Effects of Different Wind Speed Databases on the Performance of a Vertical Axis Micro Wind Turbine Integrated With a Typical Residential House: A Comparative Simulation Analysis for Five Italian Cities

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Abstract

Renewable energy technologies represent a promising option to cover the building sector energy needs. In particular, micro vertical axis wind turbines are emerging as a viable solution thanks to their ability to capture wind from all directions and efficiently convert wind energy into electric power. In this study, the performance of a 2.2 kW commercial vertical axis micro wind turbine serving a typical residential building located into five different cities in Italy (Naples, Rome, Milan, Palermo, Alghero) has been analysed by means of the TRaNsient SYStems simulation tool (TRNSYS) allowing us to evaluate the effects of climatic conditions (including wind velocity). Simulations have been performed by considering three different sources of long-term wind speed data for each city: (a) the Typical Meteorological Year version 2 weather database (TMY2), (b) the NASA LaRC POWER database, and (c) the Open-Meteo database. The results highlighted that (a) the selected wind speed datasets significantly affect the assessment of wind turbine performance, as well as (b) the proposed micro wind turbine can reduce the electric energy imported from the grid, the equivalent global CO_2 emissions and the operating costs up to 43.46%, 43.50% and 95.62%, respectively.

1. Introduction

Small-scale wind turbines (SSWTs) with power outputs less than 50 kW are gaining considerable attention from scientists because of their low maintenance costs, excellent dependability, broad operating range, and minimal environmental effect (Calautit & Johnstone, 2023; Kalashani et al., 2023). According to the International Commission of Electrotechnics (iea50, 2024), SSWTs are usually classified into 3 different categories depending on the rated power: (a) pico wind turbine with rated power not larger than 1 kW; (b) micro wind turbines with rated power between 1 kW and 7 kW; (c) mini wind turbines with rated power between 7 kW and 50 kW. There are basically two types of wind turbines (Calautit & Johnstone, 2023; Kalashani et al., 2023): (a) horizontal axis wind turbines, and (b) vertical axis wind turbines. The performance of horizontal axis wind turbines is dependent on wind direction, while vertical axis SSWTs can use wind from all directions (Calautit & Johnstone, 2023; Kalashani et al., 2023). Vertical axis SSWTs have a significant potential to be utilized and integrated into residential urban environments to limit the corresponding energy demand currently covered by fossil fuels. The challenge of estimating the feasibility of vertical axis SSWTs based on the local wind resource, which is very site-specific and less predictable than other renewable sources, is one of the obstacles to their widespread diffusion in urban settings (Calautit & Johnstone, 2023; Kalashani et al., 2023), also taking into account that the wind flow can be disturbed by the surrounding trees and buildings. This challenge can be addressed by means of dynamic simulation platforms allowing to accurately take into account the boundary conditions (Calautit & Johnstone, 2023; Kalashani et al., 2023). With reference to this point, the TRaNsient SYStems simulation tool (Klein et al., 2007) is recognized in the scientific community as one of the most detailed dynamic modelling and simulation environments because it considers the fluctuating nature of occupant-driven loads, the part-load features of generating systems,

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and the relationship between climate and system output (Rosato et al., 2020). In particular, climatic conditions (including wind speed) can greatly affect the performance assessment of vertical axis SSWTs and several databases have been developed in the last decades with the aim of accurately representing the real meteorological data of installation sites.

In this study, the performance of a 2.2 kW commercial vertical axis micro wind turbine (VAMWT) serving a typical house located into 5 different cities in Italy (Naples, Rome, Milan, Palermo, Alghero) has been analyzed by means of the TRNSYS platform (version 16) (Klein et al., 2007). Taking into account that this software platform allows us to evaluate the effects of climatic conditions (including wind velocity), simulations have been performed by considering 3 different sources of long-term wind speed data for each city: (a) the Typical Meteorological Year version 2 weather database (TMY2) (Marion and Urban, 1995; Klein et al., 2005), (b) the NASA LaRC POWER database (NASA LaRC POWER, 2003), and (c) the Open-Meteo database (Historical Weather API, 2024; Zippenfenig, 2023). The building-integrated VAMWT's energy, environmental, and financial performance has been compared to that of the same building when it is only fed by the central grid. To the knowledge of the authors no scientific studies are available in the literature with reference to the effects of different wind speed databases on the performance of a VAMWT integrated with a typical residential house upon varying the Italian cities. The main goals of the paper are: (a) assess the potential energy, economic, and environmental benefits associated with the use of a VAMWT compared to a traditional scenario for an electric demand profile typical of a residential house; (b) evaluate the effects of climatic conditions associated to different Italian cities; (c) analyze the impact of different wind speed datasets on energy, environmental and economic advantages; (d) support the use of wind energy via VAMWTs.

2. Building Electric Demand and Wind Turbine Characteristics

It is commonly recognized that a wide range of factors influence how much electricity residential structures use. For this purpose, the daily electric energy demand profiles connected to the operation of home appliances and lighting systems (excluding cooking devices as well as heating/cooling systems) have been modelled by using a novel tool created by the Loughborough University based on a stochastic method (McKenna et al., 2015). The tool enables the creation of random profiles (without a detailed definition of the building) based on a variety of parameters, including the maximum number of people, the day of the week, the month of the year, the number and kinds of household/lighting appliances. A maximum of four people is assumed in this study, together with typical household appliances (1 fridge-freezer, 1 fridge, 1 clock, 1 phone, 1 iron, 1 vacuum, 1 personal computer, 1 printer, 2 TVs, 1 microwave, 1 dish washer, 1 washing machine) and lighting systems. By merging 365 distinct daily electric load profiles with a time step of 1 minute, a reference yearly stochastic electric demand profile of the building has been defined. The electric load-duration diagram is displayed in Fig. 1, with the values arranged in descending order. This figure shows that the electric demand has a maximum of 4383 W and a minimum of 21 W; the corresponding annual electricity demand is 2408.96 kWh.

A commercial Savonius vertical axis micro wind turbine has been analyzed in this study (FLTXNY_FS_Model, 2024). The wind turbine has 2 blades, a start-up wind speed (minimum wind speed required to starts spinning, without providing electric power) of 1.5 m/s, a cut-in wind speed (speed at which a wind turbine starts generating electricity) of 2.0 m/s, a cut-off wind speed (maximum wind speed at which the wind turbine can produce usable power) of 14.0 m/s, a maximum power output of 2200 W, a rotor diameter of 0.8 m, a turbine length of 2.0 m, and a capital cost of 675.22 €. This model has been selected because it has a one power rating consistent with that required by a typical Italian house and it represents a good compromise between cost and performance.

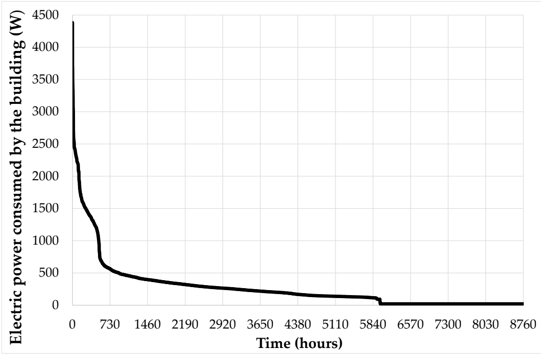

Fig. 1 – Annual electric load-duration diagram of the building

3. Simulation Model and Weather Data

The TRNSYS simulation tool (version 16) (Klein et al., 2007) has been used in this study to model the wind turbine operation as well as the related load and climatic conditions. Each physical piece of a thermodynamic equipment is modelled in TRNSYS via a mathematical tool (named "Type") that is a FORTRAN source code. In this case, the TRNSYS Type 90 has been used to model the performance of the selected wind turbine. This model requires the definition of 6 parameters (site elevation, data collection height, hub height, turbine power loss, number of turbines, logical unit of the containing power data) as well as 6 inputs (control signal, wind velocity, ambient temperature, site shear exponent, barometric pressure, performance curve of the wind turbine) to obtain 3 outputs (power output, turbine operating hours, power coefficient). The turbine power loss has been assumed equal to 0. The shear exponent determines the rate of wind speed increase as a function of height; in this study a value of 0.26 has been considered (because the fluctuations in wind resource evaluations are typically not large enough to induce significant mistakes into the estimates, it is frequently assumed to be constant). The performance curve of the selected wind turbine, which shows the power output as a function of wind velocity, is reported in Fig. 2 according to the manufacturer data in the case of the turbine is installed at a height of 9 m. Site elevation, wind velocity, ambient temperature and pressure (required as input by the TRNSYS Type 90) have been established by utilizing the TRNSYS Type 15-6 according to the selected databases. This particular Type serves as a weather data processor, facilitating the utilization of one-year-long datasets at regular intervals from an external weather data file. By utilizing this Type, it becomes feasible to incorporate climatic conditions tailored to individual cities.

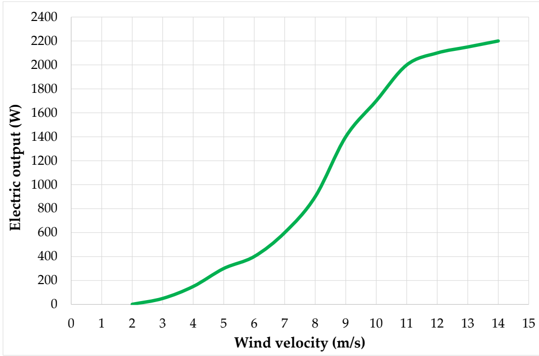

Fig. 2 – Performance curve of the selected wind turbine

In greater detail, the following five distinct Italian cities have been considered to account for the diverse climatic conditions prevalent across Italy: Naples; Rome; Milan; Palermo; Alghero. In this study three different sources of long-term wind speed data for each city have been considered: (a) the TMY2 database (Marion & Urban, 1995; Klein et al., 2005), (b) the NASA LaRC POWER database (NASA LaRC POWER, 2003), and (c) the Open-Meteo database (Historical Weather API, 2024; Zippenfenig, 2023).

The TMY2 weather data files are derived from the National Solar Radiation Data Base (NSRDB) containing hourly values of measured or modelled meteorological data for the 30-year period from 1961-1990. The Sandia method, an empirical technique for choosing certain months from many years to be concatenated in order to construct a whole year, is the foundation upon which the reference year is built. The choice of months is based on data derived from five parameters: wind speed, dew point temperature, dry bulb temperature, global horizontal radiation, and direct normal radiation. Around 1000 global locations are included, which correlate to over 150 nations. In particular, the following stations are considered in this study with reference to the selected cities: Alghero (40.63° N, 8.28° E, 40 m); Milano/Malpensa (45.62° N, 8.73° E, 211 m); Napoli (40.85° N, 14.30° E, 72 m); Palermo/Point Raisi (38.18° N, 13.10° E, 34 m); Rome/Fiumicino (41.80° N, 12.23° E, 3 m). The NASA LaRC POWER database was obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource (POWER) Project funded through the NASA Earth Science/Applied Science Program. Long-term climatologically averaged estimates of meteorological quantities and surface solar energy fluxes are included in this data. The information is available from 1981 up to a few days ahead of actual time. The dataset uses a variety of observation types, such as remotely sensed data from satellites, sea level winds inferred from backscatter returns from space-borne radars, land surface observations of surface pressure, ocean surface observations of sea level pressure and winds, and upper-air data (from pilot balloons, aircraft winds, dropsondes, and rawinsondes). In this study, weather data have been derived via the Data Access Viewer Enhanced (DAVe) system v. 2.3.1 (NASA POWER, 2024) with reference to the year 2023 according to the following weather stations: Alghero (40.56° N, 8.32° E, 37.84 m); Milano/Malpensa (45.47° N, 9.18° E, 209.03 m); Napoli (40.84° N, 14.25° E, 264.43 m); Palermo/Point Raisi (38.12° N, 13.36° E, 221.69 m); Rome/Fiumicino (41.90° N, 12.50° E, 198.41 m). In particular, hourly temporal levels averaged wind speed data at an elevation of 10 meters above the earth's surface have been used. The Open-Meteo database partners with national weather services to create open data with high resolution. It leverages a powerful combination of global (11 km) and mesoscale (1 km) weather models; weather data are presented in hourly resolution, including detailed past measurements from 1940 onwards based on various sources such as airplanes, buoys, radar systems, and satellites. In this research, the data corresponding to the year 2023 according to the following latitudes, longitudes and altitudes of the selected cities have been used: Alghero (40.53° N, 8.39° E, 19 m); Milano (45.45° N, 9.17° E, 145 m); Napoli (41.86° N, 12.54° E, 54 m); Palermo (38.14° N, 13.34° E, 38 m); Rome (41.89° N, 12.51° E, 20 m). In particular, hourly wind speed data referring to an elevation of 10 meters above ground have been considered.

Fig. 3, 4, 5, 6 and 7 report the annual wind velocity-duration diagrams (with values sorted in descending order) as a function of the long-term wind speed datasets for the Italian cities of Naples, Rome, Milan, Palermo and Alghero, respectively. These figures also report the differences between the wind velocities associated to the databases NASA LaRC POWER and Open-Meteo with respect to the values associated the TMY2 dataset (representing one of the most used climatic datasets). The data in these figures indicate that these differences are significant, varying from minimum values of -12.33 m/s, -13.80 m/s, -8.52 m/s, -17.15 m/s and -13.01 m/s up to maximum values of 10.32 m/s, 10.52 m/s, 12.22 m/s, 12.27 m/s and 14.46 m/s for Naples, Rome, Milan, Palermo and Alghero, respectively. Table 1 reports the mean annual wind speed μ and the mean standard deviation σ upon varying the city and the database. This table indicates that the TMY2 dataset provides the lowest mean annual wind speed with reference to the cities of Naples, Milan and Alghero; the database NASA LaRC POWER is characterized by the largest mean annual wind speed in the cases of Naples, Rome and Alghero. In addition, it can be noticed that, whatever the dataset is, Milan has the lowest mean annual wind speed.

4. Simulation Results

Simulations have been performed over a full year, employing a simulation time step of 1 minute. It should be underlined that the proposed model does not adjust the wind velocity data derived from the selected databases because representing a real dense urban context is challenging and out of the scopes of this paper. In addition, it has been assumed that the turbine is installed at a height of 9 m (that is the installation height of the wind turbine associated with the manufacturer performance curve reported in Fig. 2).

This section discusses the simulation findings. Fig. 8 reports the annual electric energy generated by the wind turbine as a function of both city and wind speed dataset. This plot highlights that, within a given city, the electric generation strongly depends on the database. In particular, the maximum energy generation corresponds to the TMY2 dataset for Rome and Palermo, while the Open-Meteo database provides the highest values for Milan. Additionally, it is noteworthy that the annual electric energy generation is highest in Palermo in the cases of both the TMY2 and NASA LaRC POWER datasets, while the lowest values are obtained in the case of Milan (whatever the wind speed dataset is).

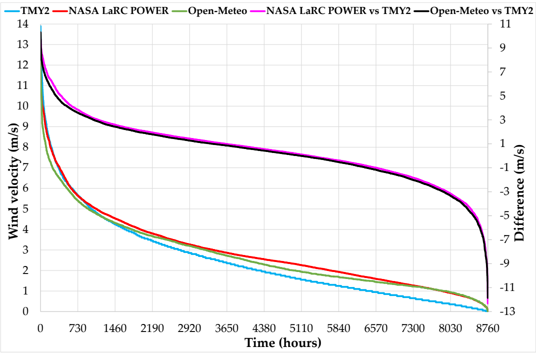

Fig. 3 – Annual wind velocity-duration diagrams for Naples

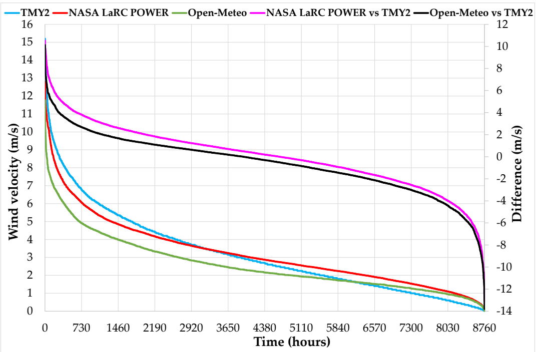

Fig. 4 – Annual wind velocity-duration diagrams for Rome

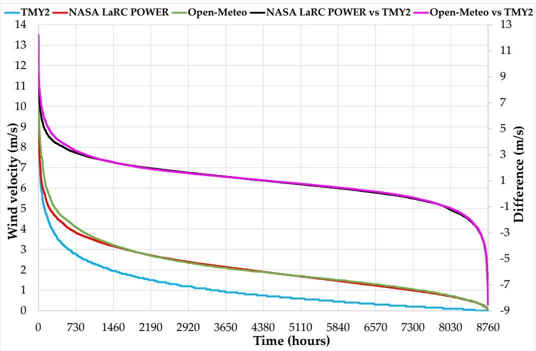

Fig. 5 – Annual wind velocity-duration diagrams for Milan

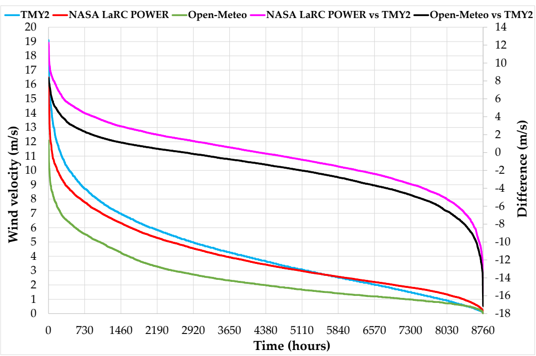

Fig. 6 – Annual wind velocity-duration diagrams for Palermo

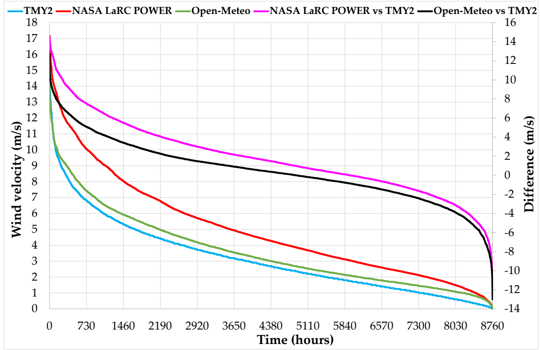

Fig. 7 – Annual wind velocity-duration diagrams for Alghero

Table 1 – Comparison among the selected weather databases.

		TMY2	NASA LaRC POWER	Open-Meteo
Naples	μ (m/s)	2.48	2.93	2.75
	σ (m/s)	2.06	1.85	1.74
Rome	μ (m/s)	3.19	3.25	2.59
	σ (m/s)	2.35	1.90	1.56
Milan	μ (m/s)	1.10	2.10	2.16
	σ (m/s)	1.14	1.21	1.34
Palermo	μ (m/s)	4.24	3.98	2.52
	σ (m/s)	2.93	2.39	1.82
Alghero	μ (m/s)	3.19	4.99	3.63
	σ (m/s)	2.35	3.13	2.38

Specifically, the annual energy generation ranges from a minimum of 138.50 kWh (in Milan) up to a maximum of 3712.13 kWh (in Alghero). For a given city, the percentage difference between the values associated to the NASA LaRC POWER dataset with respect to the values corresponding to the TMY2 database range from a minimum of -20.08% (in case of Palermo) up to a maximum of 140.80% (in case of Milan); the percentage difference between the values associated to the Open-Meteo dataset in comparison with the values corresponding to the TMY2 database range from -71.02% (in Palermo) to 183.84% (in Milan).

When the electric power generated by the wind turbine exceeds the building's electric demand, the surplus is sold to the electric central grid. Fig. 9 reports the annual electric energy sold to the grid as a function of the city and the wind speed dataset. The plot indicates that, for a given city, annual electric energy sold to the central grid significantly varies depending on the wind speed database. In particular, the maximum values correspond to the TMY2 dataset in the cases of Rome and Palermo, while the Open-Meteo database provides the highest results for the city of Milan. In addition, it can be noticed that the annual electric energy sold to the central grid is highest in Palermo in the cases of both the TMY2 and NASA LaRC POWER databases, while the lowest values are obtained in the case of Milan (whatever the wind speed dataset is). Specifically, the annual electric energy sold to the central grid is in the range between 55.76 kWh (in Milan) and 2665.23 kWh (in Alghero). For a given city, the percentage difference between the values associated to the NASA LaRC POWER dataset with respect to the values corresponding to the TMY2 database range from a minimum of -24.78% (in Palermo) up to a maximum of 199.74% (in Alghero); the percentage difference between the values associated to the Open-Meteo dataset in comparison with the values corresponding to the TMY2 database range from -77.37% (in Palermo) to 206.09% (in Milan).

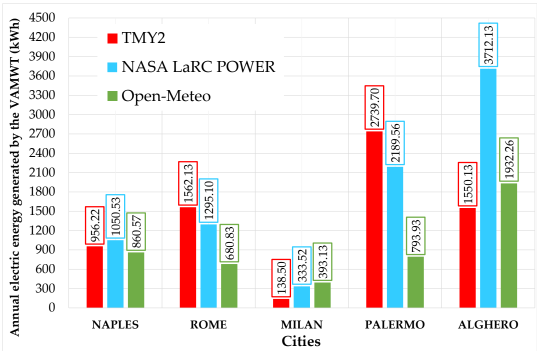

Fig. 8 – Annual electric energy production

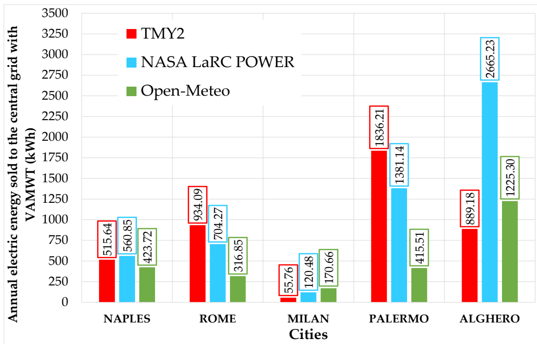

Fig. 9 – Annual electric energy sold to the central grid

If the electric power generated by the wind turbine falls short of the building's electric demand, the shortfall must be procured from the central electric grid. Fig. 10 reports the annual electric energy purchased from the grid as a function of both the city as well as the long-term wind speed data. This plot underlines that, for a given city, the influence of wind speed database on annual electric energy purchased from the central grid is relevant.

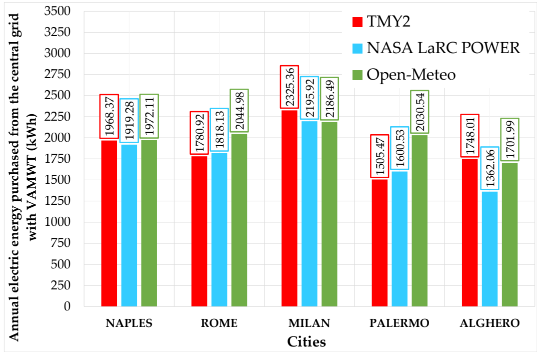

Fig. 10 – Annual electric energy purchased from the central grid

In particular, the largest values are associated to the Open-Meteo database in the cases of Naples, Rome and Palermo, while the TMY2 dataset corresponds to the highest data in Milan and Alghero. In addition, it can be noticed that the annual electric energy purchased from the grid is highest in Milan (whatever the wind speed dataset is), while the lowest values are obtained in the case of Palermo for the databases TMY2 and NASA LaRC POWER. In greater detail, the annual electric energy purchased from the grid varies from a minimum of 1362.06 kWh (in Alghero) up to a maximum of 2325.36 kWh (in Milan). For a given city, the percentage difference between the values associated to the NASA LaRC POWER dataset with respect to the values corresponding to the TMY2 database range from a minimum of -22.08% (in Alghero) up to a maximum of 6.31% (in Palermo); the percentage difference between the values associated to the Open-Meteo dataset in comparison with the TMY2 dataset range from -5.97% (in Milan) to 34.88% (in Palermo).

5. Energy, Environmental and Economic Comparison between Proposed and Reference Scenarios

A comparison between the performance of the proposed scenario, where the building is connected to both the central grid and the wind turbine, and the reference scenario, where the building is solely connected to the central grid (without the wind turbine) is carried out from energy, environmental, and economic perspectives.

The percentage difference ΔE_{el} between the annual electric energy $E_{el,imp}^{PS}$ imported from the grid in the case of the proposed scenario (including the wind turbine) and the annual electric energy $E_{el,imp}^{RS}$ imported from the grid in the case of the reference scenario (without the wind turbine) has been calculated as follows:

$$\Delta E_{el} = \frac{E_{el,imp}^{PS} - E_{el,imp}^{RS}}{E_{el,imp}^{RS}} \quad (1)$$

Fig. 11 reports the values of ΔE_{el} as a function of both city and wind speed dataset. All the values reported in this figure are negative, meaning that the proposed scenario allows to reduce the electricity imported from the grid with respect to the reference scenario, whatever the city and the wind speed dataset are. In greater detail, this figure indicates that, for a given city, the utilization of the wind turbine allows to reduce the imported electric energy from a minimum of -3.47% in Milan (city characterized by the lowest annual average wind speed) based on the TMY2 dataset, up to a maximum of -43.46% in Alghero (city with the highest annual average wind speed) considering the NASA LaRC POWER dataset.

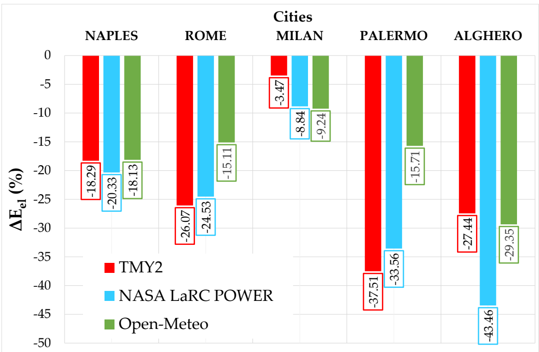

Fig. 11 – ΔE_{el} as a function of the city and wind speed dataset

In this study, the environmental impact has been evaluated utilizing the energy output-based emission factor approach proposed by Chicco and Mancarella (2008). In particular, the percentage difference ΔCO_2 between the global equivalent CO_2 emissions CO_2^{PS} of the proposed scenario (including the wind turbine) and the global equivalent CO_2 emissions CO_2^{RS} of the reference scenario (without the wind turbine) has been derived as follows:

$$\Delta CO_2 = \frac{CO_2^{PS} - CO_2^{RS}}{CO_2^{RS}} = \frac{\sum_i u_{CO_2,i}^{E_{el}} \cdot P_{el,imp,i}^{PS} \cdot STS - \sum_i u_{CO_2,i}^{E_{el}} \cdot P_{el,imp,i}^{RS} \cdot STS}{\sum_i u_{CO_2,i}^{E_{el}} \cdot P_{el,imp,i}^{RS} \cdot STS} \quad (2)$$

where $u_{CO_2,i}^{E_{el}}$ is the i-th CO_2 emission factor corresponding to the i-th electric power imported from the grid in the case of the proposed scenario ($P_{el,imp,i}^{PS}$) or in the case of the reference scenario ($P_{el,imp,i}^{RS}$) at the same simulation time, while STS is the simulation time step (assumed constant and equal to 1 minute). The values of CO_2 emission factor $u_{CO_2}^{E_{el}}$ associated to the electricity consumption in Italy depends on the location, the day as well as the time of the day. Fig. 12 indicates the values of this factor used in this study as a function of time in the cases of the selected Italian cities according to (Electricity Maps, 2024). Fig. 13 reports the values of ΔCO_2 as a function of both city and wind speed dataset. All the values reported in this figure are negative; this means that the proposed scenario reduces the CO_2 emissions with respect to the reference scenario, whatever the city and the wind speed dataset are. In greater detail, this figure underlines that, for a given city, the utilization of the wind turbine allows to reduce the CO_2 emissions from a minimum of -3.44% in the case of Milan (city with the lowest annual average wind speed) based on the TMY2 dataset, up to a maximum of -43.50% when the wind turbine operates in Alghero (city with the highest annual average wind speed) considering the NASA LaRC POWER database.

The percentage difference ΔOC between the operating costs OC^{PS} (due to the electricity imported from the grid) reduced by the annual revenue $REV_{el,sold}$ obtained thanks to the electricity sold to the central grid $E_{el,sold}^{PS}$ in the case of the proposed scenario (including the wind turbine) and the operating costs OC^{RS} (due to the electricity imported from the grid) of the reference scenario (without the wind turbine) has been calculated via this formula:

$$\Delta OC = \frac{\left(OC^{PS} - REV_{el,sold}\right) - OC^{RS}}{OC^{RS}} = \frac{\left(UC_{el,imp} \cdot E^{PS}_{el,imp} - UC_{el,sold} \cdot E^{PS}_{el,sold}\right) - UC_{el,imp} \cdot E^{RS}_{el,imp}}{UC_{el,imp} \cdot E^{RS}_{el,imp}} \quad (3)$$

where $UC_{el,imp}$ is the unit cost of electricity purchased from the grid (assumed constant and equal to 0.26 €/kWh), while $UC_{el,sold}$ is the unit price of electric energy sold to the grid (assumed constant and equal to 0.19 €/kWh) according to the current Italian market scenario (GME, 2024; ARERA, 2024). Fig. 14 reports the values of ΔOC as a function of both city and wind speed dataset. All the values in this graph are negative and, therefore, the proposed scenario reduces the operating costs with respect to the reference scenario, whatever the city and the wind speed dataset are. In more detail, this figure underlines that, for a given city, the utilization of the wind turbine allows to reduce the operating costs from a minimum of -5.16% in the case of Milan (city with the lowest annual average wind speed) considering the TMY2 dataset, up to a maximum of -95.62% when the wind turbine operates in Alghero (city with the highest annual average wind speed) based on the NASA LaRC POWER database.

The integration of the wind turbine leads to a reduction in operating costs, albeit accompanied by an additional investment cost. The simple payback period SPB, i.e., the time needed to recoup the supplementary initial investment through savings in operating costs and revenue generated from electricity sold to the grid, can be calculated via the following formula:

$$SPB = \frac{WT^{CC}}{(OC^{PS} - OC^{RS}) + REV_{el,sold}} = \frac{WT^{CC}}{(OC^{PS} - OC^{RS}) + E^{PS}_{el,sold} \cdot UC_{el,sold}} \quad (4)$$

where WT^{CC} is the capital cost of wind turbine (675.22 €). Fig. 15 reports the SPB as a function of both wind speed dataset and city. This plot indicates that SPB ranges from a minimum of 1.1 years (in Alghero according to the NASA LaRC POWER dataset) up to a maximum of 21.2 years (based on the TMY2 database for Milan); it indicates that the selected win turbine is suitable from an economic point of view (i.e., SPB is lower than the expected wind turbines' lifetime, that is equal to about 20÷25 years), whatever the city and the weather dataset are. The influence of wind speed dataset is still, not negligible also in terms of SPB.

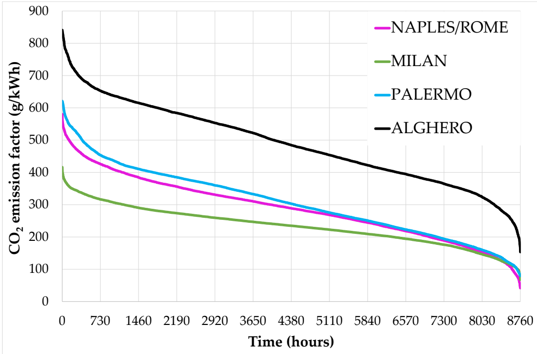

Fig. 12 – CO_2 emission factor as a function of city and time

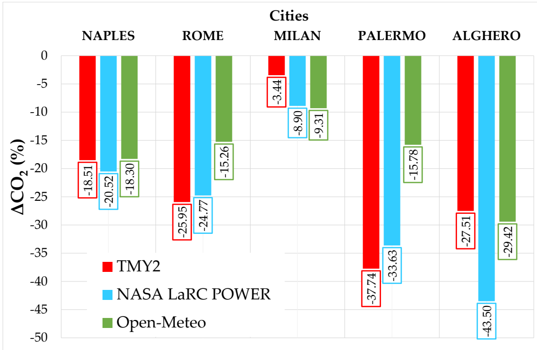

Fig. 13 – ΔCO_2 as a function of the city and wind speed dataset

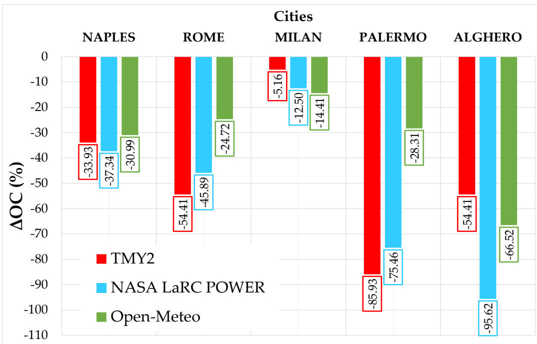

Fig. 14 – ΔOC as a function of the city and wind speed dataset

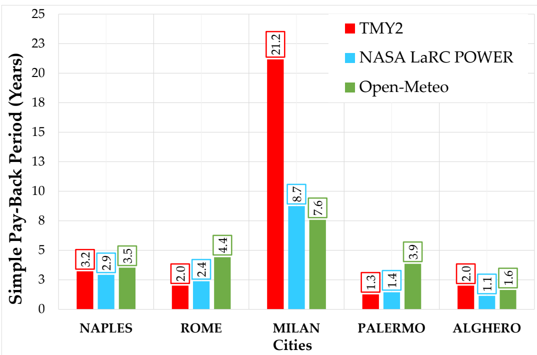

Fig. 15 – SPB as a function of the city and wind speed dataset

6. Conclusion

The effects of 3 wind speed databases on the performance of a vertical axis micro wind turbine serving a typical house have been assessed via a detailed dynamic simulation platform upon varying 5 Italian cities. The simulation outputs indicated that, whatever the Italian city and the wind speed dataset are, the selected wind turbine reduces the electric energy imported from the grid, the equivalent global CO_2 emissions and the operating costs up to 43.46%, 43.50% and 95.62%, respectively. This study also underlined that the influence of both the city and the wind speed dataset is relevant. In particular, the best results have been obtained for Alghero (city with the highest annual average wind speed) according to the NASA LaRC POWER database, while the worst data have been achieved in Milan based on the TMY2 database. A minimum simple pay-back period of 1.1 years has been obtained for Alghero in the case of the NASA LaRC POWER dataset.

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