Extreme weather data in building performance simulation

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Abstract

This research discusses two different types of extreme weather data for building simulation, the Extreme Reference Years *ERYs* and the eXtreme Meteorological Years *XMYs*, with the aim of performing a comparison analysing their impact on the assessment of building energy performance. A dataset of 12 climates is used to generate both typical and extreme weather data, whose properties are examined both in terms of selected reference months and calculated heating and cooling degree-days. Finally, EnergyPlus simulations are run to evaluate the effects of the two alternative types of extreme weather data on the simulation outcomes.

Key Innovations

- We generated extreme and typical weather data for 12 representative localities worldwide.
- We compared two different procedures for the preparation of extreme years, the Extreme Reference Years *ERY* and the eXtreme Meteorological Yeas *XMY*.
- We modelled the ASHRAE 90.1 Medium Office Building to assess the impact of using extreme weather files in building simulation.

Practical Implications

Typical reference years are no more sufficient for a comprehensive assessment of the robustness of building energy performance to climate variability. In this work we provide a comparison of additional weather data collecting extreme series suitable for the design of buildings robust to climate change scenarios. The two procedures can be easily implemented in software and allow for the generation of extreme series available in weather datasets in addition to *TMYs*.

Introduction

Since multi-year building simulations are computationally demanding, typical or reference years are usually adopted, rather than using individual years of weather data. The first definitions of typical meteorological years *TMY* and test reference years *TRY* were proposed during the 1970s (Hall *et al.* 1978), followed by several variants available in the literature (Herrera *et al.* 2017). These weather data series are generally fictitious years, made of twelve reference months of hourly series of actual weather data recordings, selected through statistical tests to maximize the representativeness with respect to multi-year series. The Finkelstein-Schafer statistics (Finkelstein and Schafer 1971) is the most frequently adopted for the preparation of a reference year. However, the selection procedure excludes months containing long extreme events which, also due to climate change, are more frequent.

In the last decade, some authors have proposed to integrate the information included in *TMY/TRY* with weather files describing extreme weather conditions. Their use allows sensitivity analyses on building performance and designs to assess and enhance building resilience in the typical range of weather conditions for a specific location. While some researchers proposed to generate extreme years by means of morphing techniques applied to the typical ones (Belcher *et al.* 2005, Cox e*t al.* 2015), others modified the very *TMY/TRY* procedure and employed actual weather data series (Crawley and Lawrie 2015 and 2019, Narowski *et al.* 2013, Eames 2016, Nik 2016 and 2017, Pernigotto *et al.* 2020). In this framework, this research aims at extensively comparing two available approaches to define extreme years.

We began with a long-term weather data series collected by NOAA for 12 worldwide locations, selected to be representative of the most important ASHRAE climate classes. For these climates, we prepared both typical and extreme weather files for building performance simulation by implementing a series of different methods proposed by the authors in previous research on Extreme Reference Years *ERY* and eXtreme Meteorological Years *XMY*. Finally, the generated weather files were used in a series of annual simulations of a selected ASHRAE reference building, using EnergyPlus as simulation model. The analysis focused both on the features of the generated weather files and on the effects on simulated energy needs and final uses, in particular for space heating and cooling.

Methods

In order to assess the potential of extreme weather data for building simulation, Typical Years, Extreme Reference Years and eXtreme Meteorological Years were developed for a sample of climates. After comparing the months selected according to the different procedures, annual simulations were run for an ASHRAE reference building, and the calculated final energy uses analysed.

Dataset of climates

In this research, we considered a set of climates, selected to be representative of the main ASHRAE 169:2020 climate classes. The 12 locations (Table 1) belong to 10 climate classes: extremely hot and humid (*0A*), extremely hot and dry (*0B*), very hot and humid (*1A*), very hot and dry (*1B*), hot dry (*2B*), warm humid (*3A*), warm dry (*3B*), mixed humid (*4A*), cool humid (*5A*), and very cold (*7*). Starting from the multi-year weather data series of the period 2004-2018 from *ISD* (U.S.A. NOAA's Integrated Surface Database), a typical meteorological year TMY_x was developed according to the technical standard EN ISO 15927-4:2005 (CEN, 2005).

Definition of ERY

Two Extreme Reference Years *ERYs* were generated for each climate, i.e., a cold (ERY_c) and a hot (ERY_h) Extreme Reference Year. As explained in Pernigotto *et al.* (2020), an *ERY* is developed following a procedure derived from the definition of Typical Year according to the technical standard EN ISO 15927-4:2005 (CEN, 2005).
In details:

1. Among the available weather variables, dry bulb temperature (for ERY_c) or dry bulb temperature and global horizontal solar irradiation (for ERY_h) are selected as primary climatic parameters p and used to calculate daily averages $\underline{p}$ for each month m and candidate year y of the series;
2. For each month m of all available candidate years, all $\underline{p}$ are sorted in increasing order to calculate the cumulative distribution function $\Phi(p, m, i)$ for each parameter and i^{th} day:

$$\Phi(p,m,i) = \frac{K(i)}{N+1} \tag{1}$$

where $K(i)$ is the rank order of the i^{th} day and N is the total number of days for a month over all available candidate years;
3. Similarly, for each month m and year y, all $\underline{p}$ are sorted in increasing order to calculate the cumulative distribution function $F(p, y, m, i)$ for each parameter and i^{th} day:

$$F(p,y,m,i) = \frac{J(i)}{n+1} \tag{2}$$

where $J(i)$ is the rank order of the i^{th} day and n is the number of days for a specific month;
4. At this stage, the statistics by Finkelstein-Schafer, F_S, is calculated:

$$F_S(p,y,m) = \sum_{i=1}^{n} |F(p,y,m,i) - \Phi(p,m,i)| \tag{3}$$

The larger the F_S value, the less a specific candidate year y for a given month m is representative of the long-term trend.
5. For each month m and parameter p, partial rankings are first prepared according to decreasing F_S values, and, then, a total ranking is determined by summing partial ranking positions;
6. Once the least representative months are identified, additional constraints are imposed for the final selection of the extreme reference months. Specifically, in case of the cold *ERY* (ERY_c) it is imposed that the monthly averages of dry bulb temperature are lower than the long-term ones while in case of the hot *ERY* (ERY_h), larger dry bulb temperature and global horizontal irradiation monthly averages are required.

Finally, discontinuities between subsequent months are fixed by means of cubic spline interpolations applied to the final 8 hours of the first month and to the first 8 hours of the second one for dry bulb temperature and relative humidity series.

Table 1: Selected climates.

ID	Zone	Location	Country	Latitude	Longitude	Altitude [m]	HDD_{18} [K d]	CDD_{18} [K d]
0A	0A	Singapore Changi Intl. AP	Singapore	N 1° 21.00'	E 103° 59.64'	7	0	3614
0B	0B	Dubai Intl. AP	U.A.E.	N 25° 15.30'	E 55° 21.84'	10	0	4094
1A	1A	Honolulu Inouye Intl. AP Oahu	U.S.A.	N 21° 19.44'	W 157° 55.74'	2	0	2627
1B	1B	New Delhi Gandhi Intl. AP	India	N 28° 34.02'	E 77° 6.18'	237	275	3042
2B	2B	Cairo Intl. AP	Egypt	N 30° 7.32'	E 31° 24.36'	116	248	2031
3A	3A	Buenos Aires Newbery Intl. AP	Argentina	S 34° 33.54'	W 58° 24.96'	6	761	828
3B	3B	Madrid Barajas-Suarez AP	Spain	N 40° 29.64'	W 3° 34.02'	610	1841	850
4A-1	4A	London Heathrow Intl. AP	U.K.	N 51° 28.68'	W 0° 27.66'	25	2442	57
4A-2	4A	Washington Dulles Intl. AP	U.S.A.	N 38° 56.10'	W 77° 26.82'	88	2300	787
5A-1	5A	Toronto Pearson Intl. AP	Canada	N 43° 40.63'	W 79° 37.84'	173	3493	431
5A-2	5A	Frankfurt AP	Germany	N 50° 1.55'	E 8° 31.28'	104	2694	278
7	7	Winnipeg-Richardson Intl. AP	Canada	N 49° 55.00'	W 97° 14.00'	239	5390	169

Definition of XMY

Among the different methods presented in previous contributions (Crawley and Lawrie 2015 and 2019) for the definition of an eXtreme Meteorological Year *XMY*, the seasonal based approaches were used in the current analysis. This choice was made since in previous studies these specific *XMYs* were observed to outperform the alternatives (Crawley and Lawrie 2019). According to the seasonal methods, the extreme months are selected in order to maximize or minimize over a 6-month period a seasonal weather variable, which is the dry bulb temperature in this case.

Two *XMYs* were prepared:

- XMY_1, built minimizing the winter average temperature and maximizing the summer average one;
- XMY_2, built according to a reverse approach, i.e., maximizing the winter average temperature and minimizing the summer average one;

As it can be noticed, while the *ERY* methodology is aimed at building hot and cold years, the *XMY* approach is different. Indeed, the two determined *XMYs* represent an extreme year maximizing both seasonal heating and cooling demands, and a mild year, which, on the contrary, minimizes them.

ASHRAE reference building

To discuss the impact of the use of different extreme years of weather data on building simulation, we selected a reference case-study, i.e., the ASHRAE 90.1-2019 Medium Office Prototype (Figure 1), characterized by 4,982 m^2 of conditioned floor area distributed in 3 floors and 18 thermal zones (4 perimetral zones, a core zone and a plenum for each floor, with the perimetral zones accounting for 40 % of the whole conditioned area). The building aspect ratio is 1.5 and the façade window-to-wall ratio 33 %.

The building envelope is made of steel-frame walls and a built-up roof, whose *U*-values are in compliance with the requirements of each ASHRAE climate class. The *HVAC* system is composed by packaged air conditioning units with a natural gas furnace, and by *VAV* terminal boxes with damper and electric reheating coils. Room ventilation is provided in compliance with ASHRAE 62.1. Interior and exterior artificial lighting systems and equipment are included in the model as well. Each system is sized according to the design day of the chosen climate condition.

For each climate and ASHRAE climate class, the corresponding Medium Office Prototype was selected. Annual simulations were run with EnergyPlus and the following outputs considered in the analysis:

- Annual power consumption for (1) space heating, (2) space cooling, (3) interior and (4) exterior lighting, (5) interior and (6) exterior equipment, (7) fans, and (8) pumps.
- Annual uses of natural gas for (9) space heating and (10) water demands.

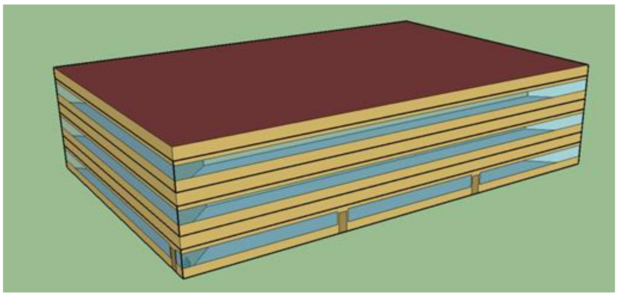

Figure 1: ASHRAE 90.1-2019 Medium Office Prototype.

Results

In this section, results are presented. The first part focuses on the selection of reference months and on heating and cooling degree-days of the developed reference years while the second part discusses the simulated final energy uses for the ASHRAE Medium Office Prototype.

Comparison of reference years

Tables 2-6 report the reference months selected for TMY_x, ERY_c, ERY_h, XMY_1, XMY_2. As it can be observed, selections in all extreme years are usually different from those in the TMY_x weather files: the fractions of entries equal to TMY_x are 5.6 % for ERY_c, 8.3 % for ERY_h, 4.9 % for XMY_1, and 7.6 % for XMY_2.

Table 2: Reference months in TMY_x weather files.

TMYx	0A	0B	1A	1B	2B	3A	3B	4A-1	4A-2	5A-1	5A-2	7
Jan	2012	2011	2015	2007	2009	2011	2009	2004	2005	2009	2004	2017
Feb	2010	2013	2004	2010	2016	2011	2016	2008	2010	2016	2005	2007
Mar	2006	2008	2007	2014	2010	2008	2009	2007	2007	2011	2010	2013
Apr	2007	2016	2013	2008	2011	2016	2018	2015	2009	2016	2008	2015
May	2006	2013	2006	2017	2008	2007	2008	2014	2009	2007	2017	2012
Jun	2004	2013	2017	2011	2013	2013	2013	2005	2010	2017	2014	2008
Jul	2013	2015	2008	2005	2014	2016	2010	2008	2009	2018	2011	2017
Aug	2016	2015	2011	2006	2006	2007	2015	2006	2009	2009	2008	2007
Sep	2018	2011	2008	2015	2011	2008	2013	2012	2008	2014	2011	2016
Oct	2016	2006	2009	2005	2016	2011	2006	2012	2007	2015	2004	2016
Nov	2011	2009	2010	2017	2017	2006	2014	2011	2009	2011	2006	2012
Dec	2007	2009	2004	2017	2017	2017	2017	2015	2016	2008	2010	2004

Table 3: Reference months in ERY_c weather files. In grey those reference months equal to TMY_x.

ERY_c	**0A**	**0B**	**1A**	**1B**	**2B**	**3A**	**3B**	**4A-1**	**4A-2**	**5A-1**	**5A-2**	**7**
Jan	2010	2017	2018	2016	2009	2014	2014	2014	2017	2017	2014	2006
Feb	2005	2015	2018	2007	2010	2016	2007	2014	2018	2018	2014	2016
Mar	2016	2018	2008	2004	2008	2015	2009	2005	2010	2016	2014	2015
Apr	2016	2017	2005	2010	2016	2015	2014	2011	2010	2010	2011	2015
May	2010	2015	2005	2013	2018	2012	2015	2018	2018	2018	2012	2018
Jun	2009	2017	2018	2012	2009	2005	2005	2006	2010	2007	2005	2018
Jul	2011	2017	2005	2004	2018	2008	2006	2018	2011	2011	2018	2012
Aug	2015	2015	2005	2005	2018	2014	2009	2013	2016	2018	2018	2011
Sep	2014	2018	2015	2015	2018	2011	2018	2016	2018	2016	2016	2009
Oct	2015	2018	2004	2017	2010	2007	2017	2006	2017	2016	2014	2010
Nov	2015	2017	2015	2004	2010	2008	2006	2015	2009	2016	2009	2016
Dec	2018	2018	2015	2004	2009	2013	2009	2015	2006	2015	2013	2015

Table 4: Reference months in ERY_h weather files. In grey those reference months equal to TMY_x.

ERY_h	**0A**	**0B**	**1A**	**1B**	**2B**	**3A**	**3B**	**4A-1**	**4A-2**	**5A-1**	**5A-2**	**7**
Jan	2018	2008	2013	2015	2008	2006	2006	2017	2011	2009	2010	2014
Feb	2008	2005	2006	2014	2004	2014	2004	2018	2010	2008	2013	2007
Mar	2004	2005	2006	2014	2011	2013	2004	2018	2005	2017	2006	2013
Apr	2011	2006	2009	2015	2011	2016	2016	2005	2007	2007	2012	2014
May	2012	2005	2015	2008	2004	2016	2008	2005	2016	2017	2010	2004
Jun	2006	2005	2012	2008	2015	2011	2007	2016	2004	2009	2012	2009
Jul	2010	2009	2010	2011	2013	2016	2014	2004	2004	2009	2011	2009
Aug	2011	2004	2006	2012	2004	2011	2004	2008	2014	2004	2006	2004
Sep	2007	2009	2012	2010	2007	2009	2012	2017	2006	2006	2010	2008
Oct	2005	2004	2006	2004	2008	2015	2005	2004	2004	2009	2016	2009
Nov	2007	2007	2012	2009	2011	2004	2005	2017	2008	2014	2017	2012
Dec	2013	2006	2016	2014	2013	2009	2012	2010	2007	2008	2016	2013

Table 5: Reference months in XMY_1 weather files. In grey those reference months equal to TMY_x.

XMY_1	**0A**	**0B**	**1A**	**1B**	**2B**	**3A**	**3B**	**4A-1**	**4A-2**	**5A-1**	**5A-2**	**7**
Jan	2018	2008	2009	2013	2008	2010	2005	2010	2014	2004	2009	2004
Feb	2013	2008	2006	2014	2012	2016	2005	2018	2015	2015	2012	2014
Mar	2008	2006	2013	2014	2012	2009	2004	2013	2014	2014	2013	2014
Apr	2016	2017	2005	2010	2016	2005	2014	2011	2017	2010	2018	2006
May	2016	2012	2005	2010	2018	2007	2006	2018	2004	2018	2018	2018
Jun	2009	2010	2005	2012	2016	2007	2017	2017	2010	2005	2018	2018
Jul	2015	2017	2015	2004	2017	2007	2015	2018	2011	2011	2006	2012
Aug	2016	2016	2005	2005	2015	2007	2009	2016	2016	2016	2018	2011
Sep	2015	2018	2015	2004	2015	2009	2018	2006	2016	2015	2016	2009
Oct	2011	2004	2005	2012	2013	2014	2010	2008	2006	2009	2010	2018
Nov	2007	2011	2012	2013	2011	2008	2008	2010	2014	2018	2016	2014
Dec	2007	2006	2005	2014	2006	2013	2007	2010	2010	2017	2010	2013

Table 6: Reference months in XMY_2 weather files. In grey those reference months equal to TMY_x.

XMY_2	**0A**	**0B**	**1A**	**1B**	**2B**	**3A**	**3B**	**4A-1**	**4A-2**	**5A-1**	**5A-2**	**7**
Jan	2016	2017	2018	2006	2010	2006	2016	2007	2006	2006	2018	2006
Feb	2010	2015	2004	2006	2010	2014	2007	2011	2017	2017	2014	2012
Mar	2016	2018	2008	2004	2018	2013	2009	2017	2012	2012	2017	2012
Apr	2012	2015	2009	2015	2007	2015	2004	2012	2018	2018	2015	2013
May	2006	2013	2006	2008	2006	2015	2004	2013	2005	2008	2010	2004
Jun	2006	2013	2013	2008	2015	2005	2007	2012	2004	2009	2009	2004
Jul	2004	2009	2012	2008	2013	2006	2011	2007	2014	2009	2011	2009
Aug	2008	2004	2010	2012	2004	2015	2004	2014	2014	2004	2006	2004
Sep	2013	2004	2012	2010	2004	2014	2008	2015	2006	2006	2010	2018
Oct	2015	2014	2015	2017	2010	2015	2014	2005	2007	2007	2006	2010
Nov	2015	2017	2015	2011	2010	2007	2006	2015	2015	2011	2009	2016
Dec	2015	2016	2015	2008	2009	2005	2015	2015	2015	2015	2015	2011

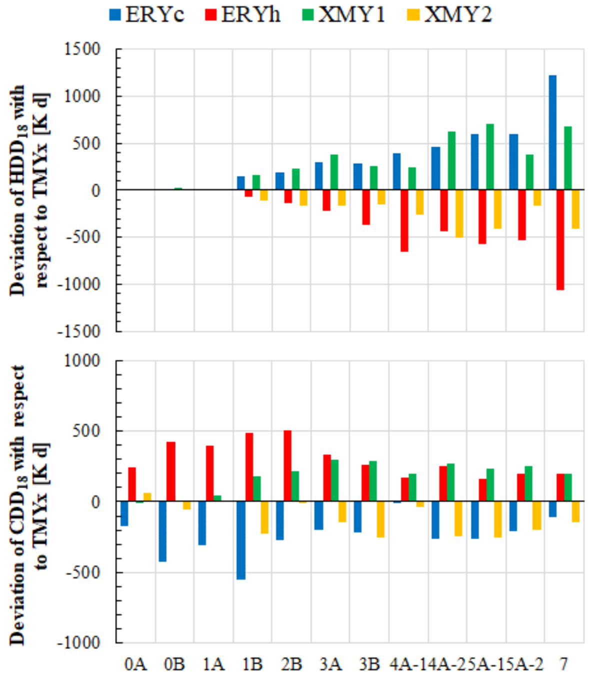

Figure 2: Deviation of HDD_{18} (top) and CDD_{18} (bottom) of ERY_c, ERY_h, XMY_1 and XMY_2 with respect to TMY_x.

Figure 2 shows the deviations of heating HDD_{18} (top) and cooling CDD_{18} (bottom) degree-days calculated for the extreme years with respect to those determined for TMY_x. In both cases, the base temperature is 18 °C. Both the cold ERY_c and XMY_1 show larger HDD_{18} compared to TMY_x, with XMY_1 usually slightly colder than ERY_c except for the climates *5A-2* (Frankfurt) and *7* (Winnipeg). ERY_h and XMY_2 are both warmer than TMY_x and the hot ERY_h has the lowest HDD_{18} for the climates *3B* (Madrid), *4A-1* (London), *5A-2* (Frankfurt) and *7* (Winnipeg). As regards the CDD_{18}, the two pairs of extreme years (ERY_h and XMY_1, ERY_c and XMY_2) show very similar values for climates colder than *3A* (Buenos Aires). On the contrary, for hotter climates (Singapore, Dubai, Honolulu and New Delhi) ERY_h is remarkably warmer and ERY_c remarkably colder than XMY_2 and XMY_1, respectively. This difference can be explained considering that *XMYs* divide the year into two halves, which are dealt in opposite ways as regards the maximization or the minimization of the seasonal dry bulb temperature.

Building energy simulation results

Figure 3 depicts the final energy uses obtained by means of EnergyPlus simulations with TMY_x weather files. Energy uses are distinguished by energy vector (power or natural gas). Furthermore, besides the total consumption per conditioned floor area, also the mix of the different uses are represented. Annual power consumptions range from 70 kWh_{el} m^{-2} a^{-1} to 100 kWh_{el} m^{-2} a^{-1}, except for climates *0A* and *0B*, whose uses are larger than 180 kWh_{el} m^{-2} a^{-1}. The major share of power consumption is due to interior equipment, and space air-conditioning is generally responsible for 20 to 40 kWh_{el} m^{-2} a^{-1} (i.e., 15 to 40 %). Again, a different behaviour is registered in Singapore (*0A*) and Dubai (*0B*), with electrical uses for space cooling larger than 80 kWh_{el} m^{-2} a^{-1} and corresponding to almost 50 % of the total power consumption. Natural gas is used for space heating (from 0 to 15 kWh m^{-2} a^{-1}) and hot water production (about 4 kWh m^{-2} a^{-1}). Climates hotter than *3A* show negligible natural gas uses, which increase up to 75 % of the total ones in colder locations.

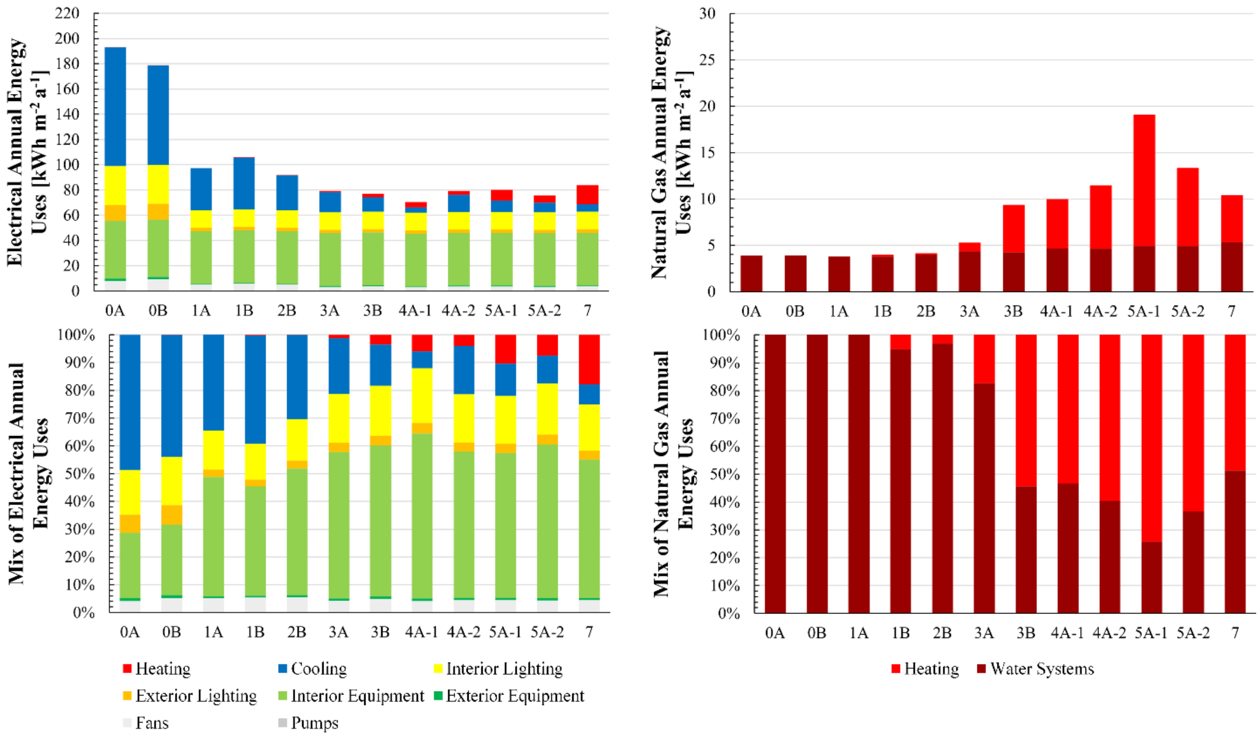

Figure 3: Results of TMY_x simulations: annual electrical energy uses (on the top left) and mixes (on the bottom left), and annual natural gas uses (on the top right) and mixes (on the bottom right).

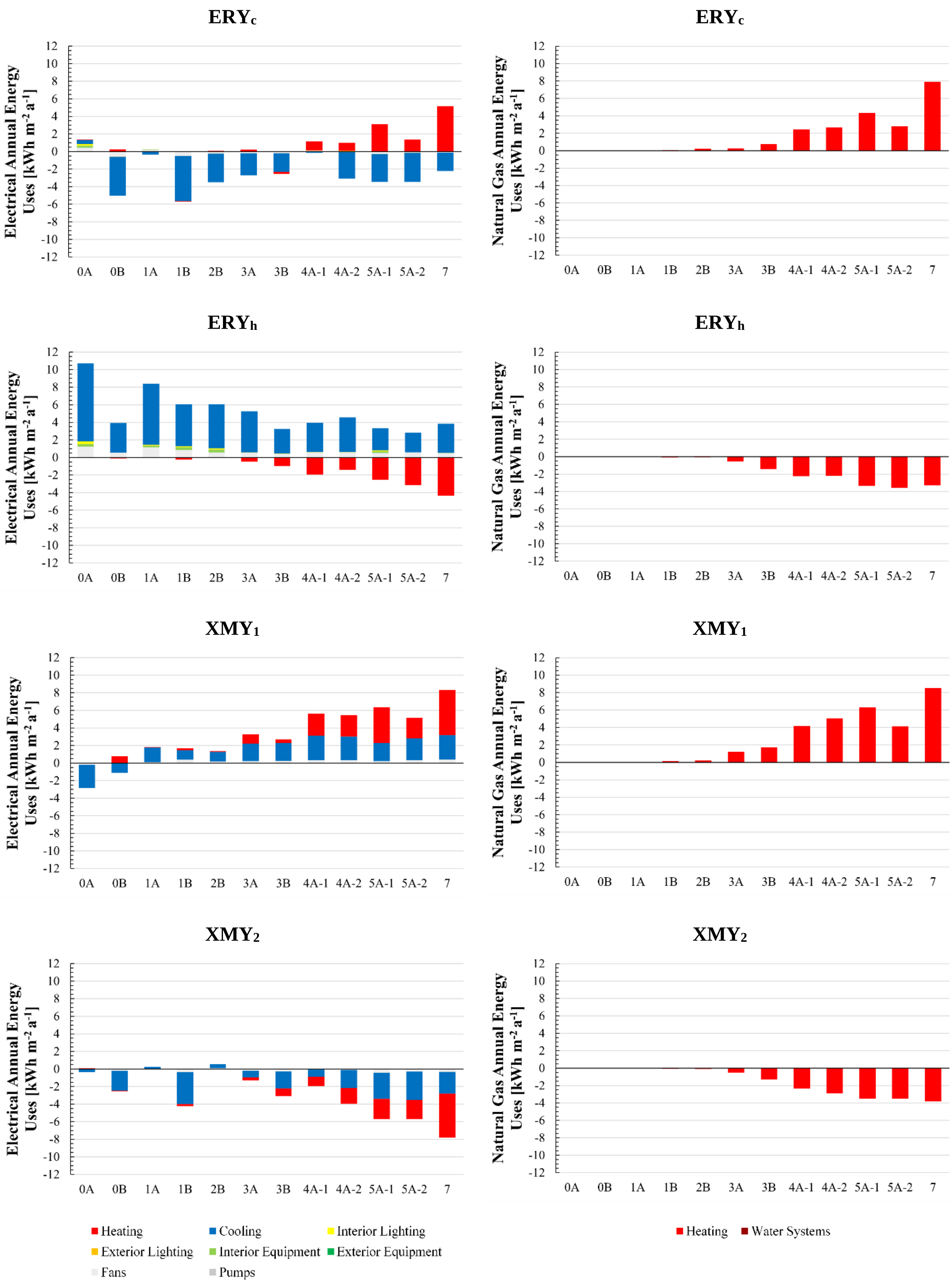

Figure 4: Deviation of final energy uses simulated with extreme years with respect to TMY$_x$ simulations: annual electrical energy uses (on the left) and annual natural gas uses (on the right).

Looking at Figure 4, it can be noticed that the adoption of extreme years has an impact mainly on final energy uses for space heating and cooling, as expected. Besides those two *HVAC* subsystems, variations in power absorbed by fans can be barely detected for the hottest climates using *ERYs*.

As regards the annual power consumption, different trends can be observed comparing *ERYs* and *XMYs*. Indeed, while the former ones show either positive deviations for space heating coupled with negative deviations for space cooling or vice versa, for the latter ones the majority of deviations are either positive or negative, meaning that all energy uses increase or decrease at the same time. Deviations of total power consumption range from -5.7 to 3.1 kWh_{el} m^{-2} a^{-1} for ERY_c, from -0.5 to 10.7 kWh_{el} m^{-2} a^{-1} for ERY_h, from -2.8 to 8.4 kWh_{el} m^{-2} a^{-1} for XMY_1, and from -7.8 to 0.6 kWh_{el} m^{-2} a^{-1} for XMY_2. The largest absolute variations are found for New Delhi (*1B*) with ERY_c, Singapore (*0A*) with ERY_h, and Winnipeg (*7*) with both XMY_1 and XMY_2. The minimum deviations, instead, are registered for Honolulu (*1A*) with ERY_c and XMY_2, Frankfurt (*5A-2*) with ERY_h, and Dubai (*0B*) with XMY_1. The building electrical energy use is generally more affected by the adoption of extreme weather data in case of hot climates for both ERY_c and ERY_h, while the opposite is true for XMY_1 and XMY_2.

Considering only those climates with deviations larger than 0.5 kWh_{el} m^{-2} a^{-1}, using ERY_c the electrical energy uses for space heating increase on average by 30 % while those for space cooling decrease on average by 22 %. The maximum percentage increase for space heating is 37 % (Toronto) while the minimum is 24 % (Frankfurt); for space cooling the maximum reduction is 44 % (Frankfurt) and the minimum 6 % (Dubai). With ERY_h, on the contrary, electrical uses for space heating are lowered by 41 % on average and those for space cooling are increased by 28 %. In this set of simulations, the maximum decrement of electrical uses for space heating is in Frankfurt (55 %) while the minimum is in Winnipeg (29 %); the increase of space cooling uses ranges from the maximum of London (78 %) to the minimum of Dubai (4 %). In the case of simulations run with XMY_1, mean percentage variations are equal to +63 % and +19 %, respectively for heating and cooling, and, for those with XMY_2 as weather file, to -36 % and -20 %. With XMY_1, neglecting the +518 % of Dubai, the maximum deviation for space heating is in Buenos Aires (+113 %) and the minimum in Winnipeg (+34 %); those for space cooling, instead, range from +65 % (London) to -3 % (Singapore). Finally, adopting XMY_2 as input, differences go from -56 % (Washington) to -26 % (London) for space heating, and from -42 % (Frankfurt) to -3 % (Dubai) for space cooling.

Regarding the final uses of natural gas for space heating, similar trends can be observed but meaningful deviations are present for climates at least as cold as those in class *3A*. The largest absolute variation is 7.9 kWh m^{-2} a^{-1} in Winnipeg (*7*) for ERY_c, -3.6 kWh m^{-2} a^{-1} in Frankfurt (*5A-2*) for ERY_h, 8.5 and -3.8 kWh m^{-2} a^{-1} in Winnipeg (*7*) for both XMY_1 and XMY_2. Neglecting variations lower than 0.5 kWh m^{-2} a^{-1}, the average increase is 53 % for ERY_c (from +156 % in Winnipeg to +15 % in Madrid), and the average decrease 42 % for ERY_h (from -65 % in Winnipeg to -24 % in Toronto). As regards the simulations with *XMYs* weather data, +83 % and -44 % are calculated as percentage deviations, respectively for XMY_1 and XMY_2, with ranges from +168 % (Winnipeg) to +34 % (Madrid) for XMY_1 and from -75 % (Winnipeg) to -25 % in Toronto.

Discussion and Conclusion

In this research, the hot and cold Extreme Reference Years *ERYs* by Pernigotto *et al.* (2020) and two eXtreme Meteorological Years *XMY* by Crawley and Lawrie (2019) were generated. After comparing the characteristics of the prepared weather data in terms of selected reference months and annual heating and cooling degree-days, EnergyPlus simulations were run for a case-study commercial building, i.e., the ASHRAE 90.1-2019 Medium Office Prototype. Annual final energy uses of power and natural gas were analysed and contrasted.

We observed that:

- The approaches behind the definition of *ERYs* and *XMYs* are very different and pursue alternative goals. While for the former ones are aimed at generating an overall hot (ERY_h) or cold (ERY_c) artificial meteorological year, the latter ones are focused on the preparation of weather files able to maximize (XMY_1) or minimize (XMY_2) both heating and cooling demands at once. Nevertheless, both types of extreme years are remarkably different from the typical year, with a degree of similarity ranging from about 5 % to about 8 % of the reference months for the analysed sample of climates, although selected by adopting a subset of the climate variables used to generate TMY_x.
- The heating degree-days of the extreme years calculated considering a base-temperature of 18 °C are higher than the TMY_x for the cold ERY_c and the XMY_1. The opposite is observed for the hot ERY_h and the XMY_2. As a whole very similar degree-days are found for the two pairs.
- A different situation is registered for the cooling degree-days with a 18 °C base-temperature. Although, ERY_h and XMY_1 show higher values compared to the TMY_x and the opposite do ERY_c and XMY_2, similarities among the components of each pair of extreme years are limited to climate classes at least as cold as *3A* (warm humid). For hotter climates, *XMYs* are closer to the TMY_x, probably as a consequence of the adopted 6-month seasonal approach, which could require customization for very hot climates like Singapore or Dubai. This result highlights the importance of broadening the set of climate variables used for selection using, for instance, humidity and solar radiation. However, attention should be paid to the cross-correlation of climate variables (e.g., the influence of radiation on

temperature), which may affect, for example, the *ERY* selection.

- The same trend is observed also for the final uses for space heating and cooling, for both power and natural gas as energy vectors. With respect with TMY_x simulations, space heating uses are increased when simulations are run with ERY_c and XMY_1 while they are decreased in case of ERY_h and XMY_2. Similarly, final uses for space cooling increase in case of ERY_h and XMY_1 and decrease for ERY_c and XMY_2. As a whole, while both ERY_c and ERY_h are needed in order to assess the maximum energy uses, XMY_1 can allow to achieve the same goal with a single simulation run.
- The final uses for space heating are very similar for both *ERYs* and *XMY*, with the latter able to lead to slightly larger values. On the contrary, the final uses for space cooling are generally larger for *ERYs*, especially as far as hot climates are concerned.

As a whole, we can conclude that the two approaches analysed in this research to build extreme years are both effective in selecting reference months remarkably hotter or colder than the typical years. As regards climates belonging to the ASHRAE class *3A* or colder, the differences between *ERYs* and *XMYs* are limited, with the latter slightly better in selecting weather conditions able to maximize the heating demand. On the contrary, *ERYs* are slightly more efficient for the identification of weather series suitable for the analysis of extreme cooling demand.

Further developments of this research will expand the scope of the analysis, including multi-year series and actual meteorological years as reference for the comparison, as well as multiple reference buildings, in order to ensure higher generalization of the findings presented in this work.

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