outcome of the simulations is that a single orientation proves to be most severe. Figure 4 shows the normalized damage function for the stucco-clad wood-framed wall facing eight different orientations. The RHT-index damage function was generated using the most severe year selected on the basis of performance ranking. The data was normalized, with 0% assigned to a lowest value and 100% assigned to the highest value. Overall, damage functions

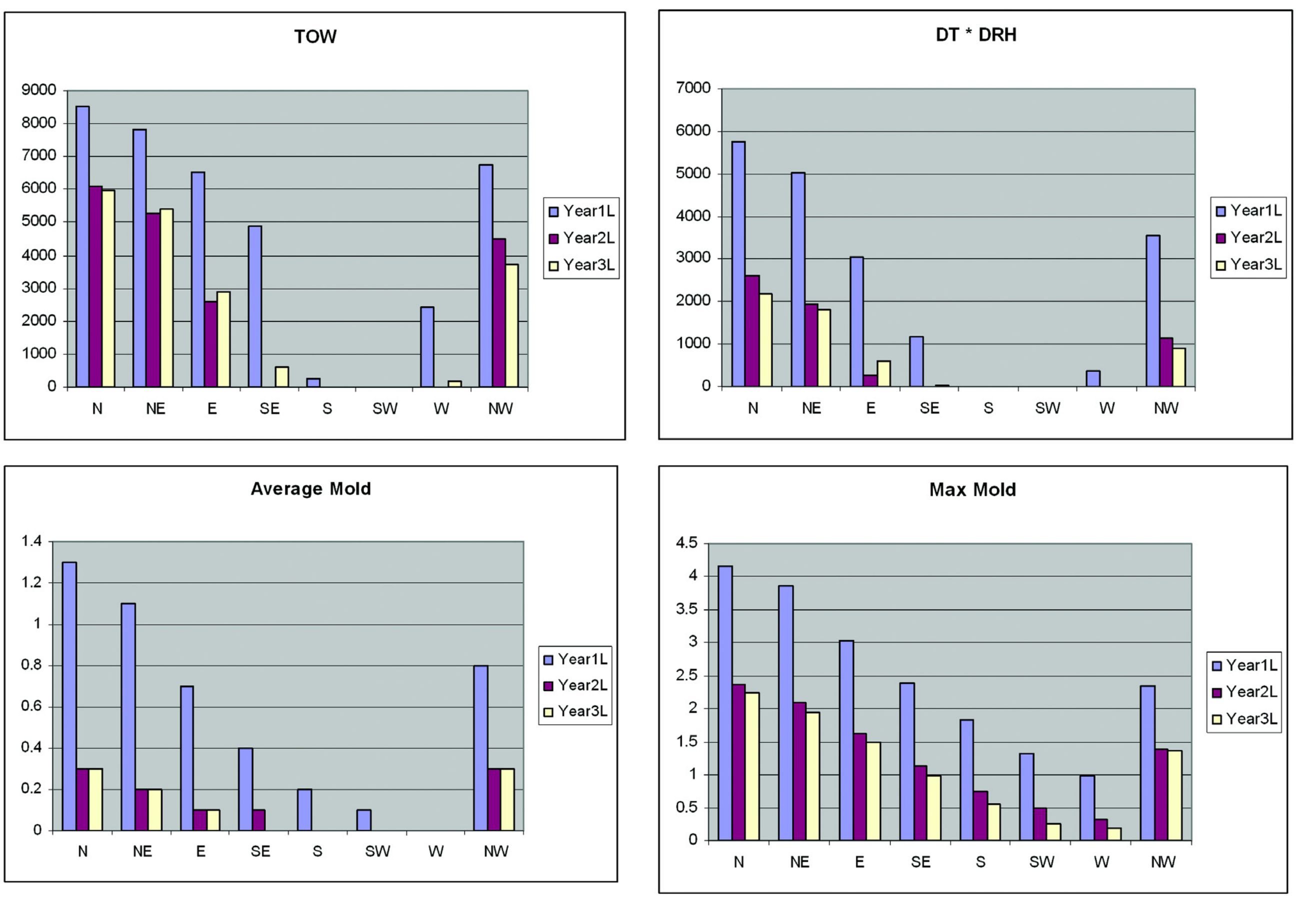

Figure 3 *Damage function values of time of wetness (TOW), RHT-index (DT*DRH), and average and maximum mold index in a location as a function of orientation. Three different weather years were used to produce the data.*

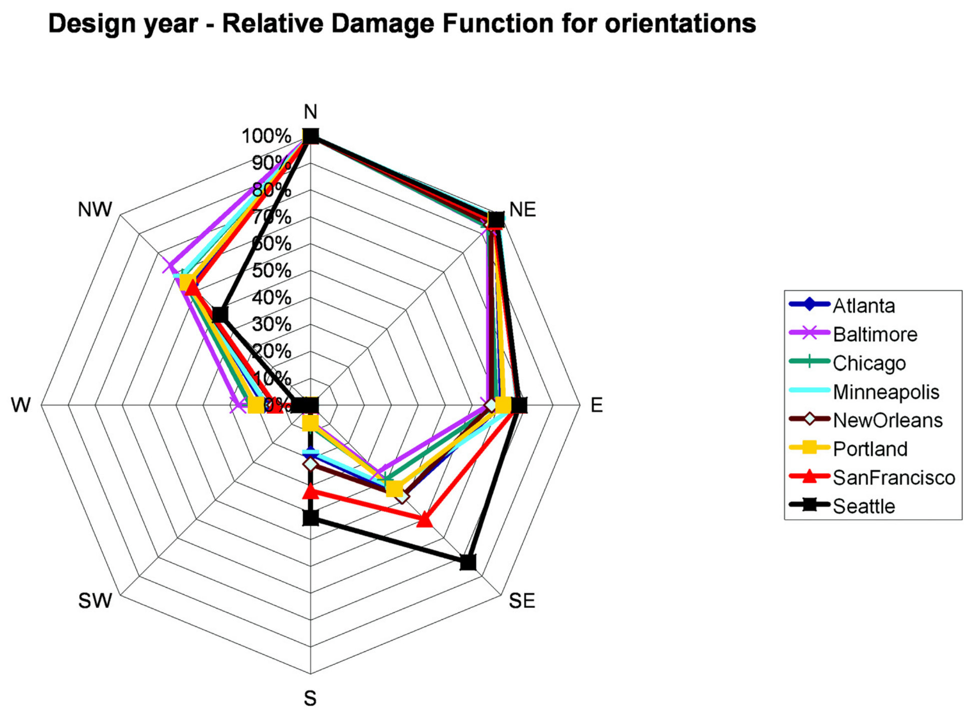

Figure 4 *Distribution of normalized damage function (RHT-index) scaled from 0% to 100% is shown for different orientations. North/northeast orientation has the highest damage function values for all 8 locations.*

TOW, RHT-Index, and Mold Index all showed similar trends in terms of orientation (Figure 4) and indicate that the north orientation was subject to highest severity.

The simulation results were used to calculate the RHT-Index in the OSB of the wood-frame wall. These results were then considered to represent the real performance of the wall. The rankings of the weather years served as reference for all other weather selection methods.

SIMULATED PERFORMANCE AND CORRELATION WITH WEATHER DATA—NEW METHOD DEVELOPMENT

A new method was developed to improve the weather selection capabilities and better match simulated performance. Statistical analyses were carried out to investigate the possibility of selecting the hygrothermal design weather year based exclusively on the weather data. Damage functions were used as key indicators of weather severity. Simulated results for the stucco-clad wood-frame wall were converted to damage function values by integrating the temperature and relative humidity in the exterior sheathing panel $(T - 0)*(RH - 70\%)$ over time. We refer to this as RHT-index.

A regression analysis was used to fit the yearly average weather data parameters under consideration. A second-order polynomial equation was used to calculate the predicted value of the damage function for each year. The function combines each weather parameter (temperature, vapor pressure, solar radiation, precipitation, etc.) weighted by coefficients (parameter). For the selected function, the damage function value is predicted for each year by minimizing the error between the damage function values resulting from simulations and calculations. The damage function is predicted using the following equation:

$$\begin{aligned} Y_{predicted} = {} & c_0 + c_1 \cdot T + c_2 \cdot RH + c_3 \cdot Rad + c_4 \cdot Cloud + c_5 \\ & \cdot Rain + c_6 \cdot Pv + c_7 \cdot WindSpeed + c_8 \cdot WindOr \\ & + c_9 \cdot T^2 + c_{10} \cdot RH^2 + c_{11} \cdot Rad^2 + c_{12} \cdot Cloud^2 + c_{13} \\ & \cdot Rain^2 + c_{14} \cdot Pv^2 + c_{15} \cdot WindSpeed^2 + c_{16} \cdot WindOr^2 \end{aligned} \quad (2)$$

where

$Y_{predicted}$ = predicted damage function value

c_i = coefficient for an individual weather parameter

and the weather parameters are year average values:

T = ambient air temperature, °C

RH = relative humidity, %

Rad = solar radiation on the wall surface, W/m^2

$Cloud$ = cloud index, nondimensional

$Rain$ = WDR on the wall, mm

Pv	=	ambient air vapor pressure, Pa (calculated from *T* and *RH*)
WindSpeed	=	wind speed, m/s
WindOr	=	wind orientation, degrees

Simulated Versus Predicted RHT-Index

Statistical analysis was applied to evaluate Equation 2 and generate coefficients to determine an overall best fit for the damage function values for each year in eight U.S. locations. The fitting of the coefficients was carried out against the damage function values for the OSB layer in the stucco-clad wood-framed wall. As an example, Figure 5 shows the predicted and simulated damage function value for Seattle, WA. Figure 6 shows predicted and simulated damage function values for 12 locations (8 locations used in parameter fitting and 4 others to validate the fit). Four other locations were used to verify that the model would work even with locations that were not part of the parameter fitting. The results showed that the model provided good predictions, not only for the original cities but also for the additional locations of Fairbanks, AK; Memphis, TN; Miami, FL; and Winnipeg, MB, Canada.

GOODNESS-OF-FIT OF THE WEATHER SELECTION METHODS

It is important to gauge a relative comparison between the different weather selection methods. A method was created to numerically compare the goodness-of-fit of picking the years with the highest damage function values. The method has the following steps and is demonstrated in Table 1:

1. Rank the weather years in decreasing order of the damage function.
2. Normalize the damage function values to have a range 0%–100%.
3. Take the top three years as selected by a weather selection method, and find the corresponding normalized damage function values as given by the simulation results.
4. Calculate the average of the normalized damage function values of the three years.
5. Compare the average normalized damage function values of the years picked by the methods. Find out which method picks three years with the highest damage function values.

The previously used approach to compare the goodness-of-fit of different existing weather year selection methods was also used with the newly developed equation-based method. In addition, all methods were also compared on the basis of how many of the three most severe years (based on the simulations) the methods picked.

The normalized damage function values were calculated for the new equation-based method as well as for the existing weather year selection methods. The average of the normalized damage function value of the three most severe years (top 10% years) was used for comparison. For the new method, the normalized damage function values were on average 85% for the eight locations investigated ranging from 69% to 94%. The average values for the existing methods varied between 49% and 63%, with a range of 13% to 85% for individual locations. Normalized damage function values of 50% would indicate more-or-less-average years and not severe years. Only the equation-based method produced consistent performance for all locations, with average damage function values over 50% in any location (Table 2).

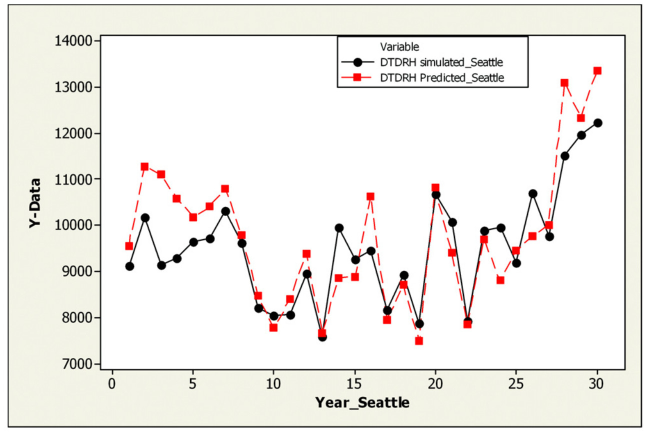

Figure 5 *Seattle, WA, simulated and predicted damage function data (RHT-index) for 30 years for the light-weight wood-frame wall.*

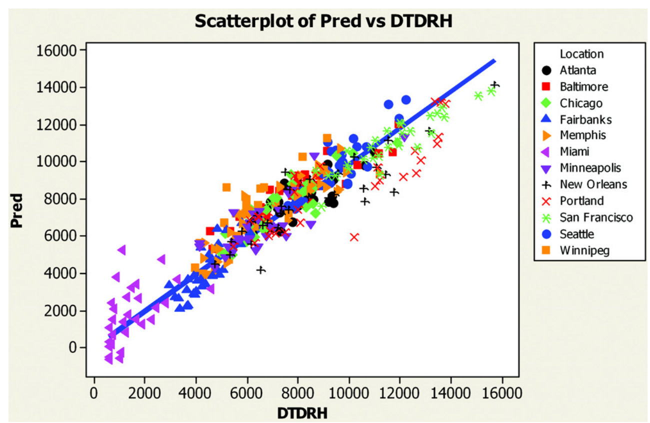

Figure 6 *Simulated damage function (RHT-index) versus the predicted (pred) damage function using the equation method. All 30 years of weather data and 12 locations are included. Fairbanks, Memphis, Miami, and Winnipeg were not part of the optimization process to find the coefficients for Equation 2.*

Table 1. Method to Numerically Compare the Goodness-of-Fit of Picking the Years with the Highest Damage Function Values

Rank by Method	Year	Rank by Simulations	Year	Damage Function Value	Normalized Damage Function
1	1983	1	1985	2501	100%
2	1986	2	1977	1998	78%
3	1961	3	1983	1765	68%
..	..	..	..	..	..
30	1973	30	1972	230	0%

Note: Ranking from the weather selection method is in the left, and the ranking of the weather years resulting from the simulated performance is on the right. The first year selected by this method is the third year based on the simulation results, and this year is at 68 percentile in the normalized range of the damage function.

Table 2. Normalized Damage Function Values Based on the Simulated Results of the Top Three Years for the New Equation Method and the Three Other Existing Methods (ANK/ORNL, π-Factor, and Moisture Index MI) (Salonvaara 2010)

	Equation Method	ANK/ORNL	π Yearly	π Winter	π Summer	MI
Atlanta	82% (2)	53% (0)	68%	26%	63%	42% (0)
Baltimore	84% (2)	45% (2)	63%	21%	60%	37% (1)
Chicago	82% (2)	73% (2)	35%	62%	49%	69% (1)
Minneapolis	69% (2)	65% (1)	42%	37%	38%	53% (1)
New Orleans	89% (2)	13% (0)	66%	45%	55%	68% (1)
Portland ME	94% (3)	53% (1)	29%	67%	26%	74% (0)
San Francisco	85% (2)	53% (1)	85%	69%	61%	80% (2)
Seattle	91% (3)	76% (1)	31%	72%	31%	83% (2)
Average	**85%**	**54%**	**52%**	**50%**	**49%**	**63%**

Note: Number of matching years (predicted) out of top three (simulated) are in parentheses.

Table 2 lists the match between the three most severe years in the simulations and the years selected by the methods for the best two performing existing methods (matching years are in parentheses after the percentage). The order of the ranking within the top three was not considered i.e., if a year was the most severe year in the simulations and the third year in the ranking by MI-method it was considered a match. With the new equation based method the authors were able to select at least two years out of three possible in all eight locations.

Reduction of Coefficients—Statistical Analysis

A widely used statistic to gauge the goodness-of-fit of a model is the coefficient of determination ($R^{2)}$. A value for R^2 equivalent to 1 indicates a perfect correlation between actual data and the regression equation; a value for R^2 equivalent to 0 indicates no correlation. As a rule of thumb, the value of R^2 should never be less than 0.75.

For more than one independent variable in the regression, R^2 is not sufficient to determine the goodness-of-fit. The standard error (SE) of the estimate of the coefficients becomes more important. The smaller the SE compared to the coefficient's magnitude, the more reliable the coefficient estimate. T-statistics (or t-values) are used to identify the significance of individual coefficients. The t-statistics are the ratio of the coefficient estimate divided by the standard error of the estimate.

The coefficient of each variable included in the regression has a t-statistic. For a coefficient to be statistically meaningful, the absolute value of its t-statistic should be at least 2.0. In other words, a variable should not be included in a regression if the standard error of its coefficient estimate is greater than half the magnitude of the coefficient (even when including a variable that increases the R^2). Including more variables in a regression results in a higher R^2, but the significance of most individual coefficients is likely to decrease.

The coefficients of the equation to estimate the damage function values were fitted using commercially available statistical software (Minitab 2007). First the regression equation used eight weather parameters (temperature, solar radiation on the wall, cloud index, relative humidity, wind speed and orientation, and rain on the wall, plus vapor pressure, which was calculated from temperature and relative humidity. Vapor pressure has a strong correlation with temperature, and it is the potential for vapor diffusion; therefore, it was chosen to be included in the analysis as an additional parameter.

Stepwise regressions methods were used to select the best subsets and statistically meaningful parameters and to elimi-

Table 3. Stepwise Regression Analysis of the Parameters for the Equation to Predict Damage Function Values as Performed by the Statistical Software

Vars	R-Sq	R-Sq (adj)	Mallows Cp	S	Rad	Cloud	T	RH	WSPD	WDIR	Rain	Pv	Rad*Rad	Cloud*Cloud	T*T	RH*RH	WSPD*WSPD	WDIR*WDIR	Rain*Rain	Pv*Pv
1	11.5	11.3	2108.7	2861.2												×				
1	11.5	11.2	2110.2	2862.0				×												
2	45.1	44.8	1176.1	2257.5								×								×
2	42.3	42.0	1253.7	2314.0			×								×					
3	66.5	66.2	581.7	1766.0								×				×				×
3	65.7	65.4	604.5	1787.4				×				×								×
4	74.8	74.5	351.9	1533.3								×				×			×	×
4	73.9	73.6	377.4	1560.9				×				×							×	×
5	79.0	78.7	238.4	1403.5				×				×				×			×	×
5	78.5	78.2	249.9	1417.1			×	×			×					×				×
6	84.0	83.8	99.1	1224.5				×			×	×			×	×				×
6	82.7	82.4	136.0	1274.2			×	×			×				×	×				×
7	84.8	84.5	79.6	1196.2				×			×	×	×		×	×				×
7	84.8	84.4	80.8	1198.0	×			×			×	×			×	×				×
8						×		×			×	×	×		×	×				×
8					×	×		×			×	×			×	×				×

Note: Crosses show the selected parameters that produce the best fit.

nate the coefficients that may not explain or improve the precision of the regression. Table 3 shows the best parameters to use when any number from 1–8 is used in the equation. For example, if the equation includes only one weather parameter, the best predictor is relative humidity. Parameters such as Mallows' Cp (Minitab 2007) can be used to estimate the quality of the regression parameters.

Mallows' Cp is a statistic used as an aid in choosing between competing multiple regression models. Mallows' Cp compares the precision and bias of the full model to models with the best subsets of predictors. A model with too many predictors can be relatively imprecise, while one with too few can produce biased estimates. A Mallows' Cp value that is close to the number of predictors (plus the constant) indicates that the model is relatively precise and unbiased in estimating the true regression coefficients and predicting future responses. The analysis shown in Table 3 indicates that the Mallows' Cp becomes close to the number of predictors already with only 8 predictors. The two eight predictor sets are equally good, the last one suggests using solar radiation, cloud index, relative humidity, rain, vapor pressure, temperature*temperature, relative humidity*relative humidity, and vapor pressure*vapor pressure as predictors.

The regression equation with these parameters becomes

$$RHT = 108307 - 241\,Rad - 1391\,Cloud - 312326\,RH + 183308\,Rain + 15.2\,Pv + 27.3\,T \cdot T + 261079\,RH \cdot RH - 0.00972\,Pv \cdot Pv \qquad (3)$$

Now all the predictors have absolute t-statistics higher than 2 (Table 4) indicating them to be proper predictors in the equation. The R-squared with eight predictors 87.2% is still about the same as the 87.3% with 12 predictors. Figure 7 combines all the simulated damage function values (RHT-integral) and the predicted values based on Equation 3 into one chart. If an ideal fit were found, the data would collapse into a straight line.

CONTOUR MAP SELECTED DAMAGE FUNCTIONS

The developed method was used to generate the design weather years for 100 U.S. locations and 7 Canadian locations. The 10th percentile weather year was selected for each location out of 30 years of weather data. The selection was based on the order of years—i.e., the selected year was the year having the third highest damage function value for the location. The damage function data (RHT-values) were used to create a contour plot of the values on the North American map, similar to IECC climate zone classification. The contour map is shown in Figure 7. The map shows similarity to the IECC classification in the way that the midwestern U.S. shows low damage function values, which is the result of drier climate. The eastern part of the U.S. shows higher damage function values, as climates in these locations tend to experience more moisture corresponding to the "moist" area of IECC. The east and west coasts in the northern part of U.S. show the highest damage function values. In the IECC classification, for example, the northwestern coast is classified as a "marine" climate zone.

One of the project outcomes included a development of software that allows the user to create files with the design weather data that meets the format requirement of various hygrothermal modeling software. The basis of this software (WeatherFile Analyzer) was developed by Karagiozis at ORNL (2002).

PERFORMANCE OF THE NEW METHOD WITH DIFFERENT STRUCTURES

The new method and its predictions were tested by running simulations for two other structures in the eight original locations, and the weather years were ranked in the order of severity based on RHT-index. The two new structures were (1) the vinyl-clad wood-framed wall, stucco replaced with vinyl siding and (2) an attic roof structure.

The rankings based on simulations (Table 5) matched 1–3 of the three most severe years as predicted by the equation method in all but one location, Portland, ME (for the roof).

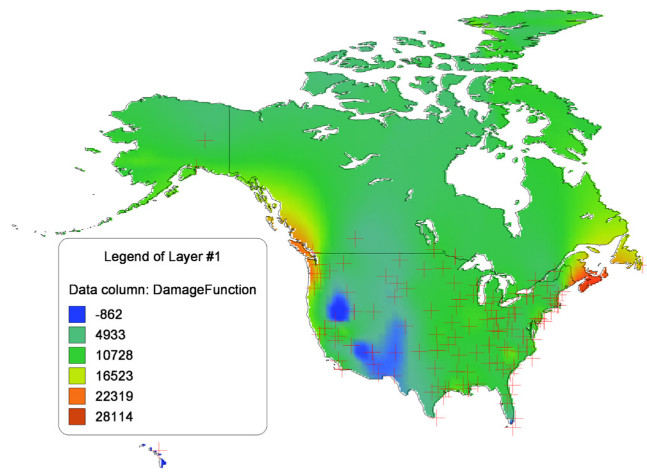

Figure 7 *Damage function (RHT-index) is shown here as a contour map in the U.S. and Canada. Crosses show the locations of the cities with data. Areas without crosses (data points) have been extrapolated by the graphics software and should not be trusted.*

Table 4. Regression Coefficients and Statistic Variables with Eight Predictors Plus Constant for Calculating the Damage Function

Predictor	Coefficient	SE Coefficient	*T*	*P*
Constant	108307	11653	9.30	0.000
Rad	–241.30	27.80	–8.68	0.000
Cloud	–1390.6	170.5	–8.16	0.000
RH	–312326	35156	–8.88	0.000
Rain	183308	9748	18.80	0.000
Pv	15.193	1.079	14.08	0.000
T · T	27.340	2.775	9.85	0.000
RH · RH	261079	25556	10.22	0.000
Pv · Pv	–0.0097163	0.0002887	–33.66	0.000

S = 1099.91 R-Sq = 87.2% R-sq(adj) = 86.9%

PRESS = 451996042 R-Sq(pred) = 86.36%

Results indicate that the selected weather years appear to be severe for different walls included in this analysis and not only for the wall used as the basis of the development of the equation-based weather selection method.

TESTING OF THE METHOD WITH EUROPEAN WEATHER

The newly developed method and its performance was tested with weather data for Holzkirchen, Germany. Most of the average yearly weather data in Holzkirchen falls between the upper and lower boundaries of the U.S. weather data for the eight locations used in the method development. The average solar radiation is lower and much of relative humidity data in Holzkirchen is higher than that used in the parameter optimization of the U.S. fit. However, the equation based on U.S. data ("U.S. fit" in Figure 8) worked quite well with Holzkirchen weather data. The equation extrapolated the predicted performance successfully. Figure 8 shows the rankings for a stucco-clad wood-framed wall (American-style stucco wall) for a masonry wall and for a metal-clad roof (ventilated under the cladding). The results for Holzkirchen, Germany, show that year 1997 is one of the three most severe years predicted with the equation method for the simulations.

CONCLUSIONS

The object of the project was to review a number of existing methods used in weather year selection for hygrothermal design analysis and develop a new method (approach) having better correlation. The choice of the weather year is critical for proper hygrothermal design analysis. Weather years applied in energy calculations were found to not be acceptable, especially as the key durability-influencing parameters are not based on the exterior temperature.

A number of critical parameters were assessed, and the orientation of the building envelope was shown to affect the wall performance the most. Indeed, the north orientation was found to be the worst factor with the highest damage function values and accumulated moisture contents. A number of previously proposed weather selection methods were tested based on simulated wall performance. The analysis included 30 years of hourly weather data for 12 locations in the U.S. and Canada. From the extensive analysis, none of the existing methods was found satisfactory, and a new method was developed to rank the years in terms of hygrothermal loads.

A simple approximate method was developed. An equation-based method (Equation 2) predicted the best performance of all the analyzed methods. This load-based approach was chosen as the final method for selecting the weather years for hygrothermal designs. The method was proven to be the most consistent and accurate of all analyzed methods in selecting the most severe years in terms of hygrothermal performance in all locations.

The method uses average weather parameters for a north-facing wall and calculates an estimate for the damage function RHT-index in the OSB layer (exterior sheathing) of the lightweight wood-frame wall. The year with the third highest RHT-index value is proposed as the year to be selected for hygrothermal designs.

A CD was created with the selected weather data for 100 U.S. location and 7 Canadian locations.

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Table 5. Number of Matching Years (Any of Top Three) Based on the Equation Method and the Simulations

Location	Roof	Vinyl
Atlanta	1	2
Baltimore	2	1
Chicago	1	1
Minneapolis	1	2
New Orleans	1	2
Portland (ME)	0	1
San Francisco	1	3
Seattle	2	3

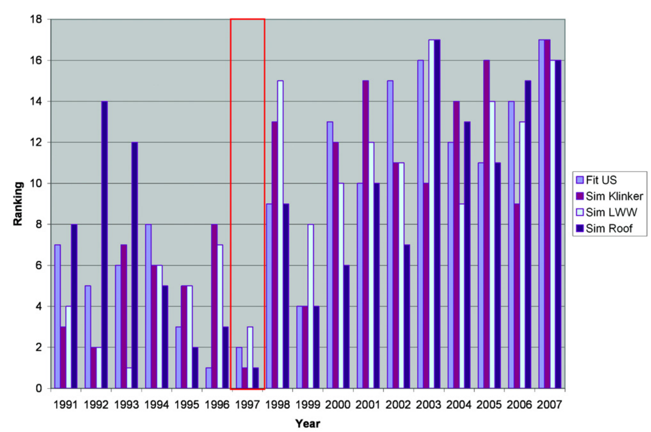

Figure 8 *Ranking of the weather years in Holzkirchen, Germany, based on the equation method (fitted with U.S. data = "Fit U.S.") and the simulation results for a masonry (klinker) wall, a lightweight wall, and a roof.*

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