

ON SELECTING WEATHER DATA SETS TO ESTIMATE A BUILDING DESIGN'S ROBUSTNESS TO CLIMATE VARIATIONS

Christian Struck¹, Pieter de Wilde², Janneke Evers³, Jan Hensen¹ and Wim Plokker⁴

¹ Department of Architecture Building and Planning,
Technische Universiteit Eindhoven, The Netherlands

² School of Engineering, University of Plymouth, Plymouth, United Kingdom

³ Adviesburo Nieman B.V., Eindhoven, The Netherlands

⁴ Vabi Software B.V., Delft, The Netherlands

ABSTRACT

The integration of techniques for uncertainty and sensitivity analysis in building performance simulation (BPS) has a number of potential benefits related to design. It allows assessing the accuracy of performance predictions; it can be used to provide concept specific design guidance, and it enables a robustness assessment of the design proposal to different future climate scenarios. The later is considered here. The problems associated with using climate data sets as input to sampling based uncertainty and sensitivity analysis techniques are; (1) these represent time series data with history, and (2) when used as reference data sets, are purpose bound. To address the problems a typical office room is exposed to measured historic weather files, projected future weather data and a derived artificial reference weather data set representative for the period and location. Its response is compared using peak cooling load as criterion for the buildings robustness. It is found that the individual artificial reference data sets are not suited to predict the peak cooling load and its uncertainty band, as they were created for the prediction of a specific performance metrics and for specific building types. However scenario based multi-year future weather data sets show the potential to be successfully used with sampling based uncertainty and sensitivity analysis techniques.

INTRODUCTION

The integration of techniques for uncertainty and sensitivity analysis in building performance simulation (BPS) has a number of potential benefits related to design. It allows assessing the accuracy of performance predictions; it can be used to provide concept specific design guidance, and it enables a robustness assessment of the design proposal to different scenarios. The later is considered here. The authors refer to building and HVAC systems design concepts as integrated building system (IBS) in the remainder of this paper.

Over their life time a building and its systems are, exposed to a great variety of operational scenarios. Those are imposed on the IBS by occupants, control regimes and external climate. As those scenarios are

likely to deviate from the original design conditions the risk exists that the IBS is not capable to maintain defined performance bandwidths. In this context the authors define robustness as: "The integrated building systems ability to maintain defined performance requirements, even if the conditions it is exposed to deviate from design conditions".

Today practitioner's oversize HVAC systems to address potential future deviations. That results in, e.g., reduced HVAC system efficiencies in part load operation. Otherwise, if sized to small, the risk exists that the system is not capable of meeting comfort requirements, thereby reducing the productivity of building occupants.

Based on the above peak loads can be considered a suitable performance metrics to assess robustness. In this paper the authors concentrate on the discussion of the peak cooling load, which is considered important in the context of the changing climate.

There are two different approaches to assess the robustness of IBS's, the absolute and the relative. The absolute assessment makes use of set maximum and/or minimum performance limits. It allows judging the system being robust or not. The relative assessment considers the rate of change, e.g., by different potential of integrated system concepts. It provides the means to rank-order the considered concepts. The relative assessment has the advantage of being applicable if there are not set performance limits available, as is the case for peak cooling load in the case study introduced later.

Uncertainty and sensitivity analysis techniques have the potential to support practitioners to quantify the risk of performance failure due to variations in operational scenarios. The derived quantitative design information might lead practitioners to size systems according to design specific load variations over the buildings lifetime rather than by applying generic safety factors.

In many BPS-tools, occupancy scenarios are defined by heat gain schedules. The related parameters can be individually perturbed assuming a distribution and used for sampling. Similarly, if multiple parameters are involved in defining scenarios, imagine a growing organization's office. A more densely populated office space also requires higher

ventilation rates. The original and densely occupied scenario can be defined as discrete sets, weighted - based on likelihood of occurrence and sampled.

Weather data sets, however, are traditionally represented as annual sets containing series of mean hourly values for parameters as dry bulb temperature, relative humidity, and wind speed. Perturbing recorded time series of one weather parameter disrupts the sets inherent history of climatic events. This means climate parameters cannot be considered continuous for sampling. The data series needs to be treated representing discrete events. Still, climate variations occur at different temporal scales, e.g., sub hourly, hourly, daily, seasonal, annual, decadal etc.

The research questions investigated in this paper are:

1. Which weather data have the potential to support the robustness assessment of IBS's?
2. How to treat scenarios, in particular climate scenarios, when using Latin hypercube sampling to facilitate an uncertainty and sensitivity analysis by regression analysis?
3. Which time scale is appropriate for the representation of climate variations?

METHODOLOGY

Literature is reviewed to establish the state-of-the-art in methods to generate climate files for representing past and future climate variations for building performance simulation.

A simulation study is carried out to investigate the applicability of different climate data sets when analyzing the uncertainty of performance metrics relevant for the robustness assessment of IBS's. The climate files for these simulations are created by combining measured historic weather data and future climate change projections for the location De Bilt in the Netherlands. From 20 years projected hourly data sets artificial reference weather data sets were derived applying procedures from standards as ISO 15927 (ISO, 2005) and NEN5060:2008 (Draft).

The simulation study is based on a typical office room. To facilitate the multiple-run simulation study a prototype is used enabling simulation automation as well as storage and easy access to the simulation results. The data analysis included normality tests for the resulting parameter distributions before applying descriptive statistics to enable comparing the response of the office room to the exposure to different climate data sets.

STATE OF THE ART

Uncertainty analysis for BPS

There are two general approaches to facilitate uncertainty analysis in BPS, the external and internal approach. They relate to the place of implementation, within or around simulation models (Macdonald,

2002). The access to the simulation model in state of the art tools is in most cases restricted, which is why the authors consider the external approach to estimate uncertainties. Furthermore, external approaches can be differentiated into global and local uncertainty analysis methods (Lomas and Eppel, 1992, Helton et al., 2006). Global uncertainty analysis results in a measure of uncertainty by addressing the entire solution space, changing all parameters simultaneously across their full range, whilst local uncertainty analysis is used to identify the individual impact of selected input parameters on the predicted performance metric.

The global method facilitated by Monte Carlo analysis, in particular Latin hypercube sampling extended with regression analysis, allows the propagation of uncertainties and the estimation of parameter sensitivities. A prerequisite of the application of the method is that the model input can be sampled. The application of the method in the domain of building simulation was successfully demonstrated with parametric model input in earlier publications (Struck et al., 2007); (Struck and Hensen, 2007). Perturbing recorded time series of climate parameter, as required by sampling schemes as Latin hypercube, disrupts their inherent history of climatic events. Rather than attempting the brute force method of simulating all available sets a more efficient way would be to identify the years responsible for the minimum and maximum value, representing the uncertainty range, for a selected performance metric.

However, one building responds different to a specific climate than another. That fact excludes the generalization of conclusions regarding the impact of a specific climate file across different building types. Efforts to map the thermal stress placed a number of building types by different weather collections have been reported, e.g., by Argiriou et al. (1999), Clarke (2001), Hensen (2005). Clarke reported the effort to introduce a climate severity index. The regression based procedure defined by Clarke (2001) improves upon the use of the degree days as severity index.

Representation of future climate variations

Weather variations occur in different temporal scales, e.g., daily, seasonal, annual, decadal etc.

The term "weather data sets" describes measured data sets indicating historic weather events for a specific location. "Climate data sets" are different as they refer to data sets that are considered representative for larger spatial and temporal scales, such as test reference years.

Traditionally, BPS tools use annual climate data containing series of mean hourly values for relevant climate parameter.

One approach to assess the design proposals robustness to climate variation is to use recorded data sets that extend as far as the expected lifetime of the integrated system, approx 30years.

However, historic data sets are unlikely to satisfactorily describe the external future climate conditions due to global warming. To represent climate change in data sets for BPS, a widely used approach is to merge projected climate change data with historic data sets (Jentsch et al., 2008); (Belcher et al., 2005); (Crawley, 2008).

In an attempt to categorize different techniques Guan (2009) refers to the method of an “imposed offset approach” which makes use of three operations of shifting, linear stretching, and shifting and stretching. The projected change is imposed on the parameter external air temperature and its probability density function is thereby, either, shifted, stretched or shifted and stretched.

The extent of weather variables for which future change projections are available differ as to which resource is used. The Royal Meteorological Institute of the Netherlands (KNMI) publishes dry bulb temperature and precipitation projections for four different climate change scenarios and time horizons.

Measured vs. Artificial reference weather data sets

The aim of performance simulations is to test alternative design options against periodic weather data. Thereby it is of interest how the building responds to average, most likely or extreme weather conditions for a specific location. Design aspects that are of interest to practitioners are utility bills, as a derivative of annual energy demand, and thermal comfort.

For that purpose reference data sets are required to serve as input to simulation programs. Following Clarke’s (2001) argumentation, “A reference data set is a weather data collection which is representative, when judged against relevant criteria”. For instance the frequency of the air temperature observed during one year can be found to be representative for a period of 10 years. Reference data sets are compiled from long term, e.g., annual, measurements of selected weather parameters.

Measured time series can be used directly as reference data sets, as is the case with years 1964/65 for the location De Bilt in the Netherlands.

Otherwise they are also used to compile artificial annual reference weather data sets. Different methods are in use resulting in different file formats. File formats are reported, for the prediction of the annual energy consumption for heating and cooling, such as the Test Reference Year (TRY), Typical Meteorological Year (TMY) and TMY2, and Weather Year for Energy Simulations (WYEC). See Clarke (2001) for an overview. The methods make use of different statistical procedures for selecting data from the measured time series; they make use of different weather parameters, and parameter weights. More methods are used to create weather data sets for the prediction of the indoor thermal comfort (NEN5060).

Hensen (1999) pointed at problems associated with artificial reference data sets. He states that weather parameters, as temperature, solar radiation and wind, are not necessarily correlated. When selecting days or months to compile an artificial reference data set, the applied parameter specific weights might not correspond to the sensitivities of building under study. Hensen refers to different building types to illustrate the problem. A building with a high window to wall ratio (solar collector) might react most sensitive to variations in solar radiation, whilst a building with no windows (shed) is expected to be most sensitive to changes in temperature.

As artificial reference data sets are typically purpose bound they need to be carefully chosen for the specific type of performance study and “ideally” also for the type of at hand.

Here we want to investigate how useful published reference data sets are compared to measured data sets for the prediction of the performance metric, peak cooling load. Peak cooling load is a performance metric required for the robustness assessment of IBS’s for which no explicit reference data set is available.

As robustness is a problem that addresses the future performance of IBS’s the available measured historic data sets are projected 30 year into the future. For that purpose climate change scenarios published by the Royal Netherlands Meteorological Institute (KNMI) are used.

The method published by the NEN 5060 was then applied to derive artificial reference data sets from the projected historic data.

Measured historic data sets

Measured historic data sets are available, originating from the KNMI, in hourly format for the location De Bilt for 30 years, from 1976 – 2005. For the simulation study the IBS was simulated with each individual weather file.

Artificial reference data sets

Four new artificial reference data sets and their underlying statistical selection procedure were published in 2008 by the NEN 5060 for performance simulation. Of those four files, one is dedicated to the prediction of annual energy consumption and three are to support the overheating risk assessment. The three files were compiled based on a statistical selection procedure using the five day mean of the dry bulb temperature. The five day mean temperature was chosen according to the time constant of buildings complying with the 2003 building regulations. The files are named 1%, 2% and 5% corresponding to the risk of the five day mean temperature to be exceeded for 1%, 2% or 5% in summer and to be undercut for 1%, 2% or 5% in winter. The data originate from a 20 year reference period, 1986 – 2005. That means the 1% year is the most extreme year as the risk that the external

temperature of the reference period exceeds or undercuts the temperature in the reference year is only 1%. Corresponding to the before, the 5% year represents the most moderate of the three.

Projected historic data sets

The measured historic data sets were projected 30 years into the future using the most extreme KNMI climate change scenario, W+. The W+ scenario is the most extreme of four scenarios. It assumes the global mean air temperature to increase by 2K from 1990 to 2050 and a change of the air flow pattern over Western Europe with more westerly winds in winter and more easterly winds in summer. The KNMI regards the published climate change scenarios as equally likely. For an impression of how robust an IBS performs, the authors consider only the most extreme scenario.

The KNMI publishes data quantifying the scenarios on their web page for impact studies for two climate parameters; dry bulb temperature and precipitation. The available data is based on a 30 years reference period, 1976 - 2005. The user can chose a location, time horizon and a scenario. In case of the dry bulb temperature, the output is provided in daily mean air temperatures for the projected reference period. The authors chose to project the reference period 30 years ahead, 2006 – 2035. The 30 years time horizon was chosen as this period corresponds with the expected lifetime of HVAC equipment. The difference between the projected daily mean air temperature and measured historic daily mean air temperatures was added to each hour of the corresponding day. Applying the procedure the authors created 20 projected data sets for the use with simulation tools. The prepared 20 years of data corresponds to the 20 year NEN 5060 reference period.

Projected artificial reference data sets

Using the projected data sets as outlined in the step before the selection procedure as defined in the NEN 5060 was used to generate four artificial reference data sets. The four artificial reference data sets, one for energy and three for thermal comfort assessment, represent the about 30 years projected reference period 1986 - 2005.

PROTOTYPING

Following the incremental research approach, improving upon the existing, external methods were considered for the integration with state of the art tools. In our case the tool, VA114 - a Dutch industry standard simulation tool to facilitate overheating risk and energy analysis was used for the simulations (VA114, 2009). The performance metrics annual demand for cooling heating and peak cooling loads were used for presenting the results. To automate the simulations and store the results in a structured and easily accessible format MATLAB R2006a was used.

CASE STUDY

The case study represents a standard, integrated building and system, office concept. The space is ventilated making use of a hybrid ventilation scheme. The air is naturally supplied and mechanically extracted. Heating and cooling is provided making by 4-pipe fan coil unit with heating set point at 21°C and cooling set point at 24°C. The space is occupied by two people from 8:00 to 18:00hours. Figure 1 and 2 show the conditioning concept and office location, respectively.

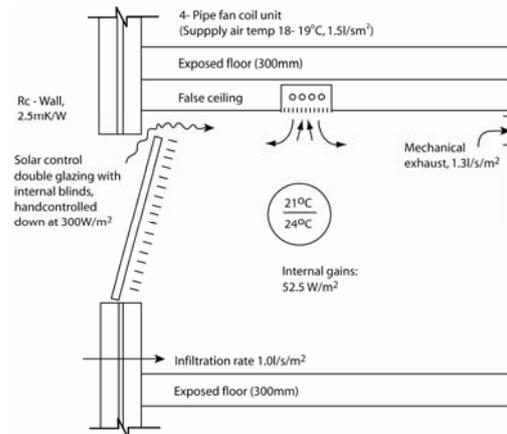


Figure 1 Office conditioning concept – Standard

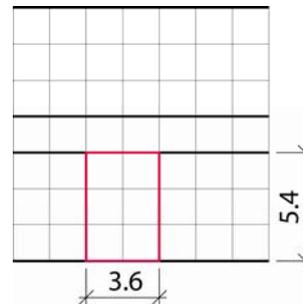


Figure 2 Floor plan and architectural grid

RESULTS

The distribution of the annual cooling demand calculated using the measured historic weather data sets from 1986–2005 is compared with data from the same reference period projected 30 years ahead applying the most extreme KNMI scenario W+.

Figure 3 indicates for the projected historic climate data sets a distribution, which is shifted right towards higher cooling demands, a greater variance when compared with results from the measured historic data.

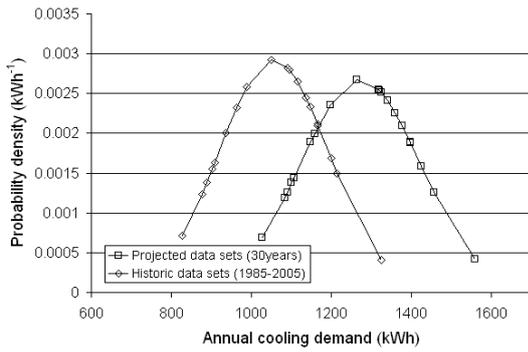


Figure 3 Probability density plot for annual cooling demand

Figure 4 indicates that the uncertainty range by the measured historic weather data sets is 345kWh for the which corresponds to the mean value (1056kWh) +/- 16%. The median from the distribution of the annual cooling loads for the historic data sets corresponds with the result from the reference year for energy demand calculations. The cooling demand calculated with the artificial reference years for comfort assessment exceeds the max. cooling demand by the historic data sets on average about 11%.

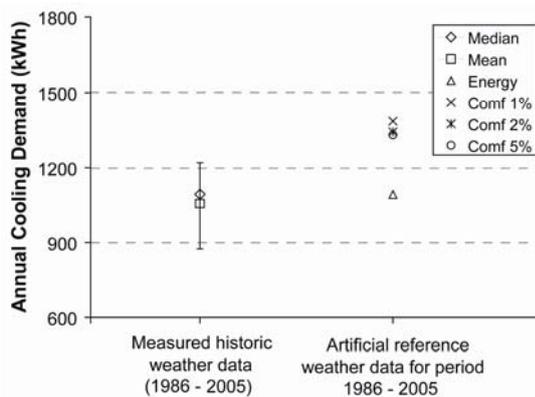


Figure 4 Annual cooling demand; from 20 measured historic weather data sets - distribution indicated by mean, median, 5th and 95th percentiles; and from 4 artificial reference weather data.

The difference between the median and mean of the distribution for the annual cooling demand indicates a slight positive skew. The normality of the distribution was tested. There are different methods to test normality of a distribution such as Lilliefors, Chi squared test among others. The authors use the skew and kurtosis statistics as described by Miles and Shevlin (2001). It was found that the deviation does not deviate significantly from a normal distribution as its skew statistic is smaller than 1.0 and is less than twice the standard error of the skew.

Subsequently, the results from the projected historic weather data are compared with results from projected artificial reference data.

Figure 5 shows the results from running the simulations with projected data series. Compared with the data presented in figure 4 the results appear to be shifted 200kWh scale upwards. The uncertainty range predicted by the projected weather data sets is 381kWh, which corresponds to the mean value (1273kWh) +/- 15%. As noticed before the value for the median of the projected data sets corresponds well with the annual cooling demand by the reference year for energy calculations. The cooling demand calculated from the projected artificial reference years for comfort assessment exceeds the max. cooling demand by the projected historic data sets on average about 9.5%. The reduction of the percentage, compared to the historic data sets, is due to the general increase of the annual cooling for the projected data sets.

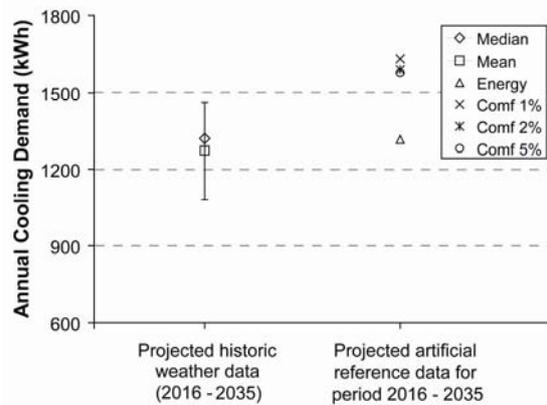


Figure 5 Annual cooling demand; from 20 projected historic weather data sets (KNMI W+ scenario) - distribution indicated by mean, median, 5th and 95th percentiles; and from 4 projected artificial reference weather data.

As the annual energy demand for cooling cannot directly be used to relate the integrated system performance to its robustness the analysis was extended to the peak cooling load.

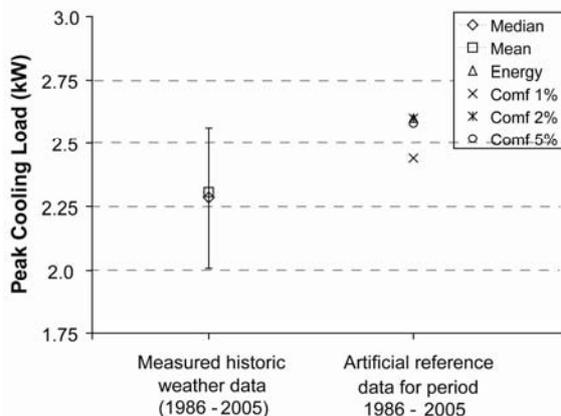


Figure 6 Peak cooling load; from 20 measured historic weather data sets - distribution indicated by mean, median, 5th and 95th percentiles; and from 4 artificial reference weather data.

Figure 6 indicates that the uncertainty range by the measured historic weather data sets is 0.55kW, which corresponds to the mean (2.36kW) +/- 12%. The peak cooling loads calculated from the artificial reference years for energy and comfort assessment appear to be clustered, in no obvious order, around values corresponding with the upper end of the results from the measured historic data sets.

The lowest peak load was calculated for Comf. 1% followed by Comf. 5% and energy data set. The maximum peak load was calculated with Comf. 2%.

Thereafter, the results from projected data sets are compared with results from

Figure 7, shows the results from running the simulations with projected historic and projected artificial reference data sets. Compared with the results from using measured historic data the peak cooling load appears to be shifted 0.2kW scale upwards.

The uncertainty range predicted by the projected weather data sets is 0.7kW which corresponds to the mean (2.5kW) +/- 13%.

As before the peak cooling loads calculated from the reference years for energy and comfort assessment are clustered, in no obvious order, around values corresponding with the upper end of the results from the projected historic data sets. The lowest peak load was calculated for Comf. 1% followed by Comf. 5% and energy data set. The maximum peak load was calculated with Comf. 2%.

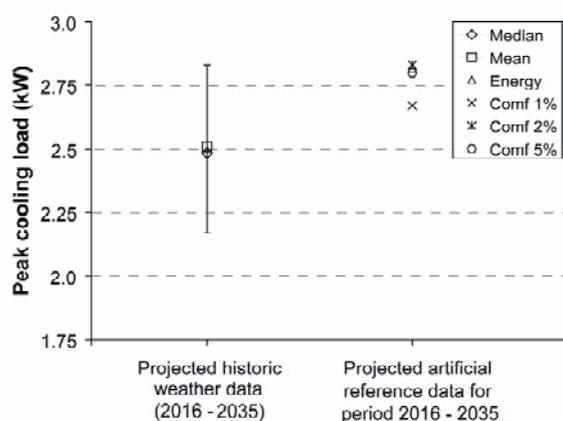


Figure 7 Peak cooling load; from 20 projected historic weather data sets (KNMI W+ scenario) - distribution indicated by mean, median, 5th and 95th percentiles; and from 4 projected artificial reference weather data.

DISCUSSION

The results for the annual cooling demand show a good agreement between the median of the measured and projected historic data sets and derived artificial reference data set for energy predictions. The observation confirms the expectation that the artificial reference file for energy consumption

simulations is well suited to represent the reference period.

When using the artificial reference years to predict the annual cooling demand two things can be noticed.

First, the most extreme data set 1% predicts the highest cooling demand and the least extreme the lowest. That indicates that the annual cooling demand of the case study is indeed dominated by the by the weather parameter dry bulb temperature.

Secondly it can be noticed that the artificial reference files for the comfort assessment lead to overestimation of the cooling demand for the case study of 11% and 9.5%.

Table 1 Annual cooling demand, Statistics

| | Measured historic weather sets | Projected historic weather data |
|-------------------------|--------------------------------|---------------------------------|
| Mean [kWh] | 1055.8 | 1272.7 |
| Stand. deviation [kWh] | 136.3 | 148.9 |
| Uncertainty range [kWh] | 345.1 | 381.0 |
| Deviation from mean [%] | +/-16.3 | +/-15.0 |

The results for the peak cooling load indicate that the artificial reference data sets are not representative for the data sets of the measured historic weather data. The results from the artificial reference data sets are clustered in no logic order around the upper end of the predicted peak cooling loads.

However, the missing logic in the order of the data points indicates that the dry bulb temperature, as selection criteria for the compilation of the artificial reference files, does not dominate the peak cooling load. The most extreme data set, Comf 1%, even shows the lowest peak cooling load!

INTGRATED BUILDING SYSTEMS

The presented study makes use of measured and projected historic data sets plus artificial reference data sets. The aim was to investigate if selected projected artificial reference data sets could be used to predict the peak cooling load which can be used to assess the a IBS's robustness.

It was confirmed that the artificial reference data cannot be used to predict uncertainty ranges for the peak cooling load, a performance metric alien to the statistical selection procedure. The selection procedure targets particular climate parameter and building types by using selection criteria specific to a certain building type for example, buildings time constant.

The different ranking of the artificial reference data sets nicely indicates the different sensitivity of the

performance metrics, annual cooling demand and peak cooling load for the specific case at hand.

Little is known about the severity of the response of specific performance metrics to the climate data used. Clarke (2001) characterized residential buildings using parameters capacity, capacity location window size, infiltration rate and insulation level to categorize typical constructions. Still the work excludes HVAC system parameters that define the response of integrate building systems to climate variations.

In the search for appropriate file formats to predict the uncertainty range for the peak cooling loads the presented artificial reference data sets for annual energy predictions and comfort assessment could be excluded. The next logical step will be to consider the set of measured historic data serving as reference period to the selection procedure, and their scenario based future projections.

The advantage of using the projections of multi-year measure historic climate files is that they can be assigned a probability of occurrence in case the information is available. That enables the use of the data sets with sampling based uncertainty and sensitivity analysis techniques. A disadvantage is the computational expense simulating the multi-year weather files. Another challenge is to store and post-process the wealth on performance data.

CONCLUSIONS

The aim of the study was to investigate if reference weather data sets, when derived from projected future climate data sets, can be used to estimate the uncertainty of critical performance indicators to facilitate a robustness assessment for an integrated building system.

It was found that the approach does not provide useful data to derive uncertainty bands, similar to the reference period as the metrics to be predicted have to comply with the original purpose of the artificial reference data set, e.g., the annual cooling load.

However the study did provide useful insights that guide towards the use of projected multi-year weather files for estimating the uncertainty of the performance metrics as peak cooling load.

The potential advantage of the projected multi-year weather files is that they are scenario based, which allows to consider them as discrete events for sampling based uncertainty and sensitivity analysis techniques.

FUTURE WORK

In order to prove the feasibility of the suggested approach of using multi-year projected weather data sets to predict the uncertainty range of the peak

cooling load, the existing prototype needs to be expanded. Furthermore, the scenario based climate files need to be prepared to facilitate the simulations.

REFERENCES

- Argiriou, A., Lykoudis, S., Kontoyiannidis, S., Balaras, C. A., Asimakopoulos, D., Petrakis, M. & Kassomenos, P. (1999) Comparison Of Methodologies For Tmy Generation Using 20 Years Data For Athens, Greece. *Solar Energy*, 66, 33-45.
- Belcher, S. E., Hacker, J. N. & Powell, D. S. (2005) Constructing Design Weather Data For Future Climates. *Building Service Engineering*, 26, 49-61.
- Clarke, J. A. (2001) *Energy Simulation In Building Design*, Oxford, Uk, Butterworth-Heinemann.
- Crawley, D. (2008) Estimating The Impacts Of Climate Change And Urbanization On Building Performance *Journal Of Building Performance Simulation* 1, Pp. 91-115.
- Evers, J. E. J., Struck, C., Hensen, J. L. M., Wijsman, A. J. T. M., Plokker, W. & Herpen, J. V. (2008) Klimaatscenario's In Gebouwsimulatieprogramma's: Eerste Gebruikerservaringen. *TvvI Magazine*.
- Guan, L. (2009) Preparation Of Future Weather Data To Study The Impact Of Climate Change On Buildings. *Building And Environment*, 44, 793-800.
- Helton, J. C., Johnson, J. D., Sallaberry, C. J. & Storlie, C. B. (2006) Survey Of Sampling-Based Methods For Uncertainty And Sensitivity Analysis. *Reliability Engineering & System Safety*, 91, 1175-1209.
- Hensen, J. (2005) Referentiejaar Of Beter Een Langere Referentieperiode? *TvvI Magazine*.
- Iso (2005) Hygrothermal Performance Of Buildings – Calculation And Presentation Of Climatic Data – Part 4: Hourly Data For Assessing The Annual Energy Use For Heating And Cooling. International Organisation For Standardization (Iso).
- Jentsch, M., Bahaj, A. & James, P. (2008) Climate Change Future Proofing Of Buildings – Generation And Assessment Of Building Simulation Weather Files. *Energy And Buildings*, Accepted Manuscript, Pp. 60.
- Lomas, K. J. & Eppel, H. (1992) Sensitivity Analysis Techniques For Building Thermal Simulation Programs. *Energy And Buildings*, 19, 21-44.
- Macdonald, I. (2002) Quantifying The Effects Of Uncertainty In Building Simulation. *Department Of Mechanical Engineering, Energy Systems Research Unit*. Glasgow, Uk, University Of Strathclyde.
- Miles, J. & Shevlin, M. (2001) *Applying Regression And Correlation - A Guide For Students And Researchers*, London, Sage Publications Inc. .

- Struck, C. & Hensen, J. (2007) On Supporting Design Decisions In Conceptual Design Addressing Specification Uncertainties Using Performance Simulation. *10th Int. Ibpsa Conference*. Tsingua University Beijing/China, International Building Performance Simulation Association.
- Struck, C., Kotek, P. & Hensen, J. (2007) On Incorporating Uncertainty Analysis In Abstract Building Performance Simulation Tools. *12th Symposium For Building Physics*. Technische Universitaet Dresden, Institut Fuer Bauklimatik