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Analyzing Wind Energy Potential Using Efficient Global Optimization: A Case Study for the City Gdańsk in Poland

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Abstract: Wind energy (WE), which is one of the renewable energy (RE) sources for generating electricity, has been making a significant contribution to obtaining clean and green energy in recent years. Fitting an appropriate statistical distribution to the wind speed (WS) data is crucial in analyzing and estimating WE potential. Once the best suitable statistical distribution for WS data is determined, WE potential and potential yield could be estimated with high accuracy. The main objective of this paper is to propose a novel approach for calculating wind energy potential. For this purpose, the Efficient Global Optimization (EGO) technique was proposed for fitting a statistical distribution to WS data and the performance of the technique was compared with genetic algorithm (GA), simulated annealing (SA), and differential evolution (DE). Performance metrics showed that EGO is providing better estimations compared with GA, SA, and DE. Based on Weibull parameters obtained by using EGO, potential WE and potential annual revenue were estimated for Gdańsk, which is the capital of Pomerania Voivodeship in Poland, in the case of having city-type wind turbines in the city center. Estimations for Gdańsk showed that city-type wind turbines might be helpful for producing electricity from WE in the city without being limited by constraints such as having a long distance between wind turbines and buildings. If such wind turbines were erected on the roofs of residential buildings, malls, or office buildings, there is a possibility that part of the electric energy needed for such buildings could be generated using WE. However, this topic should be further investigated from technical and financial perspectives.

Keywords: renewable energy; energy transition; wind energy; energy prices; efficient global optimization (EGO); Weibull distribution

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1. Introduction

The subject of the article is the issue of WE production, which is an important source of RE in the world. Undoubtedly, the topic raised is relevant to the energy transition currently taking place in most of the world's economies [1–3]. The main objective of the energy transition is to move from the dominant role of fossil/nuclear fuels to the consideration of diverse RE sources, where WE, if the physical conditions are right, can represent a significant share of the RE portfolio [4–6]. Due to the systematic growth of global energy demand, the rational use of energy from renewable sources is one of the most important elements of sustainable development, bringing tangible effects for humanity as well as energy and ecology [7–10].

It should be emphasized that the production of RE and the implementation of energy transition has been possible for two decades at least. It turns out that it was only the occurrence of appropriate institutional, economic, and social changes in economies that allowed the real energy transformation of entire economies to begin, including state structures, local governments, businesses, and citizens [11–16]. Undoubtedly, most of the significant changes are due to the globalization processes that have been developing systematically for nearly 30 years. These processes have resulted in a significant increase in the interdependence between all markets [17–20]. This has contributed to a significant increase in the socio-economic level of countries [21–24]. Global economies are experiencing strong growth, which is being attributed to the increase in investment and the level of innovation [25–30]. In addition, we should notice the increase in the level of wealth of society, the emergence of new patterns of consumption, and changes in the labour market [31–39]. All this has contributed to the fact that both the production of RE from the national level to the level of the individual consumer and other activities related to the energy transition have found ground for implementation. In the case of the European Union (EU) member states, including Poland, the processes of energy transformation are intimately linked to the achievement of the Sustainable Development Goals [40–43]. It should be noted that many efforts also indicate that the effective implementation of energy transition processes requires bottom-up involvement and consideration of energy justice [44].

Significant development of RE in Poland took place at the beginning of the second decade of the 21st century when the process of implementing the third energy package and the implementation of the ambitious goals of the EU's climate policy started to be in charge under the commitments' so-called "20-20-20 in 2020", i.e., increasing energy efficiency by controlling energy consumption more, increasing the share of RE, and reducing carbon dioxide emissions [44]. RE sources are undoubtedly seen by European decision makers as a solution to reduce emissions [4]. RE sources are an alternative to primary and non-renewable hydrocarbon fuels. Although RE is characterized by the cyclical replenishment of resources in natural processes, the level of consumption of this type of energy as a primary energy source is still low [5,6]. As shown in Table 1, the capacity of renewable sources has been increasing since 2010 and showed a significant increase in 2020. However, the capacity is not at the desired level to be able to use RE as a primary energy source.

Table 1. Installed capacity of RE sources [45].

Type of RE Installation	Installed Capacity [MW]		
	2010	2015	2020
Biogas	82.884	212.497	255.699
Biomass	356.190	1122.670	1512.885
Photovoltaics	0.033	71.031	887.434
Wind Energy	1180.044	4582.036	6347.111
Hydropower	937.044	981.799	976.047
Total	2556.423	6970.033	9979.176

Total global wind capacity is currently up to 743 GW, helping the world avoid over 1.1 billion tons of CO_2 per year equivalent to the annual CO_2 emissions in South America. However, WE sources with the capacity of 180 GW should be activated each year in the world to avoid the worst effects of climate change. This means that industry and policymakers must act quickly to accelerate the switch from traditional energy sources to RE sources [46,47].

In spite of the termination of China's feed-in tariffs (FiT) and the planned phase-out of the United States' full-rate Production Tax Credit (PTC), the world's two largest economies increased their combined market share by 15 percent to 76 percent [46].

A record for onshore installations was also achieved in the Asia Pacific, North America, and Latin America regions in the calendar year 2020. According to the International Energy Agency, in these three regions a total of 74 GW of new onshore wind power was installed. This represents a 76 percent increase in capacity over the previous year. There was just a 0.6 percent year-over-year (YoY) rise in new onshore wind installations in Europe last year, which was due to the slow recovery of onshore wind installations in Germany. There were

8.2 GW onshore installations in Africa and the Middle East last year, which is almost the same as in 2019 [46].

The main objective of this paper is to propose an approach to the problem of WE generation that will ensure the highest efficiency of the energy generation process and the economic viability of this process. In order to achieve the objective, the authors developed the following added values: an overview in terms of development of WE in Poland and Pomerania Voivodeship, which is the area in Poland with significant potential when it comes to WE, was carried out; a novel approach was proposed for fitting a statistical distribution to WS data for estimating WE potential in a more efficient way; the discussion was conducted about the potential benefits of having a city-type wind turbine in the city.

The city-type wind turbine offers a possibility to install the turbines on the top of buildings in the city and, thanks to this, residents in each building could generate part of the electricity that they need. This could potentially make the transition to WE from traditional energy sources faster, as installing this type of turbine would not require big spaces, long-lasting investment planning, or any other limitations. For these purposes, within the scope of the study, WS data in an hourly format for almost the last seven years for Gdańsk (Poland) were obtained from a third-party provider. The two-parameter Weibull distribution (TPWD) was then fitted to WS with the help of Maximum Likelihood Estimation (MLE). Efficient Global Optimization (EGO) was used on top of MLE to find optimum parameters of TPWD. Moreover, performance of EGO was compared with performance of GA, SA, and DE, which are the algorithms that have been used by researchers in the literature to fit statistical distribution to WS. To compare the performances, root mean squared error (RMSE) and coefficient of determination (R^2) were used. Parameters were obtained for each month and annual data by using each technique. Comparisons were provided. By using parameters of TPWD for annual data, potential WE was estimated for Gdańsk, which is the capital of Pomerania Voivodeship in Poland, for the case of having city-type wind turbine in the city center of Gdańsk.

The construction of the paper is as follows: Section 2 focuses on a brief history of WE in general, the development of WE in Poland, and WE potential in Pomerania Voivodeship. Section 3 describes the methodology used in the study. Section 4 covers details about dataset used in the study. In Section 5, results are discussed, while Section 6 concludes the study and provides information about potential further research studies.

2. Development of the WE Market in Poland

2.1. WE: A Brief History

WE has been used by humans for a really long time, alongside sunlight, e.g., to dry agricultural crops. It is also worth remembering that important geographical discoveries were possible thanks to WE that "powered" sailing ships [47,48].

In early 2000 BCE, Egyptians used WE to propel their boats. The Code of Hammurabi (circa 1750 BCE) shows that WE was also used in Persia. In India, in the fourth century BCE, the first windmill was used for pumping water and already in the second century BCE in China windmills were used to irrigate farmland. At the beginning of our era, the first windmills were constructed in the Mediterranean countries [48].

The first European windmills appeared in England in the 9th century, in France in the 11th century, and in the 13th century they became popular in all Western Europe. The oldest image of a windmill in Europe is on the first page of an English manuscript from 1270. Originally, the windmill was a wooden "booth" that was rotated around a centrally located pole to set the wings to the wind. The revolution in the construction of windmills was made by the Dutch, who in 1390 introduced four-wing structures. The "Dutch" type windmills gained popularity in Europe in the 17th century [48].

The industry became more interested in wind power plants in the early 1980s. As an initiative of Danish power companies, a turbine with a capacity of 660 kW was developed. The following years were marked by the resolution of many technical problems related to the generator's construction, mechanical strength, and the selection of appropriate materials for the towers and rotor blades. In the last 20 years, a real "boom" in aero energy in the world has been happening [48].

The first Polish wind turbines were erected in the 1930s in Podkarpackie, a region in the south-east of Poland. Before the outbreak of World War II, 504 wind turbines were in operation in Poland. The first Polish wind potential map was published in 1958 in the book by Rynkowski entitled *Small Wind Farms*. The first wind turbine in Poland based on the new technology was erected in 1991 in Żarnowiec, a village in the north of Poland, as a replacement for the existing hydroelectric power plant. The first Polish wind farm (6 × 800 MW) was built in Barzowice in Pomerania Voivodeship in 2001 [48].

2.2. WE in Poland and Pomerania Voivodeship

Until 2016, WE was developing well in Poland (Table 2). As a result of the entry that went into force in 2016 regarding the act on investments in wind farms, there was a stagnation on new WE projects. The barrier is the inability to meet the requirement of a minimum distance of 10 × H (H = total height of the wind turbine with the blade in full elevation) from the buildings [49,50].

Table 2. Dynamics of the WE market in Poland [51].

Year	Installed Capacity of Onshore Wind Installations [GW]
2013	3.39
2014	3.83
2015	4.58
2016	5.81
2017	5.85
2018	5.86
2019	5.92
2020	6.35
2021	≈6.80

The progressive inclusion of the most advanced projects in 2018–2020 has resulted in an increase in new onshore wind farm capacity seen in late 2020 and 2021. As a result, the installed capacity potential increased to approximately 6.80 GW [52] and in the next two or three years it is planned to exceed 10 GW [52]. The government's announcements of distance regulation are likewise positive, with the expectation of another investment "boom" of 3–4 GW by 2025 [53].

The strategic objective is to maximize the potential of Polish onshore wind energy. By 2030–2035, the Polish Wind Energy Association (PWEA) [48] anticipates that Poland will be able to generate 22–24 GW of energy from wind [53]. Clean electrical energy derived from the most sustainable RE sources is important to maintain the Polish economy's international competitiveness. Every single additional gigawatt to wind farm capacity results in significant cost savings. It has a direct effect on the wholesale price of electricity, which has decreased by an average of more than PLN 20/MWh on the wholesale market since 2007. Poland's energy system appears to be defying global trends. Fossil fuels—hard coal and lignite—continue to account for a share of domestic output; nonetheless, the share of RE continues to expand. In 2020, coal's proportion in the energy mix fell below 70% for the first time in history. In 2020, over 28 TWh of electricity was generated from RE sources, including nearly 16 TWh from WE. Poland's energy production is becoming increasingly uncompetitive as CO_2 emissions and domestic coal costs continue to grow. WE is the most advantageous alternative to fossil fuel based energy production [54].

2.3. WE in the Pomerania Voivodeship

As shown in Figure 1, at a height of 140 m the Pomerania Voivodeship has exceptionally excellent WE conditions. The Voivodeship is particularly well-suited to the growth of WE, both on land and at sea. Offshore WE might serve as a propeller for regional businesses, such as shipyards, which already supply components for the offshore industry [55].

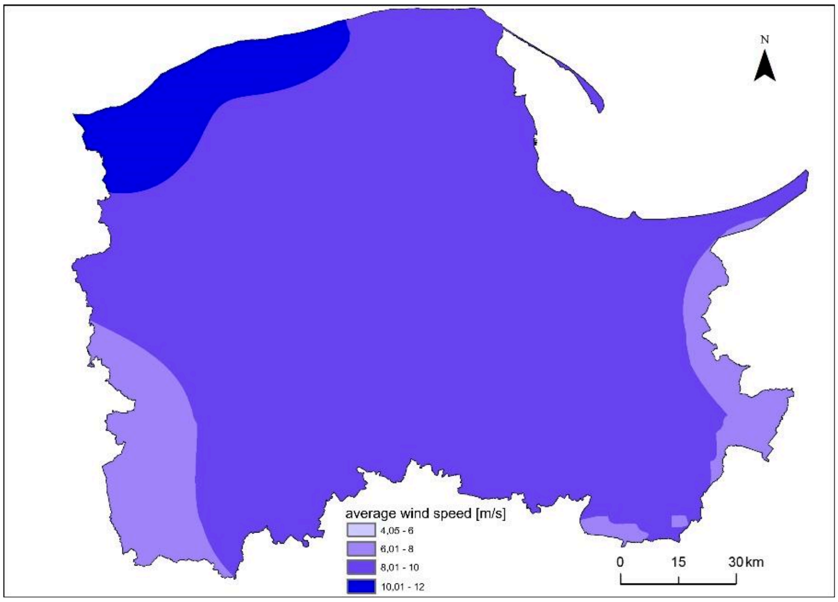

Figure 1. WS at a height of 140 m in Pomerania Voivodeship (created based on [55]).

WE capacity in Pomerania Voivodeship is 786 MW [56]. Taking into consideration the available area of the Polish exclusive economic zone (which is expected to grow to 2000 km^2 by 2030), wind conditions, productivity, and installed power density (6 MW/km^2), the theoretical potential is estimated to be 12 GW, with an approximate energy generation of 48–56 TWh, according to the draft program for the development of offshore wind energy and maritime industry.

The first wind farm in the Pomerania Voivodeship, with a capacity of 150 kW, was established in 1991 in Lisewo near Gniewino. In the same year, a 90 kW power plant was built in Swarzewo near Puck (currently closed). Since 2005, following Poland joining the EU when some legal barriers were removed, the number of investments in WE have started to increase [57].

The Energy Regulatory Office issued a license for the largest wind farm in Poland, which is located in the Pomerania and West-Pomerania voivodeships. The investment was carried out by the Potęgowo company belonging to the Israeli Mashav fund. Its power is 219 MW. The Potęgowo wind farm is located in the Słupsk and Sławno districts. It consists of 81 General Electric turbines with a capacity of 2.5 MW and 2.75 MW. For its construction, the investor received a loan from the European Bank in the amount of PLN 209 million. The total cost of the investment was PLN 1.25 billion. The farm also won an auction to supply electricity [51,58].

The Airport Wind Farm, which has a capacity of 90 MW, was officially inaugurated in the Voivodeship in 2015. PGE Energia Odnawialna S.A., a subsidiary of the PGE Capital Group, is the company that owns and operates the power plant. The Airport Wind Farm is the largest renewable energy investment made by the PGE Group since May 2014 [58].

The area available for the construction of wind farms in the Pomerania Voivodeship, including the buffer zone 2150 m from residential buildings, is 2716 km^2 (Figure 2).

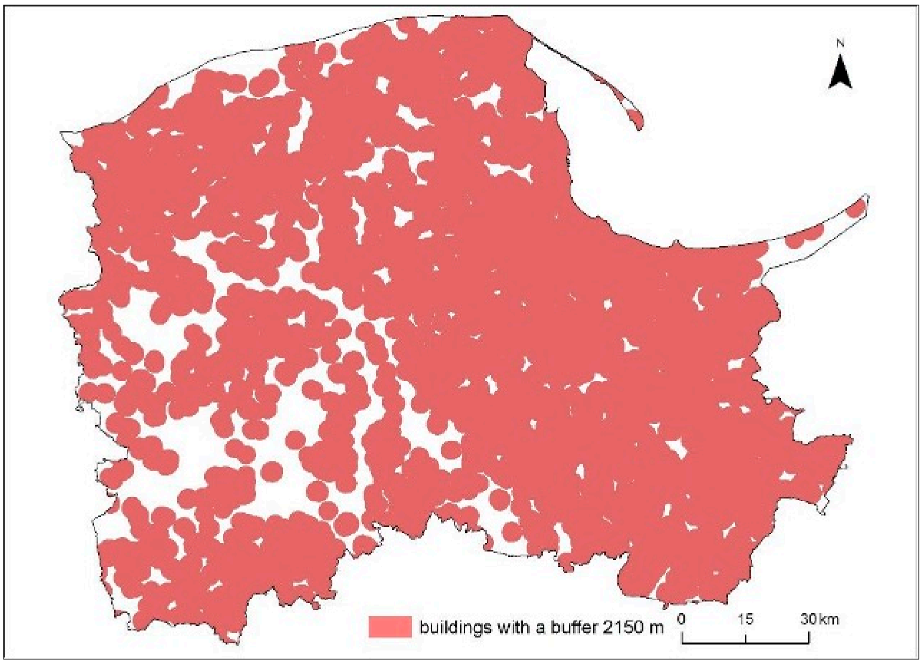

Figure 2. Buildings with a buffer of 2150 m (own elaboration).

The area available for the construction of wind farms in the Pomerania Voivodeship, including the buffer zone 2150 m from protected areas such as national parks, landscape parks, and nature reserves, is 2552 km^2 (Figure 3). The available area for wind farm construction in the Pomerania Voivodeship, including the buffer zone 200 m from forests (a condition regarding protecting bats), is 9568 km^2 (Figure 4).

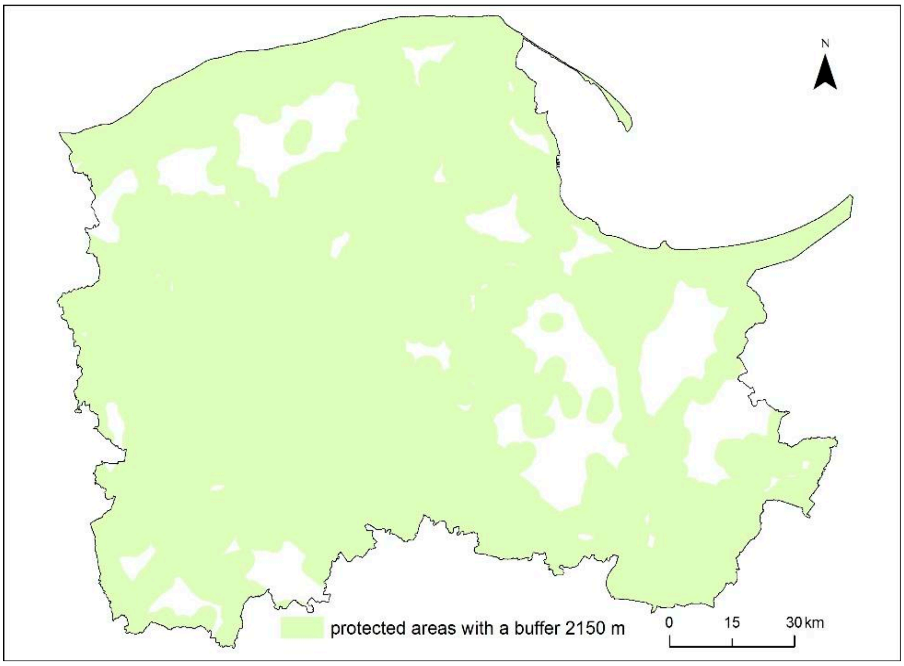

Figure 3. Protected areas with a buffer of 2150 m (own elaboration).

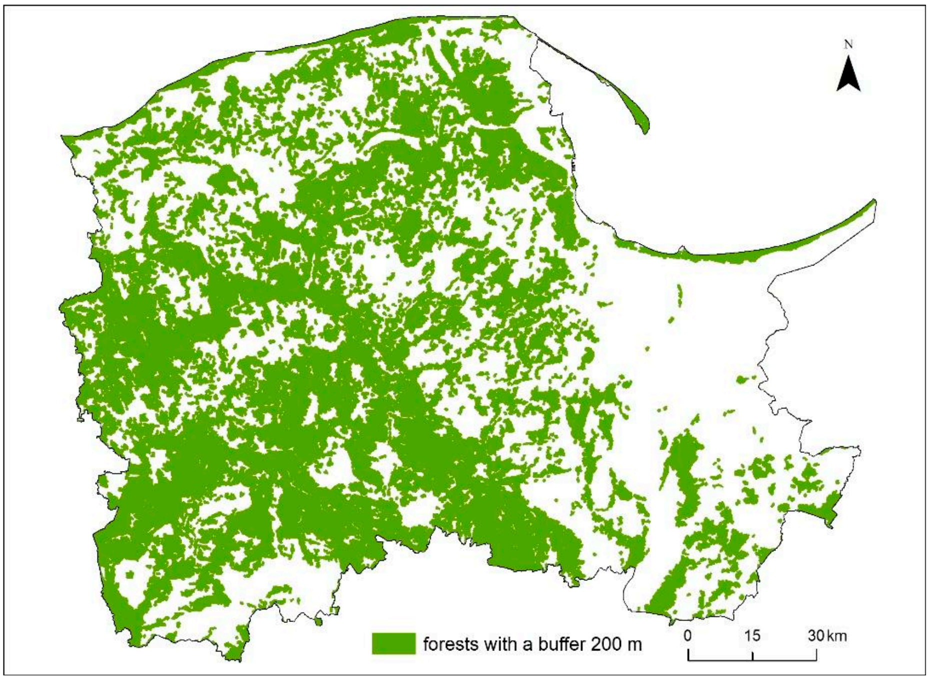

Figure 4. Forests with 200 m buffer (own elaboration).

The area available for the construction of wind farms in the Pomerania Voivodeship, including the hydrographic network and the 90 m buffer zone (propeller length 75 m increased by an additional 15 m) from the surface waters, is 3106 km^2 (Figure 5). The available area for the construction of wind farms in the Pomerania Voivodeship, including the infrastructure network and the 90 m buffer zone (propeller length 75 m increased by an additional 15 m), is 15,820 km^2 (Figure 6). Even after taking into consideration all the restricting factors, the accessible land area amounts to only 60 km^2 or less than 0.3 percent of the total land area of the Pomerania Voivodeship (Figure 7).

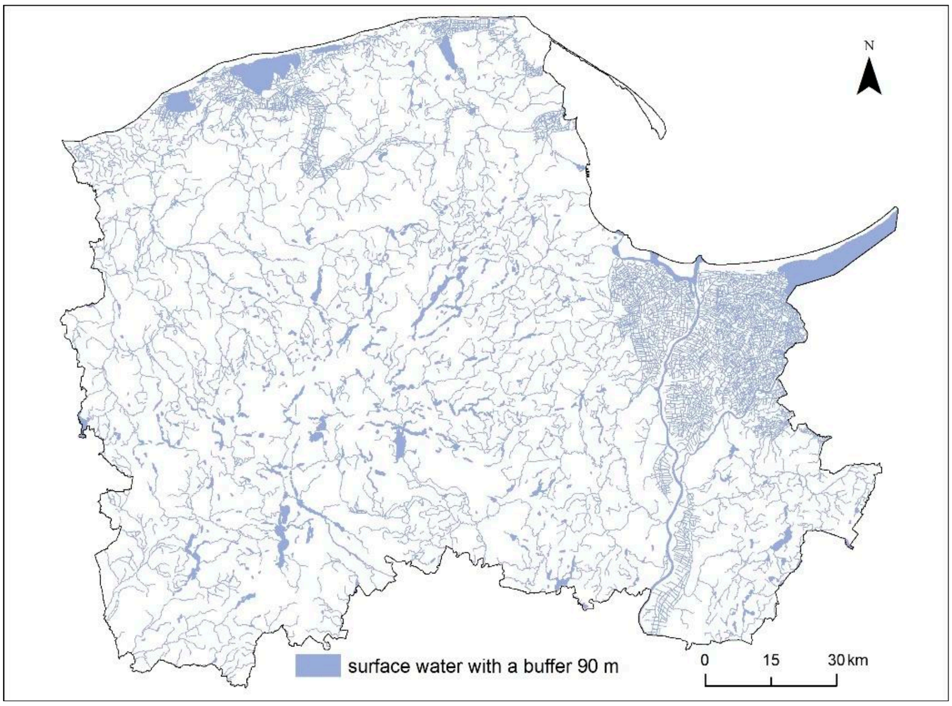

Figure 5. Water surfaces with 90 m buffer (own elaboration).

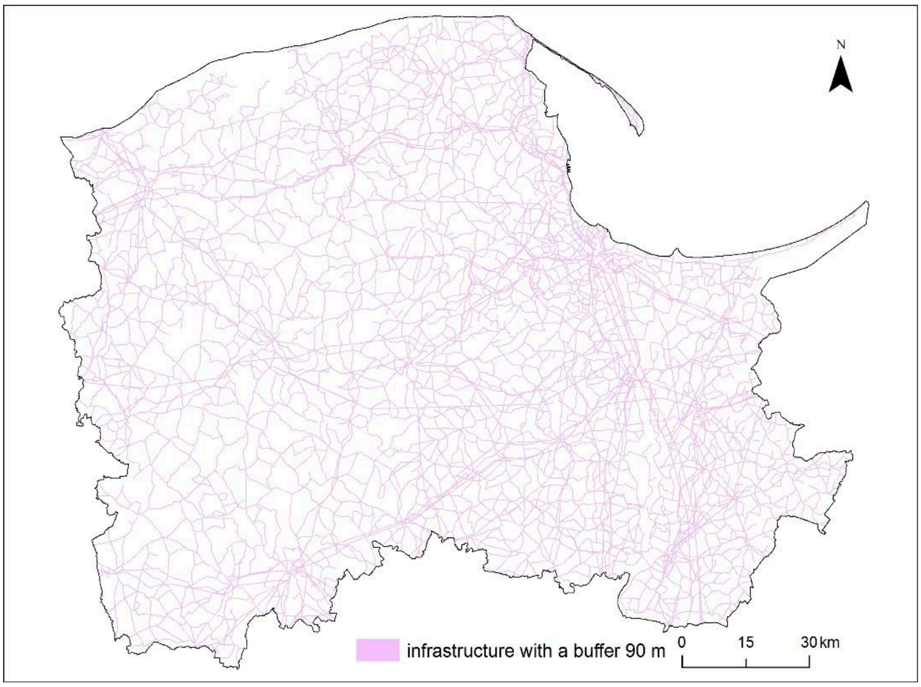

Figure 6. Infrastructure with a 90 m buffer (own elaboration).

Figure 7. Available area for constructing wind turbines in the Pomerania Voivodeship (own elaboration).

3. Methodology

In recent years, WE has made a substantial contribution to the production of clean and green energy. It is vital to be able to examine and estimate WE potential by fitting an appropriate statistical distribution to the WS data. Hourly WS data for Gdańsk over the last seven years were gathered from a third-party provider for this purpose as part of the study's scope. Then, using MLE, TPWD was fitted to the WS data. EGO, GA, SA, and DE were utilized to find the optimum TPWD parameters that maximize the likelihood function. Performance metrics were calculated to compare the performance of EGO with other methods. Following this, potential WE for Gdańsk, the capital of the Pomerania Voivodeship in Poland, was evaluated using TPWD parameters.

3.1. Parameter Estimation for Distribution of WS

Because of the intermittent nature of WS, it is necessary to understand and analyze the statistical properties of WS that have a substantial impact on WE and the design of power generators [56]. Probability distribution functions (PDF) are a way to describe how the random variables are likely to behave. The PDF can help to describe the change in WS over time. For the purpose of depicting WS patterns, several probability distributions such as Weibull, lognormal, gamma, Rayleigh, and mixed distributions are utilized, among others [52,59,60]. TPWD is widely used in the literature. The Weibull is flexible and is proven to fit WS data very well [52,61]. The parameters of the TPWD are shape and scale. An accurate assessment of the Weibull parameters is required to anticipate WE potential and understand WS characteristics. In order to determine the optimal parameters of the Weibull distribution (WD), researchers have developed a number of different ways over the years. The graphical method (GM), the moments method (MOM), the least-squares estimation (LSE), and (MLE) are the most frequently used methodologies [62,63].

Justus et al., proposed an approach [64] that employs mean and standard deviation of WS for estimating parameters of WS PDF. Stevens and Smulders used MLE to find parameters of WS PDF [63]. Jowder compared the empirical techniques to the graphical approaches and found that empirical techniques produce more accurate results [65]. For the parameter estimation, Akdag and Dinler proposed the power density factor and energy pattern factor [62]. The novel method was used for several locations in Turkey and the findings were compared with those produced using the GM and MLE methods. George compared five alternative approaches for calculating shape and scale parameters of the TPWD [66]. The maximum likelihood method outperformed among others. Chang examined six approaches for estimating the parameters of the WD: GM, MOM, empirical method (EM), MLE, modified MLE, and energy pattern factor/power density method (EPFPDM) [67].

Researchers also used the equivalent energy method to estimate parameters of the WD [68,69]. The performance of parameter estimation of the WD is also influenced by the sample size [70]. To predict Weibull parameters, probability-weighted moments based on the power density method (PWMBP) was used and PWMBP outperformed among other methods [71].

Aside from numerical approaches, a metaheuristic optimization algorithm can be used to estimate parameters. The parameters can be determined using various optimization algorithms. Chang used particle swarm optimization (PSO) to estimate parameters of the WD. PSO was used to estimate parameters using WS data collected from several climatic zones in Taiwan [68].

Wu et al. [72] proposed logistic distributions for assessing the WE potential in Inner Mongolia using maximum likelihood estimation. Using multi-objective moments, Usta et al., developed a novel approach for estimating the parameters of the WD [73]. Tosunoglu [74] focused on fitting several distributions to WS data for Turkey. MOM, MLE, and probability-weighted moments (PWMs) methods were applied. Chaurasiya et al. [75] applied nine numerical approaches for estimating the shape and scale parameters of the WD for calculating wind power in southern India. The results showed that shape and scale parameters have a significant impact on wind power calculations [76]. The least-squares method was applied to find the parameter of the WD [77,78]. For estimating the single and combined parameters of probability distributions, Alrashidi et al. [77] introduced a new metaheuristic optimization algorithm. Gungor et al. [79] explored the suitability of four different numerical approaches for estimating the WD parameters for WS data. Kumar et al. [80] concentrated on MLE using the differential evolution technique.

According to the reviewed literature, the TPWD is the most general distribution for representing WS distribution and assessing WE potential. To estimate the parameter, the researchers used a number of strategies to optimize the distribution's log-likelihood function. It is also noticed in the literature that researchers mostly use RMSE and R^2 for comparing performance of different optimization algorithms while estimating statistical distribution of WS. This study is primarily concerned with MLE and EGO.

3.2. Estimating Parameters of WD Using MLE

Modern estimation theory has application in a wide variety of fields, spanning from statistics to economics, engineering design, and many more. For a vast majority of applications, the estimation of an unknown parameter is required based on a collection of observations. Different parameter estimation methods can be found in the literature, the most common ones are GM, MLE, and MOM. Because of its theoretical capabilities, the MLE is often preferred over other methods.

The likelihood function is maximized by a set of parameters, which are MLE estimations. When fitting a distribution to the WS data, the TPWD is commonly used. The distribution function can be written as shown in Equation (11) [80].

$$f(x) = \left(\frac{k}{c}\right)\left(\frac{x}{c}\right)^{k-1} e^{-\left(\frac{x}{c}\right)^k},\ x \geq 0,\ c > 0,\ k > 0 \tag{1}$$

The WD likelihood function is as shown in Equation (1).

$$L = \prod_{i=!}^{N}\left(\frac{k}{c}\right)\left(\frac{x}{c}\right)^{k-1} e^{-\left(\frac{x}{c}\right)^k} \tag{2}$$

and its log-likelihood function will be:

$$\log(L) = Nlnk - Nclnc - \sum_{i=1}^{N}\left(\frac{x_i}{c}\right)^k + (k-1)\sum_{i=1}^{N} lnx_i \tag{3}$$

The EGO is used and compared with other techniques such as GA, SA, and DE for optimizing the log-likelihood function of the WD in this study. Detailed results are presented in the following section.

3.3. EGO

EGO is closely linked with kriging metamodeling. The EGO approach is focused on solving optimization problems in a low number of function evaluations and the approach offers clear stopping criteria based on expected improvement (*EI*). The EI function is produced based on the Kriging model. To get a new sampling point, the EI function is maximized. Then this new data point is added to the initial set. This process is repeated until the EI function value does not change significantly.

The Kriging model can be simply defined as shown in Equation (4), where $\mathbf{x}^{(i)} = \left(x_1^{(i)}, \ldots, x_k^{(n)}\right)$ and $\mathbf{y}^{\,(i)} = y\left(\mathbf{x}^{(i)}\right)$.

$$y\left(\mathbf{x}^{(i)}\right) = \mu + \epsilon\left(\mathbf{x}^{(i)}\right) \tag{4}$$

In this equation, μ is the mean of the stochastic process; $\epsilon\left(\mathbf{x}^{(i)}\right)$ is normally distributed independent error term with mean zero and variance σ^2. Correlation between $\epsilon\left(\mathbf{x}^{(i)}\right)$ and $\epsilon\left(\mathbf{x}^{(j)}\right)$ could be defined as shown in Equation (5) [81].

$$\mathrm{Corr}\left[\epsilon\left(\mathbf{x}^{(i)}\right),\ \epsilon\left(\mathbf{x}^{(j)}\right)\right] = \sum_{h=1}^{k} \theta_h \left|x_h^i - x_h^j\right|^{p_h},\ \theta_h \geq 0,\ p_h \in\ [1,2],\ i,j = (1,\ldots,n) \tag{5}$$

θ_h is importance measuring for the variable x_h and p_h is the smoothness parameter of the correlation function. μ and σ^2 are unknown. They can be estimated by using the parameters of the correlation function which are θ_h and p_h. For estimating the parameters, MLE is used. Likelihood function could be written as shown in Equation (6) [81]:

$$L = \frac{1}{(2\pi)^{\frac{n}{2}}(\sigma^2)^{\frac{n}{2}}|\mathbf{R}|^{\frac{1}{2}}} \exp\left[-\frac{(\mathbf{y}-1\mu)'\mathbf{R}^{-1}(\mathbf{y}-1\mu)}{2\sigma^2}\right] \tag{6}$$

where $\mathbf{y} = (y^{(i)}, \ldots,\ y^{(n)})$ is the n-vector for response values and 1 is a vector of ones. Since μ and σ^2 are unknown, estimations of μ and σ^2 could be calculated as shown in Equations (7) and (8).

$$\hat{\mu} = \frac{1'\mathbf{R}^{-1}\mathbf{y}}{1'\mathbf{R}^{-1}1} \tag{7}$$

$$\hat{\sigma}^2 = \frac{(\mathbf{y}-1\hat{\mu})'\mathbf{R}^{-1}(\mathbf{y}-1\hat{\mu})}{n} \tag{8}$$

By changing the Equations (7) and (8) with $\hat{\mu}$ and $\hat{\sigma}^2$ from the likelihood function, "concentrated likelihood function" is created. It depends only on θ_h and p_h. Denote that **r** gives the correlation between the error terms for **x***, which is not observed previously, and the error for **x**, which is observed previously. The correlation between those two could be written as shown in Equation (9).

$$\mathbf{r}(\mathbf{x}^*) \equiv \mathrm{Corr}[\epsilon(\mathbf{x}^*),\ \epsilon(\mathbf{x})]. \tag{9}$$

After having all the equations together, the Kriging model can be converted into the form shown in Equation (10).

$$\hat{y}(\mathbf{x}^*) = \hat{\mu} + \mathbf{r}'\mathbf{R}^{-1}(\mathbf{y}-1\hat{\mu}) \tag{10}$$

Following the process of creating the Kriging model, *EI* criteria is described as follows. Denote that the function $y = f(x)$, the improvement (I) over f_{min}, which is the minimum response value of $f(x)$. The improvement now can be defined as

$$I = \begin{cases} (f_{min} - y),\ y < f_{min} \\ 0,\ otherwise \end{cases}. \tag{11}$$

When y has normal distribution with $\hat{y}$ mean and s^2 variance, expected value of I can be calculated by following Equations (12) and (13).

$$E(I) = \int_{-\infty}^{f_{min}} (f_{min} - y)\phi(y)dy \tag{12}$$

Expected Improvement (*EI*) function can be shown as follows:

$$EI = (f_{min} - \hat{y})\Phi\left(\frac{f_{min} - \hat{y}}{s}\right) + s\phi\left(\frac{f_{min} - \hat{y}}{s}\right) \tag{13}$$

where Φ () is cumulative distribution function (CDF) and ϕ is PDF of a standard Normal distribution [81].

4. Data

The hourly WS dataset for Gdańsk (latitude: 54.352° N, longitude: 18.646° E, 10 m. height) over the last seven years between 1 January 2015 and 26 July 2021 was gathered from Open Weather Map [82]. Then, using MLE, the TPWD was fitted to the WS data for each month and the annual data. For the purpose of determining the optimal parameters of the WD that maximize the likelihood function, the SA, GA, DE, and EGO were applied and performance of the techniques was compared. Following the obtaining of the parameters, potential WE and wind power for Gdańsk, the capital of the Pomerania Voivodeship in Poland, were calculated.

The dataset contains 60,100 rows and 25 columns and it provides information about WS, minimum temperature, maximum temperature, pressure, wind angle, amount of rain, amount of snow, information about how the weather looks (rainy, snowy, etc.).

Table 3 shows summary statistics regarding monthly average of WS and minimum and maximum temperatures in Celciusº. As shown in the table, the warmest month for Gdańsk is August and the coldest month is January. Table 3 also presents the monthly average of WS (m/s) in Gdańsk. As shown in the table, the monthly average WS does not differ dramatically between months within a year. According to the table, it can be concluded that the months in which the average WS is higher than others are April, December, and May. The lowest WS average is observed in August.

Table 3. Average WS, minimum temperature, maximum temperature per month in Gdańsk between 1 January 2015 and 26 July 2021.

Month	Average WS (m/s)	Min. Temperature (Average—Celciusº)	Max. Temperature (Average—Celciusº)
January	2.72	−1.21	1.94
February	2.87	−0.58	2.77
March	3.15	2.33	5.39
April	3.51	6.15	9.61
May	3.17	10.66	14.39
June	3.02	15.65	19.24
July	3.12	16.76	19.96
August	2.38	17.17	20.85
September	2.68	13.29	16.52
October	2.77	8.29	11.25
November	2.83	4.27	6.86
December	3.19	1.86	4.48

Since obtaining the dataset from the third-party vendor was easy and quick and since the dataset contains hourly WS information for almost seven years, it was preferred to be used in the study. However, variables, including WS, in the dataset were collected by a single sensor located near the old town in Gdańsk. In conclusion to this, estimations for potential wind power were made only for this location. There was also no possibility to get WS information for different heights or for different parts of the city (e.g., parts of the city where long and tall buildings are located). For future studies, researchers plan to obtain datasets from different sources, such as local authorities or any other official sources, to be able to avoid the limitations mentioned above.

5. Results

As one of the goals of the study is fitting WS data to TPWD and estimating parameters of the distribution, an R package called "DiceOptim" was used for applying EGO, a "DEoptim" package was used for applying DE, a "GA" package was used for applying GA, and an "optimization" package was used for applying SA [83–87].

Table 4 shows the estimated value of shape (k) and scale (c) parameters of the TPWD using four different techniques. From the table, it can be concluded that there are no huge differences between the parameters estimated using the four different techniques. Figures 8 and 9 represent the histogram of observed wind speed and the estimated TPWD obtained using four techniques per each month of the year. Table 5 and Figures 10 and 11 show the performance of techniques based on two different metrics: RMSE and R^2. From Table 5 and Figures 10 and 11, it can be seen that EGO performs better than other techniques for estimating the parameters of TWPD; the larger the value of R^2 the better the performance of estimation as seen in Figure 10 that R^2 calculated for estimations.

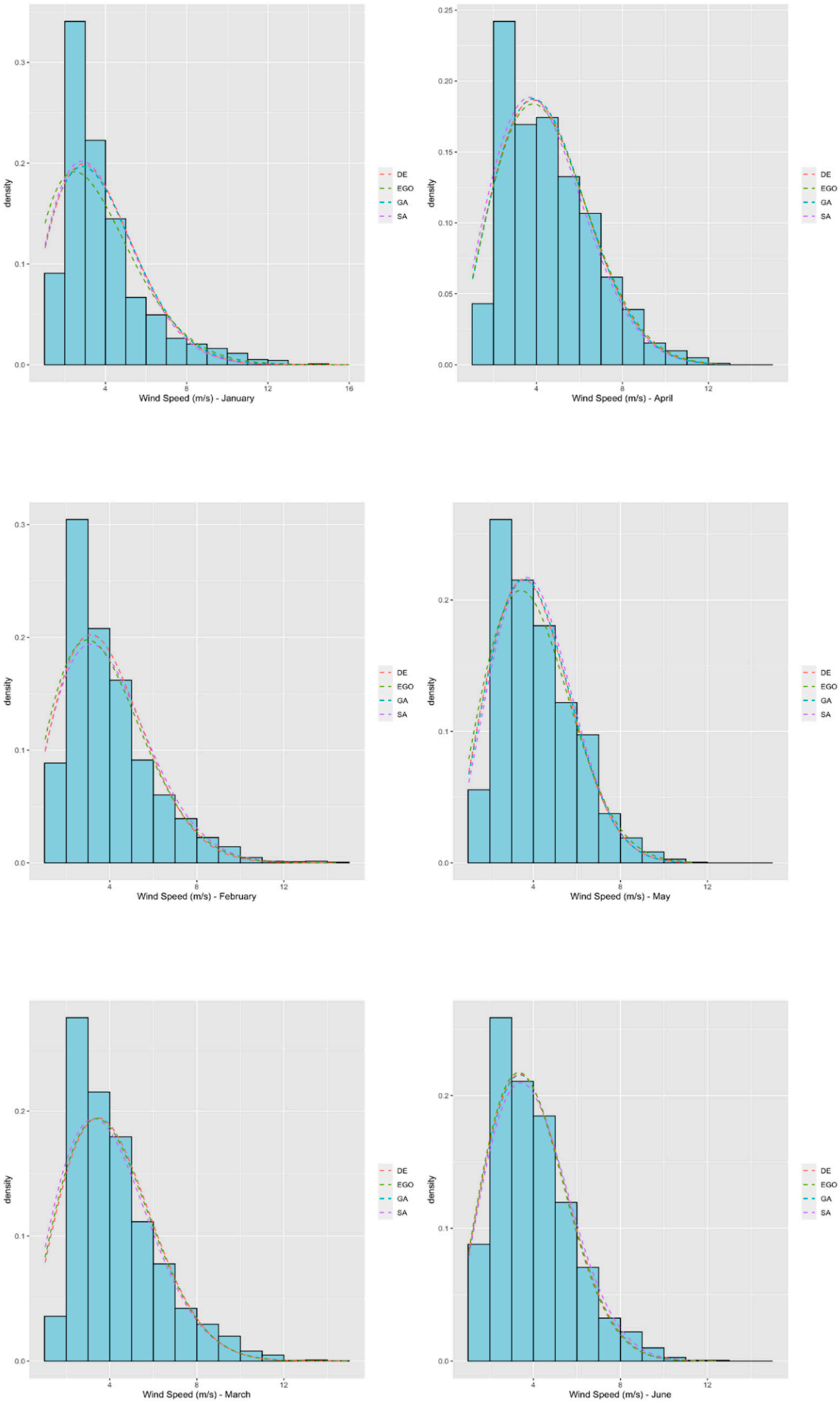

Figure 8. Monthly probability density function estimation and monthly histograms of observed WS data (from January to June) (own elaboration).

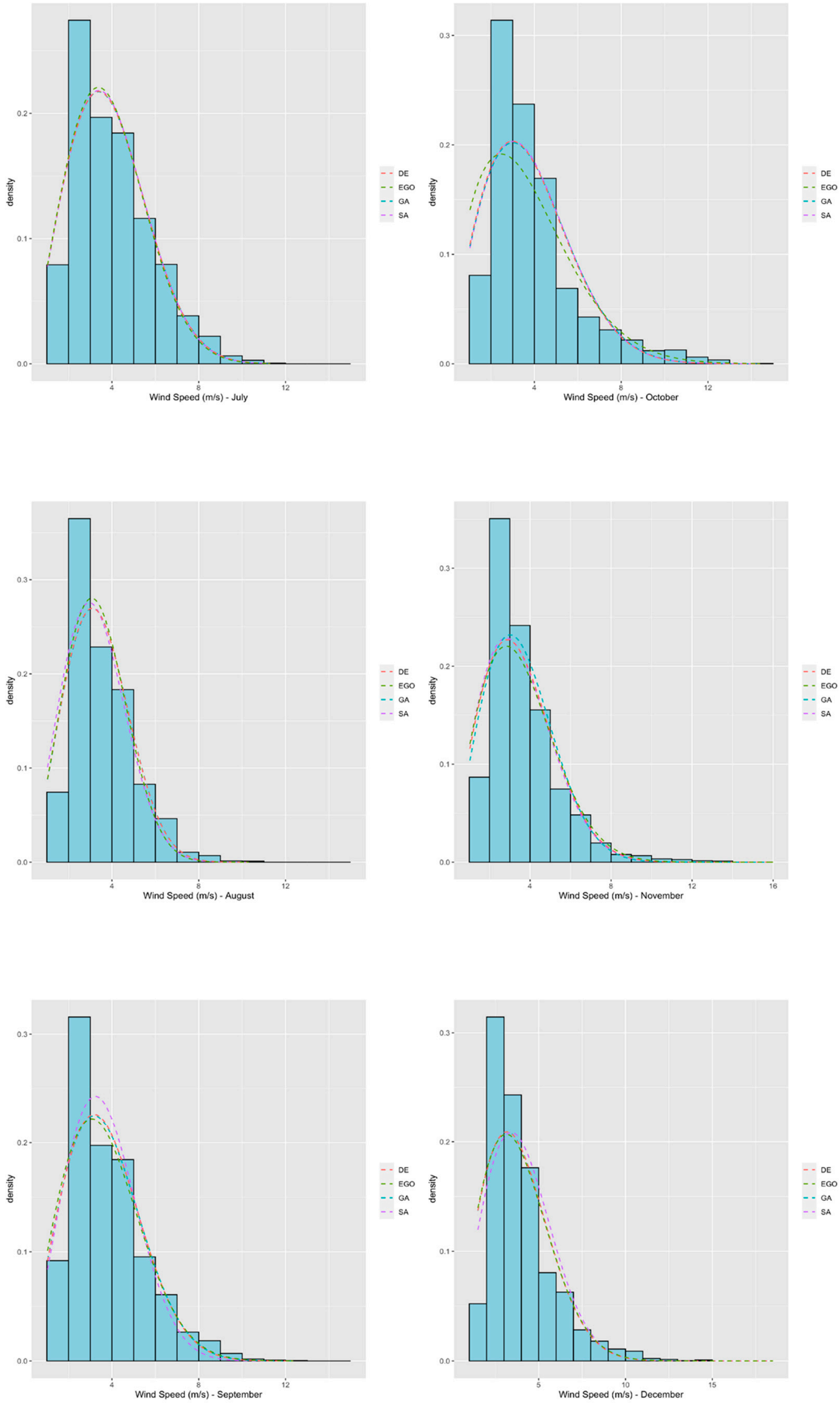

Figure 9. Monthly probability density function estimation and monthly histograms of observed WS data (from July to December) (own elaboration).

Table 4. Estimated TPWD parameters for monthly wind speed data.

Month	SA		GA		DE		EGO	
	k	*c*	*k*	*c*	*k*	*c*	*k*	*c*
January	1.93	4.15	1.91	4.23	1.93	4.21	1.72	4.11
February	2.00	4.42	2.06	4.32	2.06	4.33	1.96	4.28
March	2.06	4.51	2.15	4.64	2.15	4.64	2.12	4.60
April	2.20	4.86	2.26	4.98	2.24	4.98	2.22	5.02
May	2.44	4.56	2.38	4.50	2.36	4.48	2.23	4.46
June	2.25	4.44	2.27	4.35	2.27	4.34	2.26	4.31
July	2.31	4.35	2.30	4.35	2.30	4.35	2.32	4.31
August	2.48	3.64	2.53	3.78	2.53	3.78	2.59	3.70
September	2.41	4.04	2.24	4.13	2.26	4.13	2.17	4.09
October	2.02	4.25	2.00	4.25	2.00	4.22	1.72	4.11
November	2.09	3.86	2.21	3.96	2.11	3.91	2.04	3.94
December	2.24	4.45	2.13	4.28	2.13	4.28	2.09	4.27

Table 5. Performance comparison based on different metrics.

Month	SA		GA		DE		EGO	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
January	0.6512	0.9022	0.6496	0.9027	0.6616	0.8990	0.6136	0.9132
February	0.4967	0.9373	0.5130	0.9331	0.5007	0.9363	0.4650	0.9451
March	0.4762	0.9451	0.5178	0.9350	0.4835	0.9434	0.4758	0.9452
April	0.3828	0.9667	0.3830	0.9667	0.3856	0.9662	0.3802	0.9671
May	0.3760	0.9560	0.3732	0.9566	0.3658	0.9583	0.3665	0.9582
June	0.3632	0.9592	0.3605	0.9598	0.3358	0.9651	0.3363	0.9650
July	0.3713	0.9567	0.3672	0.9577	0.3703	0.9570	0.3599	0.9594
August	0.4569	0.8925	0.4526	0.8945	0.4487	0.8963	0.4539	0.8939
September	0.4913	0.9182	0.4471	0.9323	0.4664	0.9263	0.4234	0.9392
October	0.6639	0.8896	0.6802	0.8841	0.6649	0.8893	0.6229	0.9028
November	0.5996	0.8805	0.6262	0.8697	0.5745	0.8903	0.5636	0.8945
December	0.6441	0.8830	0.6111	0.8946	0.5934	0.9007	0.5602	0.9115

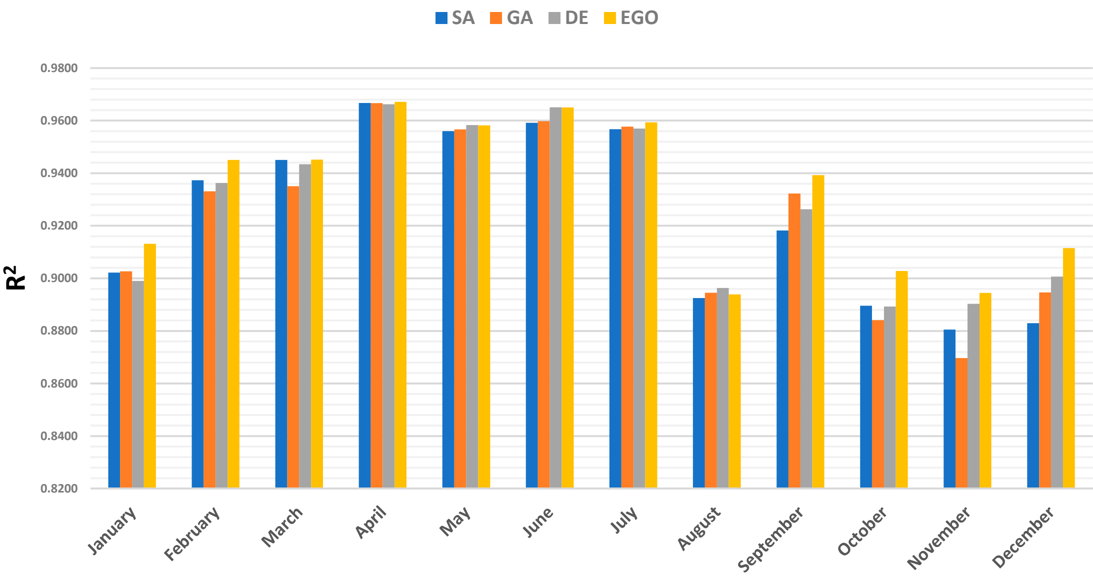

Figure 10. R-Square values for monthly parameter estimation per each technique (own elaboration).

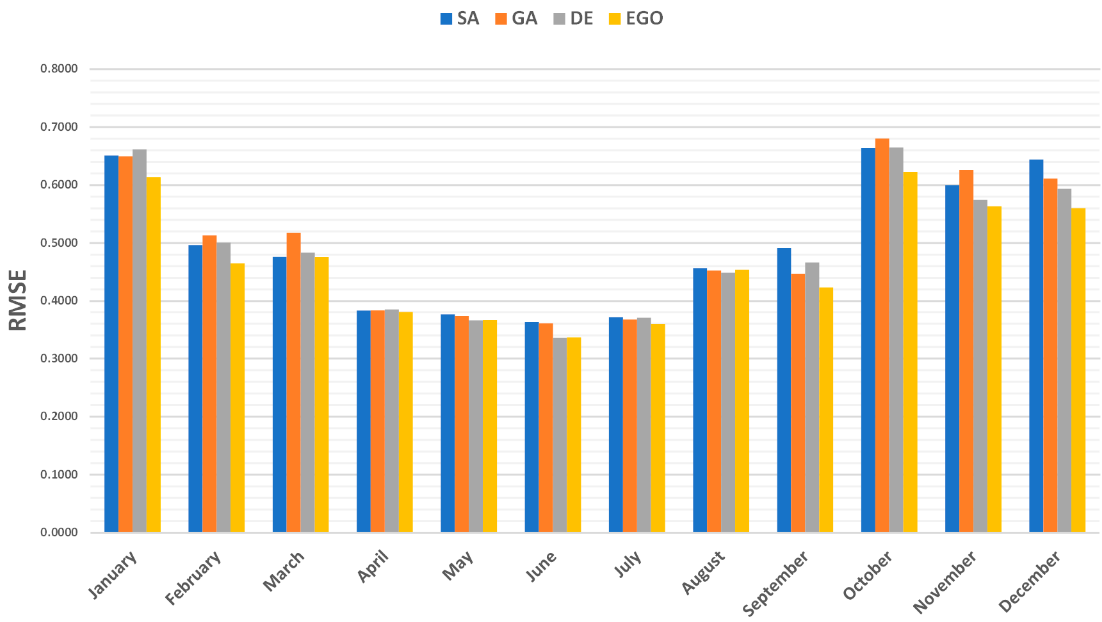

Figure 11. RMSE values for monthly parameter estimation per each technique (own elaboration).

RMSE is also one of the most common metrics to compare the techniques for distribution fitting; the smaller the value of RMSE the better the performance of estimation. Figure 11 shows that RMSE calculated for estimations based on EGO is lower than others for most of the months. Table 6 shows estimated value of shape (k) and scale (c) parameters of the TPWD for annual data using four different techniques. Figure 12 represents the histogram of observed wind speed and the estimated TPWD obtained using four techniques for annual data. From both Table 6 and Figure 12, it can be concluded that there are no huge differences between the parameters estimated using the four different techniques. Table 6 also shows the performance of techniques based on two different metrics: RMSE and R^2. From Table 6 and Figure 13, it can be seen that EGO provides the lowest RMSE and the highest R^2. In other words, EGO has the best performance among other techniques for estimating the parameters of TWPD for annual data.

In order to evaluate the wind energy potential, it is critical to estimate the TPWD parameters. EGO was utilized to estimate the parameters of TPWD in this study. EGO findings were compared with findings from the GA, SA, and DE algorithms. The EGO parameter estimation for TPWD yielded more precise outcomes. According to R^2 and RMSE, the EGO is superior to other algorithms.

Table 6. Performance comparison and parameter estimation for yearly data.

	Parameters		Metrics	
Technique	k	c	**RMSE**	$\mathbf{R^2}$
SA	2.16	4.40	0.501242	0.9300
GA	2.14	4.33	0.486022	0.9342
DE	2.15	4.33	0.482129	0.9352
EGO	2.05	4.25	0.465032	0.9397

When the Weibull is chosen as PDF, the average wind power density per square meter is calculated as shown below [87,88]:

$$P_W = \frac{1}{2}\rho\overline{x}^3 \frac{\Gamma(1+\frac{3}{k})}{[\Gamma(1+\frac{1}{k})]^3} \tag{14}$$

Based on the estimated parameters of the WD, wind power density can be calculated by using the Equation (14), where $\overline{x}$ is the average wind speed, k is the shape parameter of the WD, and ρ is the standard air density, which is assumed to be equal to 1.225 kg/m^3 [87].

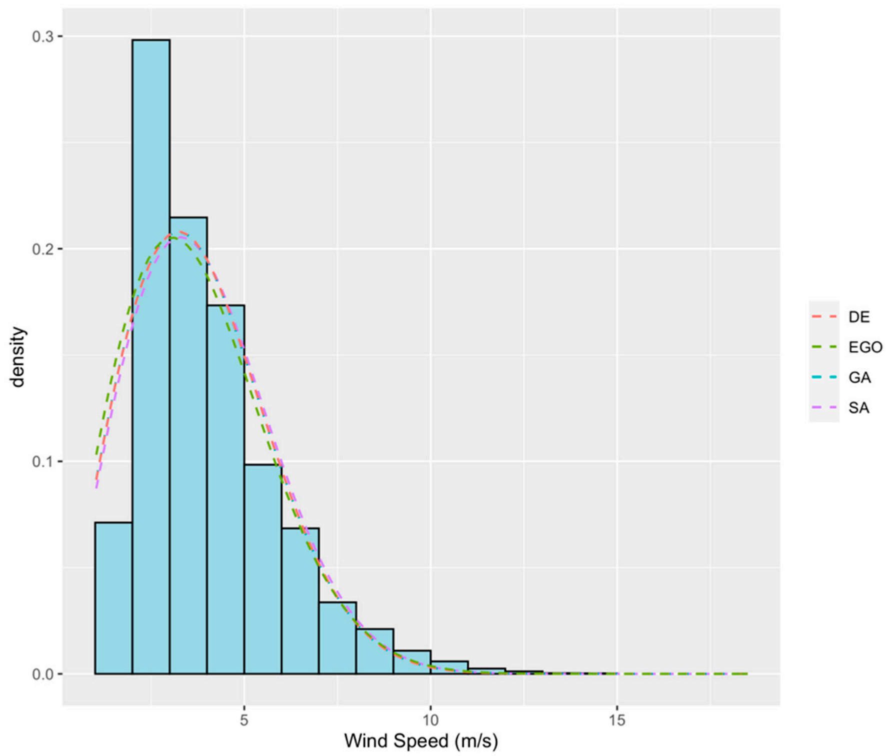

Figure 12. Probability density function estimation and histogram of observed WS for annual data (own elaboration).

k was estimated as equal to 2.05 and $\overline{x}$ is calculated as 3.81. Using Equation (14), wind power density can be calculated and it is equal to 62.89 W/m^2.

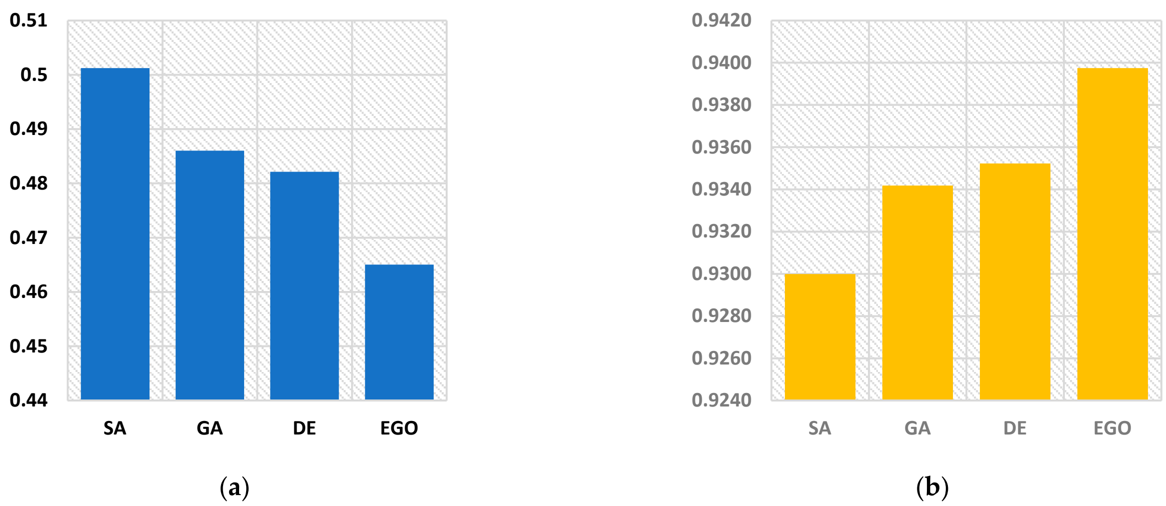

Figure 13. RMSE (**a**) and R^2 values (**b**) for parameter estimation using yearly data (own elaboration).

According to the *Small Wind Guidebook* provided by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Skystream 3.7 is a type of wind turbine that can be used in urban areas [89]. The Skystream 3.7 is a wind turbine that turns wind into usable electricity for homes and small businesses. For households and smaller businesses, Skystream 3.7 may supply 40% or up to 90% of their total energy needs [88]. Taking this information into account, potential WE is calculated under the assumption of having Skystream 3.7 installed in Gdańsk city center.

WE is calculated as shown in Equation (15). To be able to calculate potential WE, information about swept area (SWA) and power coefficient (PC) of the wind tribune must be known [90].

$$P_E = P_W * PC * SA \tag{15}$$

SWA and maximum PC of Skystream 3.7 are 10.87 m^2 and 0.4, respectively [90–92]. P_E is calculated as 273.4457 kWh. Annually, P_E is calculated as 3281 kWh. According to Rachuneo.pl [93], energy prices per kWh in Poland range between 0.69 PLN and 0.78 PLN. By using this information, approximate annual revenue could be calculated between 2263 PLN and 2559 PLN.

6. Conclusions and Recommendations

For the purpose of analyzing and estimating WE potential, it is critical that WS data are fitted to a correct statistical distribution with high precision. Then, using the parameters of the statistical distribution, potential WE and wind power can be calculated. Within the scope of this study, wind power and WE potential were calculated for Gdańsk, the capital of Pomerania Voivodeship—one of the most important regions in Poland in terms of WE potential. Goals of the study are to propose a novel approach for estimating TPWD's parameters by using EGO and to shed a bit more light on the topic of potential benefits of having city-type wind turbines in a city. For these purposes, a dataset that contains hourly WS information for Gdańsk was used. In the following step, the TPWD was fitted to the monthly and annual WS data using MLE with EGO, SA, DE, and GA. Performance of the EGO was compared with other techniques using RMSE and R^2. Comparisons showed that EGO is providing more accurate estimations than other techniques. Using the parameters of the TPWD for annual data obtained by using EGO, potential WE and wind power for Gdańsk were calculated.

Based on the calculations, by having single Skystream 3.7 wind turbines in the city center of Gdańsk, 3281 kWh energy could be generated annually and this could bring revenue between 2263 PLN and 2559 PLN. These calculations revealed that city-type wind turbines might play an important role in generating electricity from WE. Erecting large wind turbines has limitations such as long distances between wind turbines and buildings according to the official regulations. If the city-type wind turbines were to be installed on the rooftops of residential buildings, shopping malls, or office buildings in Gdańsk city center, a portion of the electric energy needed by these buildings could be generated by using WE. However, payback periods and other potential limitations should be investigated.

The most important question is how to have widespread installation of smaller urban-type wind turbines. Two important directions should be emphasized here. The first direction is the development of entrepreneurship directed to the production of green energy. Undoubtedly, an important role is played here by business angels and the creation of sustainable startups. The creation of startups can most significantly translate into the widespread establishment of urban-type wind turbines by companies and consumer households [94–96]. Many startups should succeed in the market in this matter; then there is a need to transform the startup into a listed company in order to raise the necessary funds for development. In this case, it is important to decide the appropriate capital market and the timing of the market entry [97–100]. The second course of action is to focus on grassroot civic initiatives; adequately targeted activities at the local level can play a key role in the community's approach to wind energy and the widespread use of urban-type wind turbines for energy production [101–103].

For future studies, the authors would like to consider not only calculating potential wind energy for different parts of the city but also potential challenges when it comes to installing city-type wind turbines. In addition, they aim to expand the scope of the study by calculating wind energy potential for other cities in Pomerania Voivodeship.

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