A Probabilistic Approach toward Building Energy Performance Design: A Case Study of Roof Design with Uncertainty of Weather

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ABSTRACT

Building energy simulation is commonly used to quantify the savings and/or penalties of a variety of energy efficiency techniques and to estimate monthly and annual energy consumption of the buildings. This quantification however, might not be reliable as a result of a deterministic approach in simulation. Estimated energy performance based on typical meteorological year such as TMY and weather year for energy calculation (WYEC) may not reflect the actual energy performance. In addition, TMY does not capture the extreme weather condition.

This paper investigates the long-term performance of roof designs based on a variety of different combinations of roof solar reflectance and thermal insulation. The focus is studying the potential deviation of energy performance of different roof designs based on CWEC weather data and that under long-term actual weather scenario.

INTRODUCTION

Building energy simulation is commonly used to quantify the savings and/or penalties of a variety of energy efficiency techniques and to estimate monthly and annual energy consumption of the buildings. This quantification however might not reflect the reality as a result of a deterministic approach in simulation. As suggested by Hopfe and Hensen (2011), uncertainty in simulation inputs such as physical uncertainties in insulation or scenario uncertainties in weather condition or occupancy behaviour should be taken into account. Deterministic approach ignores the uncertainties associated with building modelling. The study of De Wit and Augenbroe (2002) evaluated the effect of uncertainty in building performance assessments; according to what Jentsch et al. (2008) conducted, weather data plays an important role on building performance evaluation.

Meteorological data such as solar radiation, air temperature, and wind speed are among those parameters with most variation that influence the energy performance of the building. Hence, using a single representative weather year such as TMY may not reflect the reality and display discrepancy when compared to the use of actual meteorological year (AMY) for simulation. Hong et al (2013) evaluated the impact of using 30-year actual weather data for simulation in terms of HVAC source energy use, total source energy use, peak electric demand, peak electric demand reduction and energy savings. From the life cycle point of view, they also studied impact of weather on the long-term performance of buildings. In their study, by evaluating three types of office buildings according to two energy efficiency codes across 17 ASHRAE climate zones, Hong et al. (2013) stated that capability of typical meteorological data in considering the extreme weather condition or the regular events depends on the climate, the type of the building and the building design. Their results showed that TMY3 underestimated long-term annual energy consumption of the buildings by – 9%. In another study, Yang et al. (2008) conducted building energy simulation for office buildings in the five Chinese climate zones using AMY from 1971 to 2000 to compare the long term mean with what simulated with TMY. They found root-mean-square errors from 3% to 5%.

In fact, the building design can play a significant role in performance consistency, and reliability of building energy consumption while uncertain parameters such as weather condition are taken into account. The reliability of typical meteorological data in considering the extreme events would be even more important in design of low energy building with renewable energy generators such as zero energy buildings as both the demand and the generation sides will be uncertain according to weather variation. Robert and Kummert (2012) investigated the use of generated future weather files to evaluate the impact of using these weather files on the energy performance of an actual NZEB on a month-by-month and year-by-year for two different locations, Montréal (QC) and Massena (NY). Their simulation results for a net-zero energy home showed that the building misses the net-zero energy target for most years. They suggested that climate-sensitive buildings such as NZEBs should always be designed using multi-year simulations with weather data that take climate change into account.

In design of the building roof, previous studies mostly focused on either energy performance of the building or hygrothermal behaviour of that. An experimental study by Ramamurthy et al. (2015) in the North eastern United States for a whole year showed that roof solar reflectance and thermal insulation play significant role in reducing the heat conducted into the building. Based on their results they suggested using high reflective membranes with high R-value for cold climate. In another study by Ramamurthy et al. (2015), cost-benefit analysis conducted to select the optimum thermal resistance-solar reflectance combination of the roof. They suggested that extra insulation might not always beneficial as doubling, tripling and quadrupling the insulation level from the base case with solar reflectance

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of 0.45, requires a payback period of 13, 17 and 19 years, respectively.
However, energy performance is just one of the many factors that might be of interest; reliability and robustness of a design, describe how a design performs under extreme events (reliability) and how a design exhibits an acceptable level of variation as uncertain parameters including weather condition varies.

METHODOLOGY

This paper conducts a large-scale building performance simulation (3906 simulations) to explore the reliability in energy performance incurred in deploying the Canadian Weather for Energy Calculation (CWEC) file comparing to 30 years of actual weather data for a variety of building roof designs in Montreal, Canada. Moreover, the robustness of each roof design against the variation of weather condition is quantified using historical weather data, followed by demonstrating the impact due to the variation of weather on energy performance of buildings.

Weather data

Environment Canada (2016) offers Canadian Weather Energy and Engineering Datasets (CWEEDS); a set of hourly weather data for different locations in Canada. Depending on the location (station), datasets include the weather data necessary for urban planning and energy efficient buildings between the years 1953 and 2005. Canadian Weather Year for Energy Calculation (CWEC) is a single typical meteorological year including twelve statistically selected months from CWEEDS. The selection is carried out by a comparison of cumulative density function (CDF) of the monthly meteorological data such as solar radiation, outdoor air temperature, and wind speed for long-term (usually 30 years) dataset. In this study, the station of Montreal Trudeau international airport with station identification number 94792 was selected to investigate. For this station, the months of CWEC are selected from the years 1960 to 1989. There are a few hours in some of the years of CWEEDS dataset that solar radiation data is missed, especially the first few daylight hours of the morning; to fill in the blank points, interpolation is conducted to estimate the missing data. Figure 1 shows the variation of daily solar irradiance, air temperature and wind speed from 1960 to 1980. The box plots show minimum, lower 25 percentile, median, upper 25 percentile, and maximum daily meteorological parameter for each year.

Weather file creator

Elements a free open-source software tool is used to create weather file for energy simulation. A special feature of Elements is that some of the weather parameters will be calculated automatically according to psychrometric chart; for example, wet bulb and dew point temperature can be calculated with dry bulb temperature, atmospheric pressure and relative humidity. In addition, global solar radiation is calculated with normal and diffuse solar radiation into Elements; moreover, wind speed and wind direction are also included in the weather data (overall 10 weather parameter).

Case study

This paper investigates the long-term performance of roof designs based on a variety of different combinations of roof solar reflectance and thermal insulation. The interest is studying the potential deviation of energy performance of different roof designs with CWEC weather data and that under long-term actual weather scenario.
A big-box retail building based on the prototype building of U.S. Department of Energy is adopted for this case study. The building consists of a relatively large roof surface of 2,299 m^2. The specification of the building enclosure follows that of the National Energy Code of Canada for Buildings (NECB) (2011). A parametric study is conducted by varying the roof solar reflectance and thermal insulation level (14 roof insulation levels from 2.4 m^2-K/W to 15.4 m^2-K/W; 9 roof solar reflectance levels from 0.1 to 0.9). For each design variation (combination of roof solar reflectance and thermal insulation), 31 sets of weather data are applied (CWEC weather file and actual weather files form year 1960 to 1989). With a full factorial design, in total, 3,906 simulations are carried out through JePlus (an EnergyPlus simulation manager for parametric studies). The focus of this case study is on the design of the roof rather than on the HVAC system design, therefore the effect of HVAC system efficiency is ignored. Energy demand instead of energy consumption is thus recorded.

Performance

For each of the 126 roof designs (14 insulation * 9 solar reflectance), simulation is carried out individually for each of the 30 actual year weather data. The mean annual energy demand of the building over the 30 years is calculated. The mean of the 30 year annual energy demand is assumed to be the reference point for performance. The probability density function of the energy demand provides the chance to fit a suitable distribution over the real energy demand. For the case of building energy demand variation influenced by weather condition, lognormal distribution fitted very well on the results. Lognormal is a continuous distribution whose logarithm is a normal (Gaussian) distribution and is commonly used for reliability and risk analysis.

Reliability

First-order reliability methods

First-order reliability method (FORM) is commonly used for estimation of reliability and probability of failure of energy systems in buildings. FORM uses the first and second moments of random variables. First order reliability method for structure and hygrothermal analysis suggested by Pyetrzyk and Hogentoft (2008) and also Bastidas-Arteaga and Soubra (2014) is used in this study.
Performance function which is also a random variable can be defined as below:

$$Z = S - R \quad (1)$$

Where: Z is called performance function, S is the annual energy demand of the building simulated with CWEC, and R is the random variable of annual energy demand of the 30 actual years.

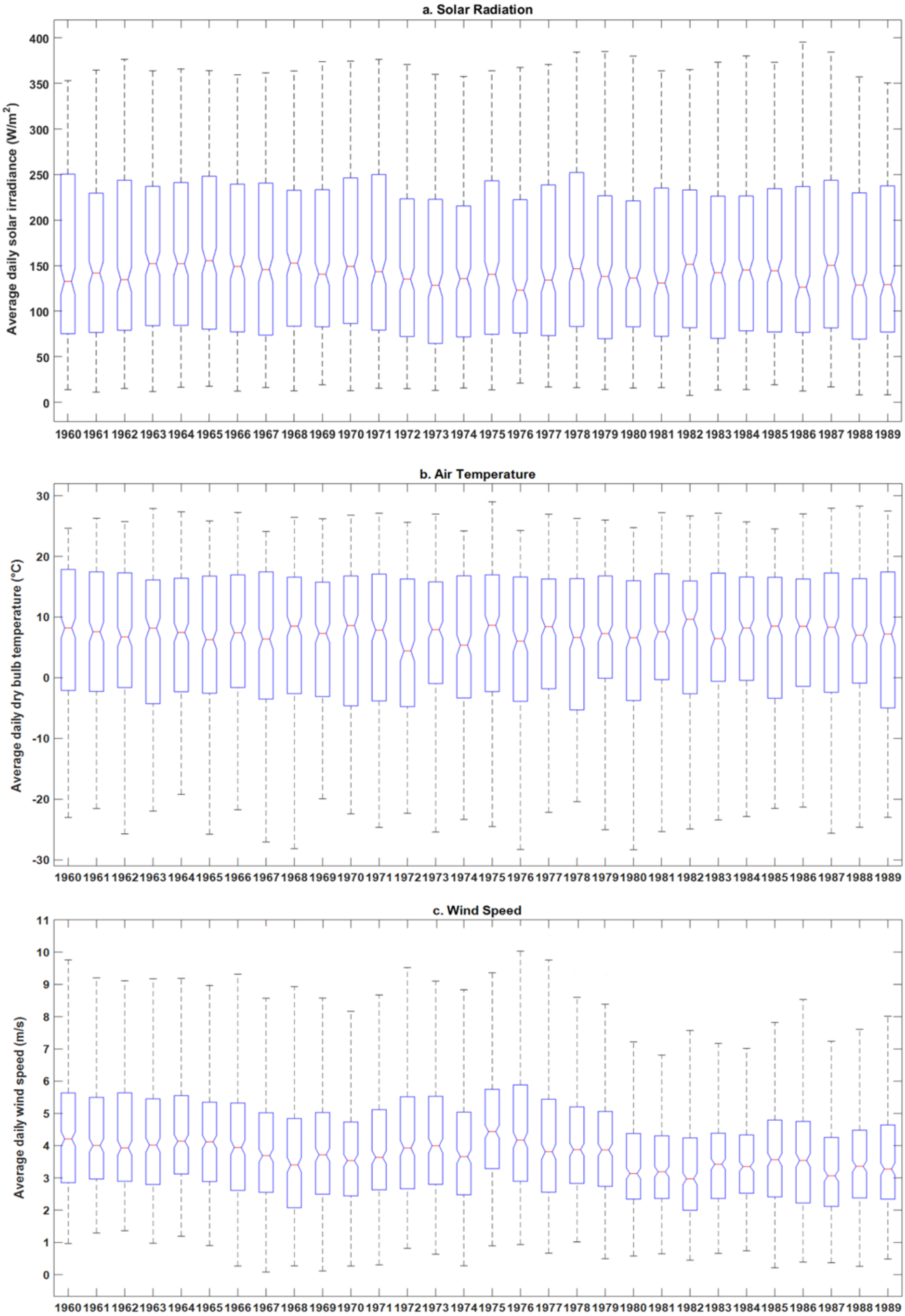

Figure 1: Variation of daily solar irradiance, air temperature, and wind speed from 1960 to 1989

Z = 0 is called the limit state function which is the boundary of reliability and failure region in the domain of basic random variables. Therefore, the probability of failure can be defined:

$$P_f = P\,[Z < 0] = P\,[S < R] \qquad (2)$$

Where: P_f is probability of failure of CWEC in considering the extreme weather condition.
If S and R were Gaussian random variable, then Z would also be a Gaussian random variable and we could state that: $\mu_Z = \mu_S - \mu_R$ and $\sigma_Z^2 = \sigma_S^2 + \sigma_R^2$
Where: μ *and* σ^2 are respectively the mean and variance of the random variables.

For the sake of brevity, CWEC is assumed deterministic and consequently $\sigma_S^2 = 0$, $S = \mu_S$
If *R* be assumed a Gaussian random variable, then *Z* would also be a Gaussian random variable such that
$\mu_Z = \mu_S - \mu_R$ and $\sigma_Z^2 = \sigma_R^2$

Therefore, the P_f could be estimated from the cumulative distribution function (CDF) of the standard normal distribution as:

$$P_f = \Phi\,(-\mu_Z / \sigma_Z) = \Phi\,(-\beta) \qquad (3)$$

Where: β is called reliability index which is also an index for quantification of risk of failure.

However, our results showed that lognormal distribution fits better than Normal distribution therefore another indicator, *Y*, is defined and the limit state function can be re-written as:

$$\ln Y = Z = \ln S - \ln R \qquad (4)$$

and the failure event can be defined as P[Y < 1] = P[Z < 0]
Now, since *ln R* is Gaussian random variables, ln Y and Z are also Gaussian random variables with mean $\ln(\mu_S)-\lambda_R$ and standard deviation $\sqrt{\xi_R^2}$ therefore the probability of failure can be defined as:

$$P_f = \Phi\,[\frac{\ln(\mu S) - \lambda_R}{\sqrt{\xi_R^2}}] = \Phi\,(-\mu_Z / \sigma_Z) = \Phi\,(-\beta) \qquad (5)$$

$$P_r = 1 - P_f \qquad (6)$$

Where: P_r is the probability of reliability of CWEC on considering the extreme event

Robustness

Robustness is defined as the degree of tolerance of the system to be insensitive to variations in both system itself and the environment (Yao et al., 2011). The general idea in robust design is to design the systems with minimum desired variation from the intended performance. Van Gelder et al (2014) suggested a probabilistic approach to optimize energy performance and robustness of that.
With inspiration from robust design in building energy performance design, this study defines the criteria of robustness for roof design as below:

$$\varepsilon = \mu_R / \sigma_R \qquad (7)$$

Where: ε is robustness index, μ_R is the mean of 30 actual years energy demand correspond to each design , and σ_R is the variance of the 30 actual years energy demand correspond to each design.

RESULTS AND DISCUSSION

The results show that reliability in employing CWEC in considering the extreme events (maximum energy demand among the 30 actual years) is highly dependent to the design of the roof. As can be seen from figure 2.a and 2.d, for a design with low level of roof insulation (2.4 m^2-K/W) and high solar reflectance (0.9), cooling and heating simulated with CWEC is quite close to the tail of the PDF of the 30 actual years energy demand of the building and this shows that less thermal insulation makes CWEC more reliable in application of simulation for extreme events. Moreover, the simulation falls far away from the mean. For example, for cooling, simulation with CWEC falls out of twice standard deviation of the distribution; and respecting to the mean, the difference between the CWEC and mean is larger for cooling in comparison with that for heating. That is because during winter in cold climates, the days are shorter, sun angle is lower, the sky is cloudier and this leads to less solar radiation available hitting the roof in winter; therefore, the difference in the major part of meteorological (solar radiation data) between CWEC and the actual meteorological data reduces.
For the design with standard level of insulation which is 5.4 m^2-K/W according to National Energy Code of Canada for Buildings (NECB) 2011, figure 2.b and 2.e show that result simulated with CWEC stands right on the first standard deviation. This means that compared to the design with low level of insulation, CWEC is less reliable in taking into account the extreme climatic event; however it is closer to the mean of the PDF and it better shows the average long-term performance of the design. In addition, with high level of insulation of 15.4 m^2-K/W and low solar reflectance of 0.1 CWEC doesn't seem reliable as simulation with CWEC is located far from the tail of the PDF, instead, it reaches very close to the mean of the long term actual years simulation that makes CWEC a suitable representative for the long term performance. Note that this is not the PDF of the standard normal distribution, it is shown to illustrate the effect of the design on reliability and robustness.
Long term mean energy performance, reliability, and robustness of all the 126 design combinations for heating, cooling and total energy demand of the building is illustrated in figure 3. As figure 3.a shows, higher

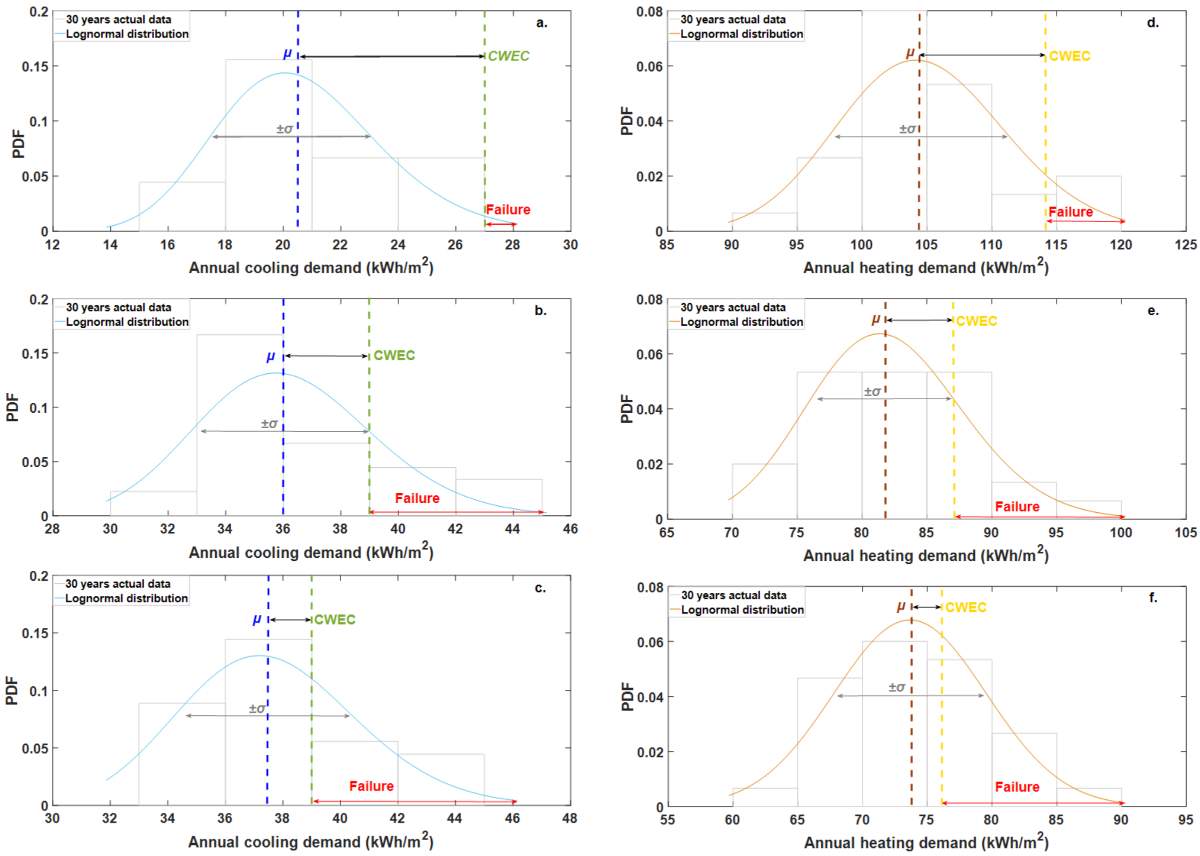

Figure 2: Probability density function of energy demand for annual cooling and heating energy demand. Figures a and d: thermal insulation 2.4 m^2-K/W, solar reflectance 0.9; b and e: thermal insulation 5.4 m^2-K/W, solar reflectance 0.7; c and f: thermal insulation 15.4 m^2-K/W, solar reflectance 0.1

level of insulation and lower solar reflectance obviously reduce the heating demand while it increases the robustness of the design. The yellow square corresponds to the design with 15.4 m^2-K/W thermal insulation and solar reflectance of 0.1.

However, with lower level of insulation the reliability of CWEC on considering the extreme events increases; it is also observed that for a fixed level of insulation lower reflectance has larger reliability.

Figure 3.b shows that with low solar reflectance the cooling demand slightly decreases as the level of insulation increases. Lower solar reflectance increases the amount of solar radiation absorbed by roof and makes the roof surface hot and this considerably increases the heat transfer from outside to inside; therefore, extra level of insulation helps preventing the heat transfer from outside to inside of the building in warm days of the year. However, increasing the level of roof insulation does not always reduce the energy demand. For high solar reflectance (cool or reflective roofs) as level of insulation increases, the cooling energy increases as well. This mostly happens in commercial buildings including retail stores where, because of high internal heat gain such as lighting, solar heat gain through the windows, occupant, and miscellaneous load, inside temperature tends to get hot; because of low roof surface temperature, the most heat transfer is from inside to outside. In this condition, more level of insulation traps heat inside the building and increases the cooling load. We also observed that lower level of insulation is associated with higher reliability of CWEC but less robustness. As the most reliable and least robust design is the roof with low level of insulation of 2.4 m^2-K/W with solar reflectance of 0.9. Whereas, increasing the level of insulation and reducing the solar reflectance increases the robustness considerably; the most robust design is the roof with 15.4 m^2-K/W and low solar reflectance of 0.1 with reliability of about 67%.

For total energy demand which is the summation of heating and cooling demand figure 3.c shows that by using high solar reflectance design, cooling demand reduction, is larger than increase in heating energy. In other words, cooling energy saving of reflective roof is greater than the heating penalty of that. This means a net annual energy saving for reflective roofs; For example, for low level of insulation of 2.4 m^2.K/W, changing solar reflectance from 0.1 to 0.9 decreases the cooling energy from 38 to 20 kWh/m^2 (18 kWh/m^2) saving. Whereas, it increases the heating energy by 10 kWh/m$^{2.}$ This means 8 kWh/m^2 net annual total energy saving for reflective roof (Figure 3.c); this is because during winter in cold climates, the days are shorter, sun angle is lower, the sky

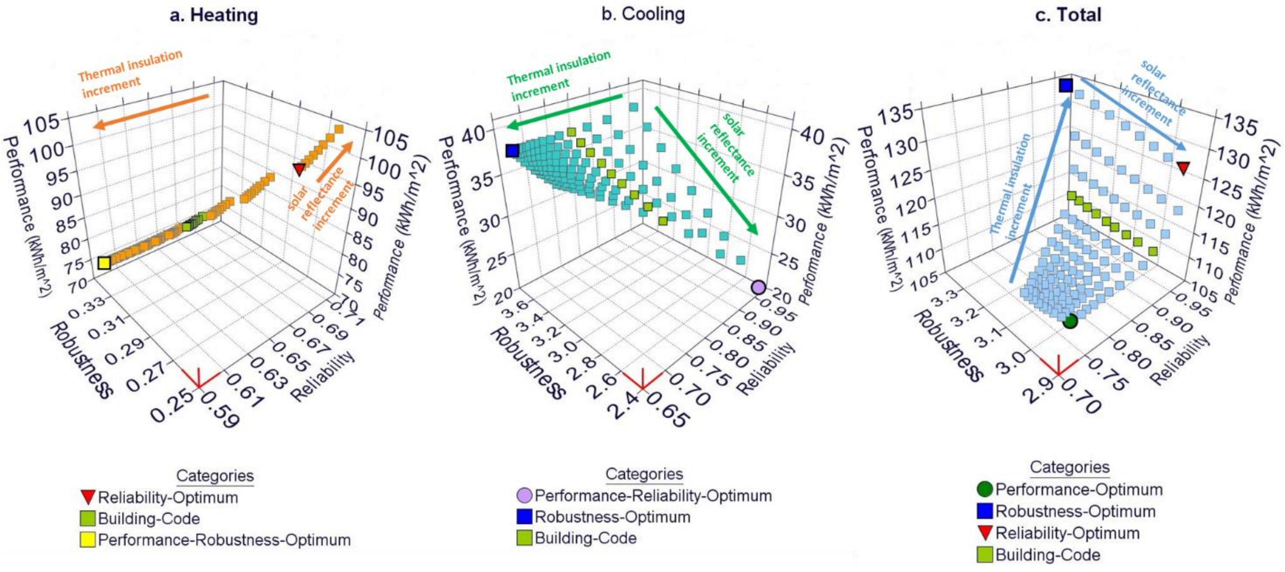

Figure 3: Average performance, reliability and robustness of all the roof design configuration

is cloudier and this leads to less solar radiation available hitting the roof in winter. However, from the overall point of view lowering the solar reflectance reduces the robustness of design whereas it increases the reliability of CWEC simultaneously such that the most robust design consists of insulation level of 2.4 m^2-K/W with solar reflectance of 0.1 and the most reliable design is the same insulation level with solar reflectance of 0.9. Moreover, although increasing the level of roof insulation reduces the energy demand of the building, it dramatically reduces the robustness of the design and the reliability of CWEC on considering the extreme weather condition.

CONCLUSION

As the result showed, design can have a great impact on reliability of a typical meteorological data including CWEC. With lower level of insulation, the energy demand simulated with CWEC is very close to the tail of the PDF of the 30 actual-years simulation (high reliability). In design of the building roof, solar reflectance and thermal insulation play significant role in long term performance, reliability and robustness. Regarding the total annual demand, the best design combination is the high solar reflectance with high level of insulation in cold climate; such that it reduces the cooling demand in cooling season while it decreases the heating demand in heating season.
Although with high level of insulation the effect of solar reflectance would be minor, in lower level of insulation, solar reflectance has a great impact on objectives of the design. Moreover, the simulation with building code (NECB, 2011) showed a mediocre result among the performance, reliability, and robustness; however, the building code suggests only the roof insulation not roof solar reflectance whereas at the standard insulation level, solar reflectance has a great effect on robustness and reliability of CWEC on taking account the extreme weather condition.
It should be mentioned that some of the above statements are resulted from the case study of a retail store building with flat roof in cold climate and they may or may not be applicable for other case studies.

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