Evaluation of weather datasets for rural energy communities simulation

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Abstract:

Rural areas are strategic assets to ensure sustainable energy transition due to their potential to implement renewable energy production. In this context, the EU seeks to promote synergies between renewable energy deployment and rural development, through several funding programs and supporting policies that benefit both parties. Consequently, the number of rural Energy Communities is increasing, and researchers are focusing on optimizing their designs. In this regard, one critical aspect when simulating the energy demand of Energy Communities is the use of weather data which are mostly not available for specific locations. In these cases, data from nearby urban centers are typically used, if available. But these data may not be representative of the typical weather conditions of the specific rural area under study which will negatively affect such design. In this context, this paper studies the impact of using urban areas' weather data when designing Energy Communities in the nearby rural areas. Therefore, the case study of the Tarragona province in Spain is presented, driven by 43 weather stations homogeneously distributed across the region. Findings reveal higher correlation in temperature and solar irradiation between local data and province's capital data than with third-party data, despite climatic differences. Heating degree day analysis indicates third-party's data closer to reality. Given Spain's heating demand, accurate data is crucial for HDD, therefore, when local data is unavailable, third-party data is recommended, despite lower correlation.

Keywords:

Renewable energy; Rural energy communities; TMY (Typical Meteorological Year); Weather datasets.

1. Introduction

Increasing global energy demand and costs have been catalyzed by growths in global population and in the technological input required to drive economies [1]. This is also projected to be amplified by the rising global temperatures due to global warming. Resultant effects have been seen in rising energy prices due to the domination of energy supply from non-renewable resources. International agreement was reached, with clear road maps to reduce the emission of greenhouse gases (GHGs) with clean and renewable energy resources [2]. The UNEP Emissions Gap Report 2022 [3] indicates that to attain the goal outlined in the Paris Agreement [4] to reduce global temperatures increase to below 1.5 ^{o}C, the current global emissions of GHGs must be cut by 45%. This calls for greater penetration of cleaner energy into the global energy scenario. Following this, the European Union (EU) has committed to the attainment of 32 % renewable energy inclusion in its member states by 2030 [5]. An even bolder commitment of attaining 42% inclusion of renewable energy inputs into its nation energy mix by 2030 has been made by Spain [6]. Realizing these goals will require paradigm shift in all sectors, especially in electricity production as the supply of electricity drives many sectors (industrial, residential, services, transportation, etc). Hence, there is a need to deviate from the traditional centralized system of power generation to a distributed one which is capable of flexibly accommodating inputs from complimentary renewable energy sources. The creation of energy communities has been demonstrated to be a viable approach to meeting energy targets in the EU [7]. The EU in its Green deal commitment to meet emission targets, recognizes and supports Renewable Energy Communities (RECs) as essential components of energy transition [8]. This energy model also has the potentials of promoting self-consumption, reducing energy cost to consumers, and job creation. Thus, a demand is placed on member states to develop national policies and legal frameworks to promote participation of their stakeholders. However, the current Spanish energy regulatory framework has limited widespread roll-out of these RECs [9-10].

https://doi.org/10.52202/069564-0156

To maximize self-consumption and stabilize the national electricity grid, different types of renewable systems can be combined into a hybrid renewable energy system (HRES) [11]. Spain possesses vast renewable energy potentials which places it at advantage of benefiting from the HRES scenario [12]. On the other hand, the building sector accounts for about 43% of the total final energy consumption with about two-thirds of this from the residential buildings [13]. According to the International Energy Agency (IEA), the Spanish residential sector reliance on energy from fossil fuels still accounts for more than 50% of the sectors' final energy consumption [14]. This is even more prominent in the rural areas of the country. Therefore, energy transition efforts from the angle of the building sector are crucial. To this end, the EU directive 2010/31/EU and its amendment 2018/844/EU are legislative frameworks binding on member states to improve the energy efficiency of their buildings. Apart from participating in the energy demand side, buildings are also expected to participate in the supply side through the incorporation of available renewable energy technologies [15]. The idea is to achieve nearly zero energy buildings (NZEBs) or even positive energy buildings (PEBs) [16]. The excess energy generated by a PEB may then be consumed by another member of its HRES or exported to the national grid.

Dynamic numerical simulation has for some time, been an indispensable tool for HRES and NZEB researchers/designers in improving buildings' and HRES' energy efficiencies. The energy models utilized are usually run with weather data generated for the climatic conditions around the facility and they are often with some measure of uncertainties [17]. Different procedures have been used to construct typical annual weather data by statistically processing a multi-year (usually 10 years or more) actual weather data set as means of forecasting future weather conditions [18]. The Typical Meteorological Year (TMY) method was developed by Hall et al. [19] at Scandia laboratories, using Filkenstien-Schafer method, was modified into TMY2 and later, TMY3, by the National Renewable Energy Laboratory (NREL). The American society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) commissioned the International Weather Energy Calculations (IWEC) which was later updated to International Weather Energy Calculations 2 (IWEC2) [20]. The International Organization for Standards (ISO) also presented a procedure (ISO 15927-4:2005) for constructing a reference year of hourly values of meteorological data [21].

The reliability of the results obtainable from a building's or/and HRES' energy performance simulation depends on the accuracy of the weather data file utilized for the corresponding facility's location. The weather data used to compute typical weather conditions are typically obtained from historical measurements from weather stations which are usually situated at capital cities or airports. Since rural communities are usually far from such locations, their climatic conditions may differ from those around the weather stations. This will introduce errors when assessing energy performances in the rural areas [22]. However, generating the weather data for a specific location through any of the established procedures can be very demanding. A simpler alternative is to patronize the services of a third-party company which will generate the needed weather files while specifying the preferred meteorological model and the geographic location of concern.

In summary, the constitution of energy communities in the rural areas requires a precise evaluation of the energy performance of the involved buildings. However, according to the literature reviewed, no studies have yet to specifically investigate the impact of utilizing non-local meteorological data on these communities' design. This paper, therefore, seeks to fill this research gap by examining the implications of using data from various common sources, such as the capital city of the region or third-party providers, in comparison to employing local weather data in the design of rural energy communities.

2. Methodology

2.1. Data gathering and preparation.

The multi-year weather data supporting this work have been recorded by the weather stations owned by METEOCAT (Meteorological Service of Catalonia) during the period 2010 - 2019 at the 12 different locations around the province of Tarragona in Spain. The locations and main characteristics of these are presented in Figure 1.

The METEOCAT weather dataset include among others, 30-minutes measures of the following meteorological variables: dry-bulb temperature, wind velocity, relative humidity, global solar irradiance, maximum dry-bulb temperature, minimum dry-bulb temperature, maximum relative humidity, and minimum relative humidity. Despite the good quality of these measured weather data, it contained small gaps of usually a few hours, mainly in the wind speed data. Therefore, the linear interpolation technique was employed to fill in the missing data.

In building energy simulation, typical meteorological year weather data is usually a synthesized single year of weather data that represents multiple years of historical weather data. The collected weather data were then used to construct typical weather years according to the TMY. This method extracted a monthly weather dataset each, for all the calendar months, which typifies the weather characteristics of each location, from the historical data. The twelve selected typical months, which do not necessarily belong to the same year, were then concatenated to create a typical year.

municipalities	population	altitude	latitude	longitude
Amposta	**21317**	**3 m**	**40.7078**	**0.6321**
El Perelló	2846	179 m	40.8729	0.7158
El Vendrell	38891	59 m	41.2155	1.5212
Falset	**2724**	**359 m**	**41.1537**	**0.8195**
Horta de Sant Joan	1138	515 m	40.9513	0.3056
L'Espluga de Francolí	3717	446 m	41.3924	1.0989
Prades	**602**	**926 m**	**41.3148**	**0.9816**
Roquetes	8159	1055 m	40.797	0.3182
Tarragona	**135436**	**5 m**	**41.1039**	**1.201**
Vila-rodona	1299	287 m	41.3073	1.3626
Vinebre	427	53 m	41.185	0.5938
Vinyols i els Arcs	2193	29 m	41.0802	1.0666

Figure. 1. A map of the province of Tarragona, indicating the locations of the weather stations analyzed in this study and their key characteristics. The four stations examined in this paper are highlighted for reference.

The TMY methodologies build upon the original method by Hall et al. [23] which utilizes the following nine parameters that are considered with daily frequency: minimum, maximum and mean values of dry bulb air temperature (ºC) and dew point temperatures (ºC); maximum and mean values of the wind speed (m/s); and the cumulative global horizontal solar radiation (Wh/m^2). The weather data obtained from the different meteorological stations did not include the data for dew point temperature but this was determined from the data for relative humidity and dry bulb through psychrometrics.

 https://doi.org/10.52202/069564-0156

In the TMY procedure, the Finkelstein-Schafer (FS) [24] statistic was calculated to determine the typical weather months for a calendar year. The FS statistic defines the absolute value of the difference between long-term data and each of the historical candidate months. That is, for each weather data month, all historical months were evaluated and the month which matched most statistically to the long-term weather pattern was selected. The procedure is summarized below.

a) The daily means $\bar{p}$ were calculated from the parameter *p* values of the data series.

b) For each calendar month, the cumulative distribution function ($CDF_{p,m,i}$) of the daily means for all the years in the dataset was calculated by sorting all the daily means values in increasing order and then ranking them using Eq. (1):

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

where *K*(*i*) is the rank order of the *i* values of the daily means of a month *m* in the total data set and *N* is number of days for the month in the total data set.

c) For each year of the dataset, the cumulative distribution function ($CDF_{p,m,y,i}$) of the daily means within each month was calculated by sorting all values for that month *m* and year *y* in increasing order and then ranking them using Eq. (2),

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

where *J(i)* is the hierarchical order of the values *i* of the daily means within that month and year while *n* the number of days in the specific month.

d) For each month, the FS statistic were then calculated for each parameter according to Eq. (3) & (4):

$$FS_{(p)} = \frac{1}{n}\sum_{i}^{n} \delta_i\,, \tag{3}$$

where δ_i is absolute difference between the long-term data CDF and the historical candidate month data CDF, and *n* is the number of readings in a month.

$$\delta_i = \sum_{i=1}^{n} \left|CDF_{p,y,m,i} - CDF_{p,m,i}\right| \tag{4}$$

e) The TMY procedures introduced a weighted sum of the single FS statistics calculated for every parameter for each month as in Eq. (5). The weighting factors W_p attributed to each of the nine weather parameters vary according to their importance on building energy demandand are presented in Table 1. The month with minimum weighted sum of FS displays the most similar weather pattern to the long-term historical weather.

$$WS_p = \sum W_p * FS_{(p)} \tag{5}$$

The hourly weather data belonging to the minimum WS were then used to fill up the corresponding month of the twelve-month weather file.

Table 1. Weighting factor used for each meteorological parameter.

Meteorological Parameter	**TMY** [24]
Maximum dry-bulb temperature	0.042
Minimum dry-bulb temperature	0.042
Mean dry-bulb temperature	0.083
Maximum dew point temperature	0.042
Minimum dew point temperature	0.042
Mean dew point temperature	0.083
Maximum wind speed	0.083
Mean wind speed	0.083
Global horizontal solar radiation	0.500

Also, the TMY for each of the 12 municipalities were obtained with the Meteonorm software which has a database with information from more than 7700 weather stations distributed around the world. The main advantage of the Meteonorm software is its ability to generate weather date for user-defined locations by interpolating data from nearby weather stations in combination with data obtained from satellites [25, 26].

2.2. Data analysis

The four locations selected for this study, are each considered to be representative of the 12 different climatic typologies of the province. Tarragona's (the capital) station is coastal, Amposta stations is pre-coastal, Falset is inland at 259 meters above sea level, and Prades is also inland but at the highest altitude of about 926 meters. It should also be noted that the weather station at Prades usually records the lowest temperatures during winter in the province.

A correlational analysis of weather parameters (ambient temperature, relative humidity and total solar irradiation) from the TMY of Tarragona, which was determined from historical data; the TMY for each of the three locations as determined from their historical data and also the TMY obtained for each location from Meteonorm, was performed. The Taylor Diagram provides a second approach for comparing weather data from the on-site weather station, Meteonorm, and the province capital's weather station. This method uses statistical metrics, such as the Pearson correlation coefficient (R), the centered root-mean-squared error (RMSE), and the normalized standard deviation (σ), to visually represent how closely a weather parameter sample matches the local observation.

A comparative study of the Heating Degree Days (HDD) and the Cooling Degree Days (CDD) were then conducted for the municipalities. The HDD relative to a base outdoor temperature of 18 ^{o}C were integrated from mid-October to mid-April, while the CDD relative to a base outdoor temperature of 24 ^{o}C were integrated from mid-April to mid-October. For each municipality, the values of the HDD and the CDD obtained from the TMY built using the climatic data of its meteorological station were compared with the TMY of the capital (Tarragona) and with the TMY obtained from the Meteonorm software. The method used for calculating the degree days are as defined in [27].

3. Results and discussion

3.1. Typical Meteorological Months

Table 2 shows the monthly weather data that were selected to assemble the typical meteorological year for each of the location considered in this study, based on the TMY procedure.

Table 2. Selected typical months for the different locations based on the TMY procedure.

Location	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Amposta	2018	2013	2014	2016	2012	2018	2013	2015	2016	2012	2016	2012
Falset	2015	2015	2014	2016	2012	2016	2013	2017	2016	2019	2016	2014
Prades	2013	2015	2014	2018	2014	2016	2013	2015	2016	2015	2016	2012
Tarragona	2013	2013	2014	2016	2016	2018	2010	2015	2016	2019	2016	2012

3.2. Taylor Diagram

The Taylor diagram is a useful graphical display of the statitiscal summary of how different models' performances match each other in terms of correlation, root-mean-square difference and ratio of variance [28].

The weather data from on-site weather stations, the province capital's weather station, and third-party software (Meteonorm) are compared using the previously introduced statistical metrics and displayed in a Taylor diagram for each of the three selected municipalities (Amposta, Falset, and Prades), based on three meteorological variables (temperature T, relative humidity RH, and global horizontal irradiance GHI).

In Amposta (Figure 2), T and GHI from the province capital's weather station have higher correlation with the on-site data (R=0.92 and R=0.93) than the Meteonorm's data (R=0.82 and R=0.73) obtained for the location.

RH however, generally showed much lower correlation (R=0.65 for the capital and R=0.21 for Meteonorm). The standard deviations are similar in all cases, below the 10% compared with the reference, except for the T of Meteonorm's data, around 21%.

In Falset (Figure 3) and Prades (Figure 4), T and GHI from the province capital's weather station also have higher correlations with the on-site data than Meteonorm's data, while RH has lower correlations. In these two locations, the standard deviation for all parameters is within acceptable values in all cases, less than 20% different from the reference data. It is noteworthy that Meteonorm's data are worse than the province capital's data in all locations, despite significant climatic differences between some of the municipalities. Although it is expected that Amposta and the province capital would have similar data, as they are both located on the coast with a Mediterranean climate, Prades and Falset have different climates and are located at higher altitudes than the capital.

 https://doi.org/10.52202/069564-0156

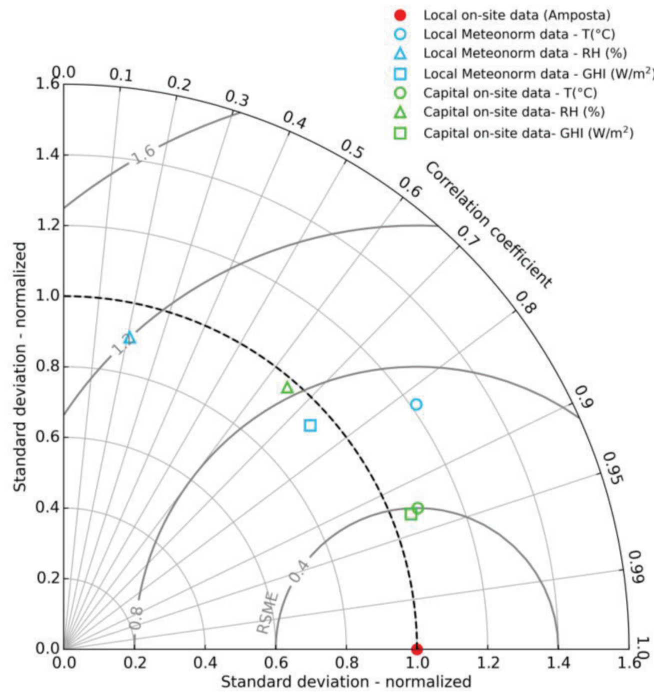

Figure. 2. Normalized Taylor Diagram for Amposta municipality, which compares the Amposta on-site weather station data (as reference) with Amposta third-party Meteonorm data, and with the province capital's weather station data for the TMY 2010-2019.

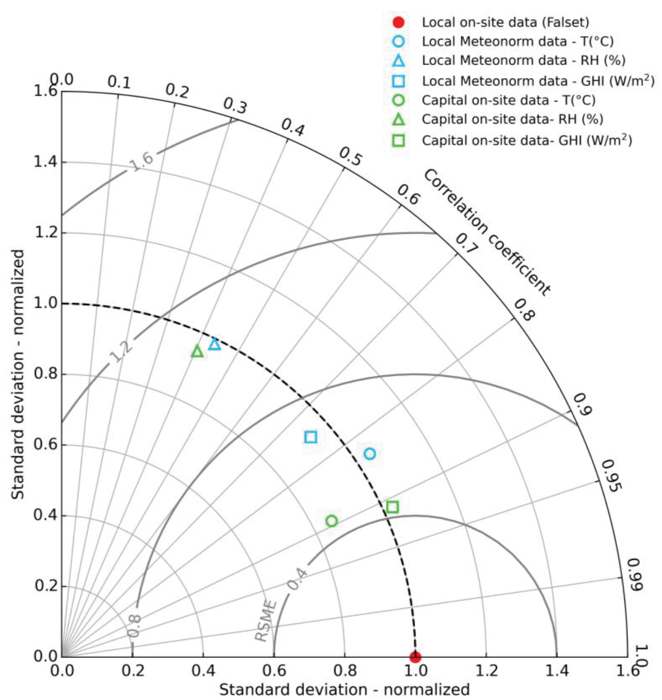

Figure. 3. Normalized Taylor Diagram for Falset municipality, which compares the Falset on-site weather station data (as reference), Falset third-party Meteonorm data, and the province capital's weather station data for the TMY 2010-2019.

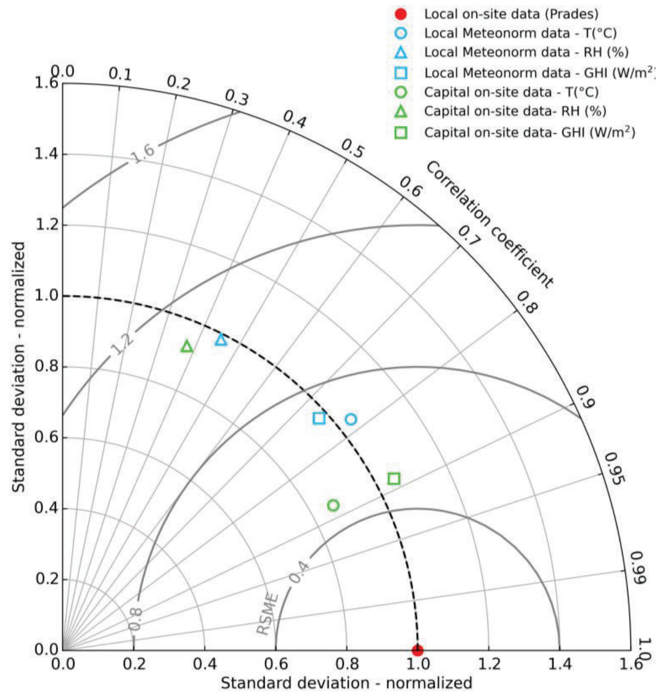

Figure. 4. Normalized Taylor Diagram for Prades municipality, which compares the Prades on-site weather station data (as reference), Prades third-party Meteonorm data, and the province capital's weather station data for the TMY 2010-2019.

3.3. Heating degree days (HDD) and Cooling degree days (CDD)

To evaluate the impact of typical weather data sources on building energy demand prediction for the three locations (Amposta, Falset, and Prades), it is crucial to analyze the representative Cooling Degree Days (CDD) and Heating Degree Days (HDD) of the different weather datasets. To this end, Figure 5 presents a comparison of the HDD and CDD values obtained from the TMY built using climatic data from each local weather station (On-site TMY), the TMY built using climatic data from the province's capital weather station (Capital TMY), and the TMY generated for each location using the Meteonorm software (Meteonorm TMY).

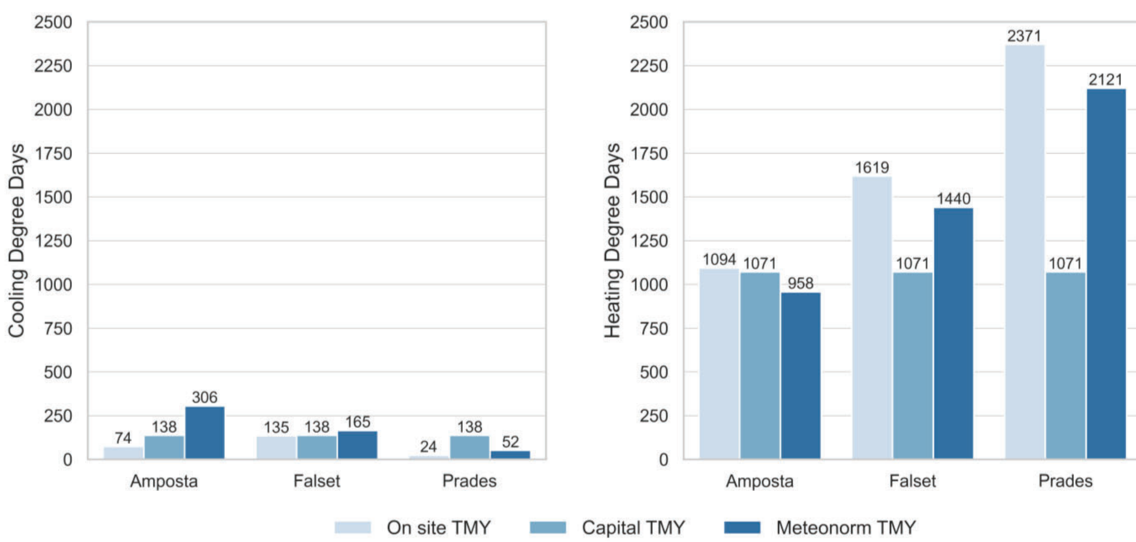

Figure. 5. Cooling Degree Days (left) and Heating Degree Days (right) for the 3 municipalities in the study (Amposta, Falset and Prades), computed from 3 different TMY 2010-2019 datasets: on-site weather station data, province capital's weather station data, and third-party Meteonorm data.

For the coastal municipality of Amposta, which is assumed to be more climatically similar to the provincial capital, the CDD values show significant deviations. Specifically, the onsite weather dataset resulted in CDD

https://doi.org/10.52202/069564-0156

which deviated from those from Tarragona's weather dataset by -86%, and even larger deviation of -300% from those given by the Meteonorm weather dataset. With respect to HDD, the onsite weather dataset minimally deviated from Tarragona's weather dataset by +2% while significant deviation of +12% from the Meteonorm's dataset is observed. These deviations are consistent with the Degree Days presented on the METEOCAT website for Amposta and Tarragona [29]. Concerning the implications for building energy demand, using the weather datasets from both the capital or Meteonorm would result in a large overestimation of cooling energy demands of buildings in summer. On the other hand marginal underestimation of heating demand of buldings in winter would result from the use of weather dataset from the capial while significant underestimation would result with the use of Meteonorm's dataset.

The CDD from the onsite weather dataset at Falset, which is located inland and at an altitude of 359 meters, are similar to those resulting from the capital's dataset with a minor deviation of about -2% while a larger deviation of about -22% resulted compared to the Meteonorm's dataset. However, the onsite weather data HDD show a larger deviation of about +34% from the capital's dataset and about +11% from the Meteonorm's dataset. This imply that using weather dataset from Meteonorm will result in significant overestimation of buildings' cooling demands in summer while datasets from both the province's capital and Meteonorm will result in significant underestimation of buildings' heating demands in winter.

Finally on Prades, which experiences considerably colder winters than the other locations (as evidenced by the onsite HDD values in Figure 5), the onsite weather dataset's CDD deviates with +475% and +116% with respect to the capital's and Meteonorm weather datasets respectively. The HDD from the onsite weather dataset on the other hand, deviates with +55% and +11% from the capital's and meteonorm's datasets respectively. Therefore, there is the risk of significantly underestimating buildings' heating demands during winter if the local weather dataset are not utilized, especially by using the weather dataset from the provincial capital. Additionally, significant overestimation of buildings'cooling energy demands will result from using weather datasets from both the province's capital and Meteonorm in summer.

Overall, and considering that in the period between 2010-2020, heating accounted for 41.5% of the total energy consumption in the residential sector in Spain, while air conditioning only accounted for 1% [31], it is crucial to properly size the heating system as opposed to the cooling system. Thus, in cases of extreme winter temperatures, it is more advisable to use Meteonorm data instead of relying on data from the provincial capital.

3.4. Conclusions

The objective of this research is to show the impact of using approximate meteorological data instead of using real local weather data in the design of rural energy communities. The study was conducted in twelve rural municipalities in the province of Tarragona, which have on-site data from local weather stations, with focus on three of them. Thus, for each location, the data from the local Typical Meteorological Year (TMY) computed from the on-site data were statistically compared, in terms of correlation, root-mean-square difference and ratio of variance, with data from the TMY of the province's capital and the TMY obtained using third-party software, Meteonorm. Additionally, the typical cooling and heating demands in buildings at each location were estimated using Cooling Degree Days (CDD) and Heating Degree Days (HDD) for the three meteorological datasets: referencial on-site data, province's capital data, and Meteonorm's data. The results show that, in all three case studies, the correlation of temperature and solar irradiation parameters between the local data and the data from the province's capital was higher (R=0.85-0.90) than with those from Meteonorm (R=0.70-0.85). This is despite the apparent climatic differences between the capital, in the coast, and the inland municipalities of higher-altitude. It should also be noted that the relative humidity data had correlation values lower than R=0.5 with respect to both the province's and Metenorm's data, indicating that they are unreliable for replacing the on-site data in any case. Furthermore, the analysis of CDD indicates that the data from the provincial capital is closer to the real local data than the data provided by Meteonorm. However, for HDD, the opposite is true, as the data from Meteonorm was found to be closer to real data, with deviations of 11%, compared to the deviation of 34-55% with the data from the provincial capital. Given that the heating energy demand in the residential sector in Spain represents 41.5% of energy consumption in average, while cooling demand barely reaches 1%, it is vital to use the data that best approximates reality with respect to HDD. Therefore, when local meteorological data is not available, third-party data yields better results in HDD analysis than the weather data of the provincial capital, though with low worse correlation. However, it is advisable to study to what extent the deviations found affect the definition of specific building design parameters for rural energy communities.

Acknowledgments

The authors would like to acknowledge financial support from the "Agència de Gestió d'Ajuts Universitaris i de Recerca (AGAUR)" from "Generalitat de Catalunya" [2022-FISDU-00128]; the "Ministerio de Ciencia, Innovación y Universidades" of Spain [PID2021-127713OA-I00, PID2021-123511OB-C33, PID2021-

124139NB-C22 & TED2021-129851B-I00]; and “Ministerio de Ciencia, Innovación y Universidades” of Spain through the Recovery, Transformation and Resilience Plan; “The European Union – NextGenerationEU”; and “Universitat Rovira i Virgili” [2021URV-MZ-11].

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