INTERNATIONAL BUILDING PERFORMANCE SIMULATION ASSOCIATION ENGLAND

Proceedings of BSO-V 2020
5th Building Simulation and Optimization Virtual Conference
21-22 September 2020
Loughborough, UK

Influence of weather data morphing in urban building simulation. A case study

Vincenzo Costanzo, Gianpiero Evola, Marco Infantone, Lugi Marletta

Università degli Studi di Catania, DIEEI, Viale Andrea Doria 6, 95125 Catania, Italy

Abstract

One issue related with dynamic energy simulation of buildings is the need to use accurate weather data to perform reliable analyses. In particular, available weather data often refer to rural sites (e.g. airports), and as such they are not suitable for the simulation of buildings located in urban areas. Amongst the tools available to provide specific weather data for urban sites, the Urban Weather Generator (UWG) has recently raised increasing attention. This tool estimates the local hourly air temperature and humidity in urban contexts starting from weather data coming from a rural weather station nearby, and accounting for the Urban Heat Island (UHI) effect due to buildings and various anthropogenic heat sources within the urban settlement.

The aim of this paper is to discuss the uncertainty that the choice of the weather dataset introduces in the outcomes of dynamic energy simulations for buildings located in urban areas. To this aim, different weather datasets are considered, corresponding to: i) the weather file available in the EnergyPlus database for the airport of Catania (Southern Italy), ii) its UWG morphed version, iii) a more recent weather dataset released by the Italian Thermo-Technic Committee (CTI) and iv) its morphed version.

The paper comments on the differences amongst these data, along with their impact on the calculation of the heating and cooling load for a representative multi-storey apartment block.

Introduction

Dynamic energy simulation has become an indispensable tool for a detailed analysis of indoor thermal comfort and thermal energy needs of buildings (Hensen and Lamberts 2011). Indeed, it is only through a dynamic simulation based on hourly or sub-hourly weather datasets that it is possible to investigate the response of a building to variable temperature, wind and solar irradiance (Clarke 2001).

However, all building energy models are affected by uncertainties in the input parameters, and this is the main reason for the gap between simulated and actual performance (De Wilde 2018). Amongst the sources that may cause this gap, a recent paper from (Lupato and Manzan 2019) showed that using outdated climate data can easily underestimate cooling energy needs up to 93% in the warmest cities of Italy, while also overestimating heating energy needs up to 44% in the coldest cities.

In the last decades, several research groups have developed hourly weather datasets specifically designed to be used in building energy modeling tools. Each of these datasets contains a year of hourly data (8760 hours) that is able to represent long-term statistical trends and patterns in weather data over a longer period of record (usually 10 years or more), since no single year can represent the typical long-term weather patterns (Crawley, 2007).

Many weather datasets have been developed worldwide (IWEC International Weather for Energy Calculations, CWEC Canadian Weather for Energy Calculations, CTYW Chinese Typical Year Weather etc.) and many existing datasets have been updated (TMY2, TMY3, WYEC2) referring to more recent periods of record.

Users of energy simulation programs thus have a wide variety of weather data from which to choose; nonetheless, the use of different weather datasets in simulation tools can result in large discrepancies among the results. As an example, Crawley compared energy simulation results obtained using a set of locally measured hourly weather data for the 1961-1990 period of record (SAMSON) and typical weather datasets (TRY, TMY, TMY2, WYEC, and WYEC2) for a prototype office building under eight different climates in the US (Crawley 1998). The findings showed that using the TRY dataset induces the greatest variation in both total annual energy consumption (from -2.3% to +5.4%) and peak heating load (from -43.7% to -2.8%), depending on the location considered, while the simulations with TMY2 or WYEC2 datasets more consistently match those carried with the actual locally measured weather data.

One more issue concerning typical weather data sets is that, although they provide a good representation of the weather variables if compared to the long-term average, they are still not able to reflect the trend of variation of these variables due to climate change effects (Crawley, 2015). The record period for TMY selection should accordingly contain recent meteorological data, and be long enough to reflect the climate change trend (Pernigotto et al. 2014). Moreover, typical weather datasets are generated by monitoring stations usually placed outside urban areas, but urban climate differs from these conditions because of modified patterns of solar radiation, wind, temperature and relative humidity

(Santamouris 2014; Martin-Vide, Sarricolea, and Moreno-Garcia 2015). The main causes of this effect relate to structural and land cover differences of urban and rural areas, as well as to the heat and moisture release from people and their activities (anthropogenic sources) that all contribute to alter surfaces' energy and radiation balances, making urban temperatures higher than rural ones (Oke 1976; Oke 1982).
In light of the issues highlighted so far, this study aims to analyze the influence of different weather datasets on the results of dynamic energy simulations of residential buildings located in the city center of Catania, a city with hot-humid climate located in Southern Italy. In particular, any differences arising from the use of different weather datasets will be highlighted, and secondly, simulations will be repeated after a weather data morphing process to reflect the conditions due to the Urban Heat Island effect.

Methodology

The research presented in this paper is organized according to three steps. First, a comparison is made between two available datasets originating from different weather stations in a rural context close to Catania (Southern Italy), and referring to different decades. Then, a morphing procedure is applied to both weather datasets in order to adapt them to an urban context, thus assessing the potential UHI intensity. Finally, all the previous datasets are used as an input to the dynamic simulation of a real residential multi-storey building located in the centre of Catania, aimed to verify how the choice of the weather file affects the calculation of the energy demand for space heating and cooling.

Rural weather datasets used

Two different TMY-type weather datasets are used as a baseline: the ITA_Catania-Fontanarossa.164600_IGDG weather file retrievable from the EnergyPlus website in the .epw format (EnergyPlus 2019), and the CTI-ENEA Test Reference Year – Catania (CTI 2019).
The ITA_Catania-Fontanarossa.164600_IGDG weather file refers to the Italian dataset Gianni De Giorgio (IGDG); it is a typical year based on a 20 years' period of record spanning from 1951 to 1970, with data recorded from the weather stations of the Meteorological Service of the Italian Air Force. The weather file shows some gaps: as an example, the wind speed recorded at 10 m above the ground in about 1700 hours has zero value. In these cases, an average value between the preceding and the following data entries have been applied.
On the other hand, the CTI-ENEA Test Reference Year is a typical meteorological year developed by the Italian Thermo-Technic Committee (CTI), released in 2015 for 110 localities throughout the country. The typical meteorological year has been calculated according to the procedure described in the standard (UNI EN ISO 15927-4 2015) and consists of 12 characteristic months chosen from an archive of meteorological data actually detected for a period of time preferably greater than 10 years. In particular, the data used for the construction of the typical meteorological year for Catania station refer to an 8-years evaluation period, from 2002 to 2009.
The data provided by the CTI have thus the undeniable advantage of being based on more recent surveys, even if a period of 8 years might not be long enough to adequately represent long-term trends. However, the meteorological variables contained in this dataset cannot be used directly in building performance simulation tools because they are formatted differently. To overcome this issue, the software tool Element (BigLadder 2019) is used in this research for processing the data and creating the file in the required .epw format.

Weather data morphing: the Urban Weather Generator (UWG)

The Urban Weather Generator (UWG) model has been developed by Bueno et al. by coupling an atmospheric model with a Building Energy Model (BEM) (Bueno et al. 2013). The advantage of using UWG instead of other tools is that it first estimates the hourly urban canopy air temperature and relative humidity, and then generates a morphed weather file in .epw format that captures the UHI effect and is compatible with many tools for building energy simulation.
Apart from the meteorological variables gathered from an .epw file deriving from a rural weather station, UWG requires information about the detailed urban morphology: starting from a 3D model, the algorithm calculates the average building height, the site coverage ratio (i.e. the ratio of the buildings footprints to the urban site area) and the facade-to-site ratio (i.e. the ratio of the buildings facades to the urban site area). When working in the Grasshopper environment, such information can be provided as an input to the software through the Dragonfly tool, which also calculates some geometric parameters needed by UWG for the morphing procedure (see Table 1).
In order to estimate the shaded surfaces in the canyon due to trees and shrubs, as well as their latent heat fluxes, the ratio of trees coverage and the pervious surface fraction are additional parameters that the user has to provide. For what concerns the sensible heat fluxes exchanged within the canyon, it is important to highlight that the UWG separates the component due to vehicles, street lighting and pedestrian activities from that due to buildings (i.e. the heat released from HVAC systems).
Finally, the optical and thermal parameters of all the surfaces enclosing the urban canyon (streets, pavements, facades and roofs) are required to estimate the absorbed shortwave solar radiation and the emitted longwave radiation within the Urban Boundary Layer (UBL).
The main UWG input parameters necessary for the weather data morphing procedure are listed in Table 1. These values have been obtained after a sensitivity analysis conducted on some uncertain parameters (heat fraction released to canyon, sensible heat due to traffic, pavement and vegetation albedo namely), which showed that – apart from the geometric data – the most sensitive input value is the heat fraction released to the canyon. However, the influence of this parameter on the outdoor

air temperature prediction is lower than 0.5 °C. Interesting studies have been published by Salvati et al. to show the importance of the different parameters in the morphing procedure in some case studied (Salvati 2017, Salvati 2019).

The reference site is located in the city center of Catania, and more specifically in a densely built residential and commercial area (350 x 300 m^2) defined by Corso Italia on the north side, Viale della Libertà on the east side, via Umberto on the south side and via Crispi on the west side respectively. The area shows a good mix of buildings with different functions and age of constructions, as depicted in Fig. 1 with different colors.

Table 1: UWG input parameters

User's input	Heat fraction released to canyon	0.5 (-)
	Pavement albedo	0.2 (-)
	Vegetation albedo	0.2 (-)
	Walls albedo	0.35 (-)
	Roofs albedo	0.35 (-)
	Sensible heat due to traffic (peak value)	15 W/m^2
	Floor height (residential buildings)	3 m
	Floor height (office buildings)	4 m
	Glazing ratio (residential buildings)	0.14 (-)
	Glazing ratio (office buildings)	0.20 (-)
	Windows SHGC	0.65 (-)
Calculated by Dragonfly	Average building height	15 m
	Site coverage ratio	0.43 (-)
	Façade-to-site ratio	1.31 (-)
	Tree coverage ratio	0.03 (-)
	Grass coverage ratio	0 (-)
Default values	UBL daytime height	1000 m
	UBL night time height	80 m
	Inversion height	150 m
	Circulation coefficient	1.2 (-)
	Exchange coefficient	1 (-)

Dynamic energy simulations

The apartment block highlighted in red in Fig. 1 is a residential premise with nine floors that has been chosen as a representative example of the most widespread typology in the area. The energy demand for space heating and cooling will be calculated only for this block.

This building has the external walls composed of two layers of clay bricks (12 cm plus 8 cm) from the outside to the inside respectively, with an air gap of 8 cm in the middle and a layer of cement plaster of 2 cm on both sides. The slabs and the roof are made of lightweight concrete (22 cm) and concrete screed (5 cm) with a top layer of tiles (1.5 cm). Finally, the windows have double glazing and an aluminum frame with thermal break. The resulting U-values are 1.18 W/(m^2 K), 1.32 W/(m^2 K) and 1.69 W/(m^2 K) for the walls, slabs and windows in order. For the sake of appraising the differences in the energy performance when the envelope is insulated, another set of simulations is run by keeping the same constructions but adding a layer of EPS in order to comply with current Italian building codes prescription. In this scenario, the resulting U-values are 0.36 W/(m^2 K) and 0.28 W/(m^2 K) for walls and slabs respectively.

The apartments are supposed to be occupied by people at 100% of the occupancy rate (0.04 people per square meter) during the night (from 10 pm to 7 am), at 85% from 7 am to 8 am and from 6 pm to 10 pm, and at 25% during the remaining hours.

The internal heat gains are summarized as follows:

- people involved in sedentary activities, releasing 120 W of sensible heat;
- artificial lights with power density of 6 W/m^2;
- other electric equipment with power density of 4.8 W/m^2.

These data are used – along with the geometrical information and considering one thermal zone per floor – for simulating the energy performance of the selected building in Honeybee for Grasshopper (Honeybee software 2019), based on the EnergyPlus simulation engine. The heating season runs from December 1st to March 31st (set point temperature of 20 °C, setback temperature of 16 °C), while the cooling season spans from June 1st to September 30th (set point temperature of 26 °C, setback temperature of 30 °C).

Figure 1: Case study area in Catania (on the top) and distribution of building typology (on the bottom). The building used for dynamic simulations is highlighted in red in both panels.

Results and discussion

Differences between IGDG and CTI datasets

The weather stations used in the construction of the IGDG and CTI datasets are very close to each other, but the surroundings of the CTI weather station are characterized by the presence of low-rise warehouses at approximately 300 m distance. This implies that some differences between these two datasets – reported in Fig. 2 as monthly averages – can be due to both boundary conditions and climate change over the years. If looking at this figure, it appears that the temperatures recorded in the CTI dataset are constantly higher than those of the IGDG dataset, with a maximum difference of 2 °C in the monthly average (January). As for relative humidity, IGDG usually reports higher values than CTI, especially in summer where the maximum difference is 9% in August. As far as monthly global horizontal irradiation is concerned, CTI mean values are higher than IGDG throughout the year, with peak differences by up to 55% in winter (November to March). However, the biggest difference is found when comparing wind velocity: in fact, IGDG values are constantly higher than those recorded by CTI station (around 44% yearly, but with peak differences by around 58% in July and October). In both cases, the wind velocity is measured at 10 m above the ground but it is likely that the surrounding buildings affect the wind pattern around the CTI weather station.

Differences between rural and urban weather data

The analysis of the IGDG and CTI weather datasets after the morphing procedure reports noticeable differences in all the main weather variables, especially in terms of air temperature and relative humidity. Indeed, as shown in Fig. 3, the average UHI effect (i.e. the difference between the urban "morphed" temperature and the original temperature in the rural area) is higher than 1 °C for almost every month of the year when considering the IGDG dataset, with a peak of 1.8 °C in October. On the other hand, starting from the CTI data, the UHI effect is more pronounced, as it is always higher than 1.5 °C on average every month, with a peak of almost 3 °C in November.

Two concurring effects may explain the difference in the UHI magnitude between the datasets: the first one is the lower wind velocity reported in the CTI rural data (see Fig. 2), which reduces the amount of heat discharged by convection out of the urban canyon. The second one is the longer use of HVAC systems to cool buildings down because of the higher outdoor air temperatures, which in a vicious cycle raises the magnitude of waste anthropogenic heat released to the canyon, at least in the summer (cooling mode).

In terms of relative humidity, a dryer air is expected throughout the year when considering the morphed versions of both the datasets, as reported in Fig. 3. The trend of the difference is very similar to that described for the air temperature, with the higher difference predicted for the CTI dataset again, the relative humidity being lower than the rural case by more than 8% on average every month. In the case of IGDG dataset, the difference is always below 9% on a monthly basis.

Negligible differences – always below 0.2 m/s – are found in terms of wind velocity for the IGDG dataset, while the CTI shows higher differences, up to 0.4 m/s in April. An explanation of this trend may be found in the algorithm used by the UWG for defining the friction and exchange velocity values (Bueno et al. 2014).

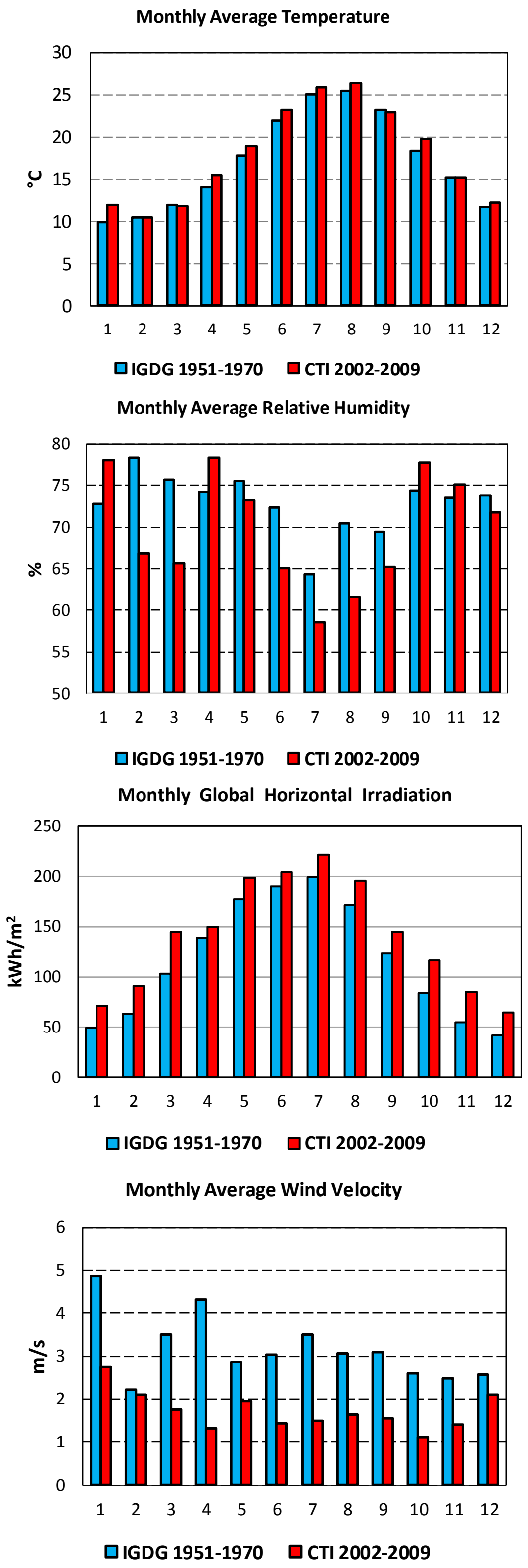

Figure 2: Comparison between IGDG and CTI weather datasets. Monthly average values

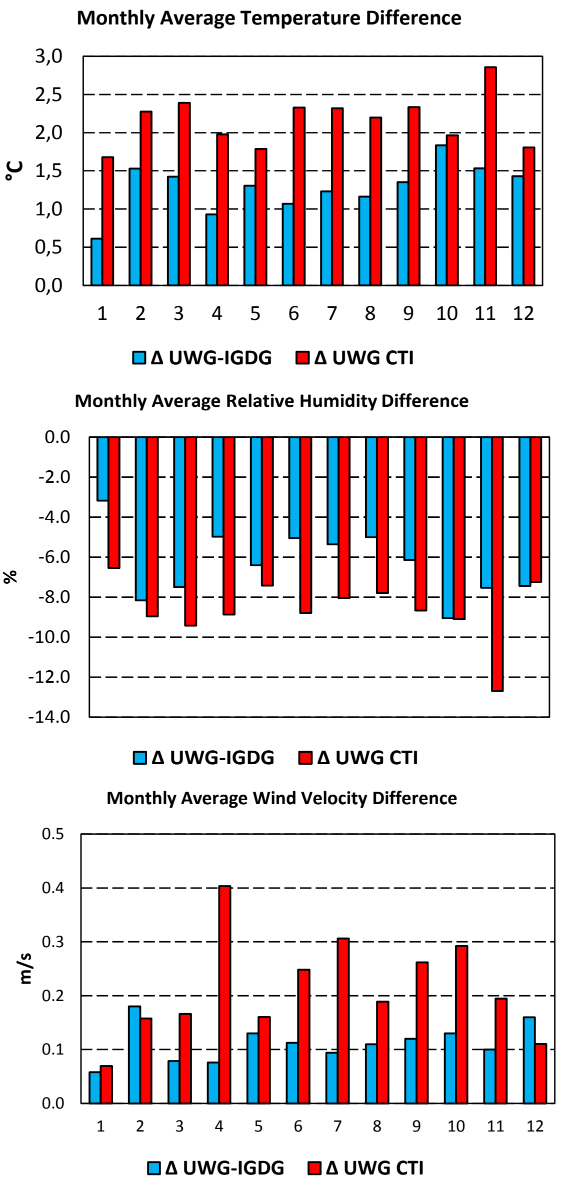

Figure 3: Monthly average difference between rural and morphed weather datasets

Impact on the energy demand of buildings

Uninsulated building. The use of the different weather datasets previously described is likely to have a strong impact on the predicted energy demand of the buildings located within the urban area. In order to verify this assumption, the top diagram of Fig. 4 shows the average heating and cooling demand for the uninsulated building highlighted in Fig. 1: the heating needs decrease from 40 kWh/m^2 to 29 kWh/m^2 when using the CTI dataset instead of IGDG. Instead, the cooling needs increase from 15 kWh/m^2 to 16 kWh/m^2 for the same scenario.

Moreover, if one compares the results obtained using the standard rural IGDG weather dataset to those coming from the corresponding morphed version, the reduction in the heating needs (from 40 kWh/m^2 to 31 kWh/m^2) is almost counterbalanced by the increase in the cooling needs (from 15 kWh/m^2 to 20 kWh/m^2). The total energy needs only show a slight decrease (from 55 kWh/m^2 to 51 kWh/m^2).

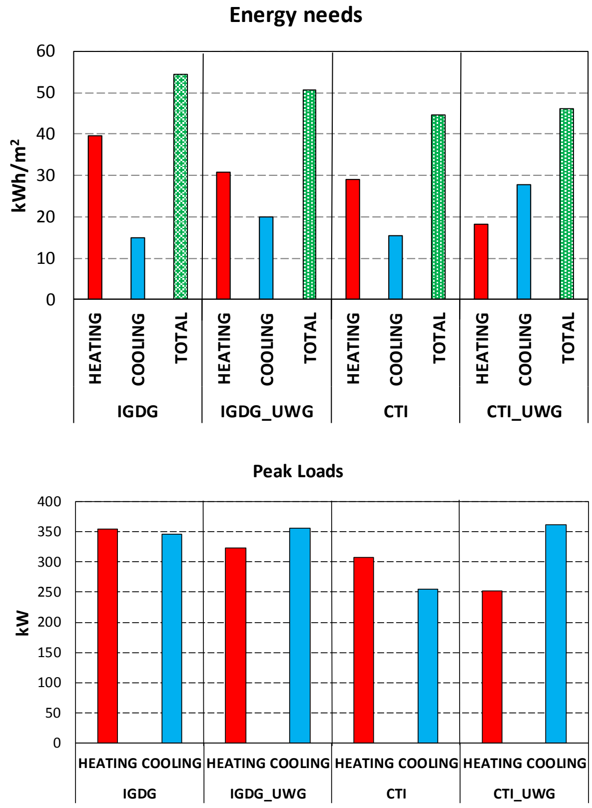

Figure 4: Energy needs (on the top) and peak loads (on the bottom) calculated with the different weather datasets (Uninsulated envelope scenario)

Furthermore, when applying the CTI morphed weather data instead of the original rural CTI data, the heating needs are reduced to 18 kWh/m^2, while cooling needs are increased up to 28 kWh/m^2. This makes the total energy demand resulting from the morphed CTI dataset slightly higher than for the rural condition (46 kWh/m^2 against 44 kWh/m^2), but still lower than the value predicted with the IGDG rural and urban cases, respectively.

In terms of peak loads, it is interesting to observe a reduction during the heating season when comparing the rural sets with the corresponding morphed version. In the case of the IGDG data, this reduction amounts to 31 kW (from 355 kW to 324 kW), while if considering CTI data it is of about 57 kW (from 308 kW to 251 kW). On the contrary, the peak cooling loads are increased after the morphing procedure by just 9 kW when considering IGDG weather data (from 346 kW to 355 kW), and by 107 kW with CTI data (from 255 kW to 362 kW).

Insulated building. If one now looks at the energy figures for the insulated envelope (see Fig. 5), it emerges that the heating needs are significantly lower than in the uninsulated case (26 kWh/m^2 against 40 kWh/m^2 for the IGDG rural scenario), while cooling needs keep almost the same. The resulting effect is a sensible reduction of the total energy needs, which in this case amount to around 40 kWh/m^2 in all scenarios. As expected, the biggest difference in the energy needs of the building after the morphing procedure is found when using the CTI data (cooling needs step from 17 kWh/m^2 to almost 30 kWh/m^2), because of the higher UHI effect predicted by the UWG. This makes the total energy needs after the morphing procedure higher than in the rural case (40 kWh/m^2 against 35 kWh/m^2 namely).

When it comes to peak loads, a general reduction of peak values is first noticeable in all scenarios if comparing Fig. 5 with Fig. 4. More specifically, in Fig. 5 one can observe how the morphing procedure always leads to a reduction in the heating peak loads (from 248 kW to 218 kW for IGDG data and from 225 kW to 170 kW for CTI data respectively) and to an increase in the cooling peak loads. This increase turns out to be more pronounced for the CTI data (227 kW of the rural case against 300 kW of the urban case) than for the IGDG data (from 326 kW to 350 kW) because of the higher UHI effect predicted by the UWG software as already reported in Fig. 3.

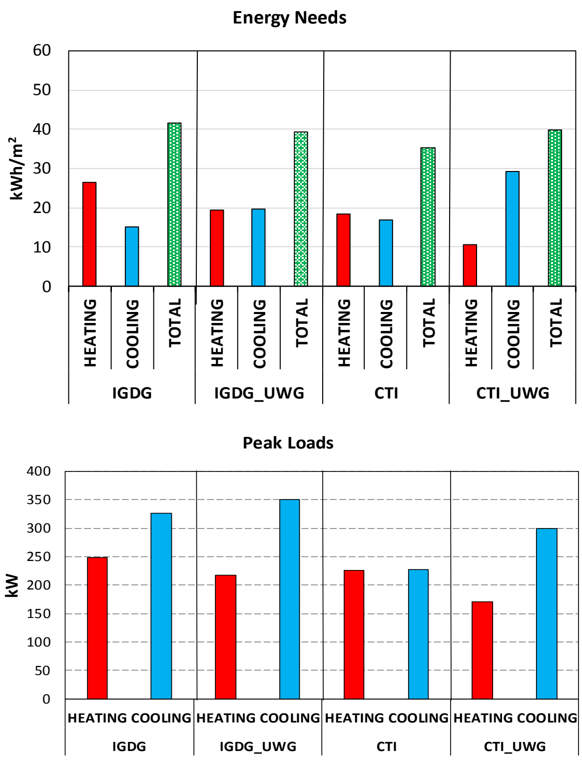

Figure 5: Energy needs (on the top) and peak loads (on the bottom) calculated with the different weather datasets (Insulated envelope scenario)

Conclusions

This paper discussed how different weather datasets, referring to a city located in the hot–humid climate of Southern Italy, affect the results of the dynamic energy simulations for a typical residential multi-storey building. The analysis of two different weather datasets, namely the Italian dataset Gianni De Giorgio (IGDG, measurement period 1951-1970) and the Italian Thermo-Technic Committee (CTI) dataset (measurement period 2002-2009), revealed higher air temperatures (peak difference of 2 °C in January), lower relative humidity (peak average difference of 9%), higher solar irradiation (up to 55% in summer months) and lower wind velocities (about 44% on a yearly basis) pertaining to the most recent CTI data.

Then, the morphing procedure carried out through the Urban Weather Generator (UWG) showed that a pronounced UHI effect, with urban temperatures overcoming the rural ones by almost 2 °C on average in a year, is predicted when using the CTI data. In the case of the IGDG data, this figure amounts to around 1.3 °C.

The impact of the UHI effect on the energy demand of a typical multi-storey residential building located in the city center is not negligible. While the heating energy demand decreases by around 25% and 34% for the IGDG and CTI cases respectively for an uninsulated building, the cooling energy demand raises up significantly (by 33% for the IGDG dataset and by 86% for the CTI dataset). Comparable figures are found for the insulated building scenario. Differences are found also in terms of peak loads, with a reduction by 9% and 18% in the heating peaks and an increase by 3% and 42% in the cooling peaks for IGDG and CTI datasets respectively.

The results highlight the need to use more recent weather datasets that have embedded the effects of climate change through the years. Moreover, it is of utmost importance to account for the UHI effect in dynamic energy simulations of buildings located in urban areas; to this aim, an available a tool is the UWG, which allows weather data morphing with sufficient reliability, while also generating suitable .epw files. The UWG also runs in the Grasshopper environment thanks to the Dragonfly plugin.

References

BigLadder software. Accessed March 26, 2019. https://bigladdersoftware.com/projects/elements/

Bueno, B., Norford, L., Hidalgo, J. and G. Pigeon (2013). The urban weather generator. *Journal of Building Performance Simulation 6(4)*, 269-281.

Bueno, B., Roth, M., Norford, L. and R. Li (2014). Computationally efficient prediction of canopy level urban air temperature at the neighborhood scale. *Urban Climate 9*, 35-53.

Clarke, J.A. (2001). Energy Simulation in Building Design. Butterworth-Heinemann, Oxford (UK).

Crawley, D.B. (1998). Which weather data should you use for energy simulations of commercial buildings? ASHRAE Transactions, 498-515.

Crawley, D.B. (2007). Creating weather files for climate change and urbanization impact analysis. *Proceedings of Building Simulation Conference*, 1075-1082.

Crawley, D.B. and L.K. Lawrie (2015). Rethinking the TMY: is the “typical” meteorological year best for building performance simulation? *Proceedings of Building Simulation Conference*, 2655-2662.

CTI Energia Ambiente (Comitato Termotecnico Italiano). Accessed March 26, 2019. https://www.cti2000.it/

De Wilde, P. (2018). Building Performance Analysis. Wiley Blackwell, Oxford (UK).

EnergyPlus Weather Data. Accessed March 26, 2019. https://energyplus.net/weather

Hensen, Jan L.M. and R. Lamberts (2011). Building Performance Simulation for Design and Operation. Taylor & Francis, Abingdon (UK).

Honeybee software, 2019. Accessed April. https://www.ladybug.tools/honeybee.html.

Lupato, G. M. and Manzan (2019). Italian TRYs: New weather data impact on building energy simulations. *Energy and Buildings 185*, 287-303.

Martin-Vide, J., Sarricolea, P. and M.C. Moreno-Garcia (2015). On the definition of the urban heat island intensity: the ‘rural’ reference. *Frontiers in Earth Science 3(24)*.

Oke, T.R. (1976). The distinction between canopy and boundary-layer urban heat islands. *Atmosphere 14(4)*, 268-277.

Oke, T.R. (1982). The energetic basis of the urban heat island. *Quarterly Journal of the Royal Meteorological Society 108*, 1-24.

Pernigotto, G., Prada, A., Costola, D., Gasparella, A. and J.L.M. Hensen (2014). Multi-year and reference year weather data for building energy labelling in north Italy climates. *Energy and Buildings 72*, 62-72.

Salvati, A., Coch Roura, H. and C. Cecere (2017). Assessing the urban heat island and its energy impact on residentialbuildings in Mediterranean climate: Barcelona case study. *Energy and Buildings 146*, 38-54.

Salvati, A., Monti, P., Coch Roura, H. and C. Cecere (2019). Climatic performance of urban textures: Analysis tools for a Mediterranean urban context. *Energy and Buildings 72*, 162-179.

Santamouris, M. (2014). On the energy impact of urban heat island and global warming on buildings.. *Energy and Buildings 18*, 100-113.

UNI EN ISO 15927-4:2005. Prestazione termoigrometrica degli edifice – Calcolo e presentazione dei dati climatici – Parte 4: Dati orari per la valutazione del fabbisogno annual di energia per il riscaldamento e il raffrescamento.