Using Weather Data For Predictive Control

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For building design and design of space conditioning systems (which starts with calculating space conditioning loads), weather information for the building's location is essential. The traditional approach has been to use information on temperature and humidity extremes (for example, the design conditions data tabulated in Chapter 14 of *ASHRAE Handbook—Fundamentals*) to determine design cooling and heating loads and specify cooling and heating equipment accordingly.

However, buildings typically operate at design conditions for only a small fraction of the year, operating at part load the rest of the time. Information on the variation of temperature, humidity, and insolation throughout the year is needed to enable the most efficient, cost-effective equipment and control strategies to be specified and to assess how well the building will perform through an entire year.

Once a building has been constructed and occupied, real-time weather information for both the area and at the actual building location and short-range weather forecasts potentially can be valuable input to a building control system that is managing temperature set points, variable capacity cooling and heating equipment, and thermal storage.

A common use of real-time information is to adjust various setpoints based on the outdoor temperature. An example of where a forecast of local weather conditions is needed is the control decision of whether and how much to precool a building in the early morning hours, both to take advantage of lower overnight heat rejection temperatures and to reduce peak electric demand later in the day. If the weather forecast is for a hot, humid day, a higher level of precooling might be used.

Another example is optimum management of active thermal storage, such as ice storage, which is primarily used to reduce peak electric demand and the associated demand charges.

In many cases, more energy is needed to produce a given amount of cooling via ice storage than cooling directly. The cost savings of avoided electric demand charges can justify this penalty.

Weather forecast information can be used to determine how much storage is likely to be needed to meet the peak cooling load on the next day, allowing only as much ice to be frozen in advance as needed, limiting the energy penalty to the level necessary to minimize peak demand.

Unlike the often erroneous weather forecasts encountered when trying to plan one's outdoor activities several days in advance, short-term forecasts (less than 24 hours in advance) tend to be reasonably accurate. However, available weather forecasts tend to be applicable to a region, or to a specific location in a region. Weather modeling can bridge the gap between the available forecast and the specific building location.

Weather data obtained through modeling and forecasting is essential for building energy use simulation. Examples of building simulation tools include DOE-2 and EnergyPlus. These modeling tools require hourly typical weather-year data that is obtained as preformatted typical weather-year data points.

Typical weather year data options include ASHRAE's Test Reference Year (TRY), Weather Year for Energy Calculations (WYEC), International Weather for Energy Calculation (IWEC) and the National Climatic Data Center's (NCDC) Typical Meteorological Year (TMY). The data sets differ in the methodology used to construct a typical weather year and in the weighting factors given to specific weather parameters included.[1]

TRY is one of the earliest weather data sets. It includes dry-bulb, wet-bulb, and dew-point temperatures, wind speed and direction, and cloud cover and type. One of its two main shortcomings is that solar insolation must be inferred by the modeling software used.

Secondly, TRY data is constructed from one year of actual weather data; given a multiyear sample of hourly weather data the most extreme months are rated and marked, the year remaining with unmarked months is then chosen as the representative typical weather year. This methodology excludes extremes, constructing the typical year from milder data. After TRY, ASHRAE constructed the WYEC and IWEC data sets, which include solar insolation data.

As a solution to finding a better typical weather year that includes typical extremes as well as averages, NCDC and Sandia National Laboratory constructed the TMY selection method and data set.

Instead of choosing a single year of actual weather data, each month from a given multiyear sample of weather data was rated by solar radiation, dry-bulb and dew-point temperature, and wind speed relative to the long term distributions of these climatic factors over the multiyear period. The months most similar to the long-term distribution were chosen. Also, the data of TMY includes solar insolation.[2]

With so many options as input for typical weather year, does choice of weather data affect building simulation? In a comparison of TRY, TMY, TMY2, TMY3, and WYEC selection methods, the weather models constructed correlated well with the averages for the reference 30 years of observed hourly weather data. For dry-bulb and dew-point temperatures, and global horizontal irradiance, the R squared values were between 0.97 and 0.99 or better. None of the weather data did well with predicting direct normal irradiance.[3]

Seo, et al., found that when a typical weather year is chosen as outlined by TMY and IWEC protocol from 30 years of observed weather data, the resulting peak energy demand analyses differ by at most 5%. Nonetheless, TMY selection methods obtain results closer to simulations using the averages of the 30 years of observed data.[1]

When the same building simulation was run for varying typical weather year data sets (TRY, TMY and TMY2, WYEC and WYEC2) and compared against a simulation using the average from 30 years of observed weather data (1961–1990), it was found that TRY varied the most from the 30-year averages. The TMY simulated solar insolation values were close to the 30-year averages and the WYEC simulations closely followed the average design temperatures and degree days. Neither WYEC nor TMY outperformed the other.[2]

The reduction of a building's energy consumption by using model predictive control depends on the accuracy of the control system's weather forecasting. Model Predictive Control (MPC) systems use various algorithms and time horizon lengths to predict future weather from externally or locally collected weather data.

A comparison of Simple Prior Moving Average (SPMA), Exponentially Weighted Moving Average (EWMA), and two types of Neural Network (NN) time series algorithms showed that models using SPMA or EWMA are less complex and costly to implement and operate, and are more accurate than NNs.

When a model based on each technique was used to predict Dry-Bulb Temperature (DBT), Global Horizontal Irradiance (GHI), and Relative Humidity (RH), it was found that GHI was best predicted by EWMA models, DBT by SPMA models, and RH was well-predicted by all models. DBT is among the most important weather factors for determining building energy use and was very poorly predicted by the focused time delay NN. Overall, it was shown that less-complex time series models outperformed the more complex NN models for the six-hour horizon required to perform MPC.[4]

Energy Saving Potential

Real-time and forecast weather information is an essential element of several energy-saving equipment and operational strategies that are the subject of ongoing research and early product introductions.

Operational strategies that can be used to control HVAC systems include Rule-Based Control (RBC) and Model Predictive Control (MPC). RBC manages the building's HVAC system based on predefined responses for given sets of conditions. MPC uses a weather prediction algorithm in concert with building energy simulation and thermal comfort requirements to determine the HVAC load and load adjustments for a building over a given time horizon. Based on the predicted load requirements and thermal comfort requirements of the building, the control system most effectively uses the HVAC components to heat and cool the building, while trying to minimize energy used.[5]

If the control system can predict the weather conditions, the HVAC system and thermal storage properties of the building shell can be used most effectively to maintain desired indoor air temperature and quality while using the least energy.

The lynchpin of weather-based predictive control is forecasting. Zavala, et al., studied the difference between empirical and physics-based weather modeling. A comparison of the empirical Gaussian Process (GP) model and the physics based Weather Research and Forecast (WRF) model found that the WRF provides more useful 24 hour forecasts for MPC control. Its errors are less than or equal to 5°C (9°F), and its uncertainty bounds contain the true temperature.

Unlike WRF, GP's uncertainty bounds do not accurately contain the actual ambient temperature, leading to overshoots of the thermal comfort zone. This demonstrates that for this application, WRF is the better choice. GP and other empirical models capture the periodicity of the climate observed and are less computationally expensive and equally accurate when shorter time horizons are used.[6]

By using a building's thermal mass for energy storage, heating and cooling demands can be shifted to off-peak electricity hours. MPC can determine when to begin night cooling of a building, or heating, based on predicted weather. MPC has successfully shifted heating and cooling demands to off-peak hours.[6]

One building controls manufacturer, in collaboration with the Swedish Meteorological and Hydrological Institute, studied the use of weather data to control energy supply to a building's HVAC system. The results demonstrated savings of 20 kWh/m^2·yr (6.3 kBtu/ft^2·yr), or 10% of heating costs in the homes studied in Sweden. The control unit requires hourly weather data. It calculates an Equivalent Temperature (ET) that takes into account the effects of outdoor air temperature, solar radiation, and wind on indoor air temperature. The ET is then used to regulate the buildings heating and cooling. In addition to energy savings, indoor air temperature was more stable. The unit is also built to learn from previous weather forecasts.[7]

Predictive control is not limited to commercial buildings. Another manufacturer produces a thermostat with wirelessly generated and managed climate control for residential buildings. The thermostat and the manufacturer's servers communicate via the household's Internet connection. After an initial data gathering phase, a household thermal profile based on consumer use and behavior and 24-hour local weather forecasts is compiled. This profile is used to implement "energy-smart" heating and cooling control. Additionally, the system does not override cost saving temperatures set by the user.

A trial in 2,000 households by Oncor Utilities in Texas resulted in heating and air-conditioning power cuts of 20% to 30% and annual savings up to $400. It also achieved complete AC turnoff at peak hours due to precooling.[8]

These examples indicate that approximately 10% of the energy to condition buildings can potentially be saved by the use of control algorithms using forecasted weather conditions.

Market Factors

The hourly data weather data sets and a variety of hour-by-hour building energy modeling software are readily available. Access to the weather data sets and building energy modeling software like Energy Plus is inexpensive or free.

Detailed hour-by-hour modeling using hourly weather data sets has become commonplace in the evaluation of design alternatives and the design of HVAC systems for larger buildings. For residential and small commercial buildings, calculating design loads based on high and low design temperatures is still common practice. The economic issue is when the added cost of the more involved hour-by-hour modeling exercise can be expected to be justified by helping to guide the selection of equipment that provides significantly better part-load performance, resulting in tangible benefits of lower total annual energy cost and better comfort control in the building.

The implementation of using real-time, modeled, and forecast weather information in control systems that optimize the operation of buildings is in its infancy, as discussed earlier. Commercial products have begun to emerge. For example, the *Dallas Morning News* reported that the residential system described previously can be installed for $19.95.[9]

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