Abstract—Wind turbine blades have been constantly increasing since wind energy becomes a popular renewable energy source to generate electricity. Therefore, the wind sector requires a more efficient and representative characterization of vertical wind speed profiles to assess the potential for a wind power plant site. This paper proposes an alternative characterization of vertical wind speed profiles based on Ward’s agglomerative clustering algorithm, including both wind speed module and direction data. This approach gives a more accurate incoming wind speed variation around the rotor swept area, and subsequently, provides a more realistic and complete wind speed vector characterization for vertical profiles. Real wind database collected for 2018 in the Forschungsplattformen in Nord- und Ostsee (FINO) research platform is used to assess the methodology. A preliminary pre-processing stage is proposed to select the appropriated number of heights and remove missing or incomplete data. Finally, two locations and four heights are selected, and 561588 wind data are characterized. Results and discussion are also included in this paper. The methodology can be applied to other wind database and locations to characterize vertical wind speed profiles and identify the most likely wind data vector patterns.

Index Terms—Clustering algorithm, wind speed, data management, power generation.

I. INTRODUCTION

DURING the last decade, larger grid-connected wind energy solutions have been getting more attention and being more economically feasible [1]. In fact, the swept area of wind turbines is related to their power: more power requires a larger diameter [2], [3], and subsequently, global market for small wind turbines is being less popular. The wind turbines are thus designed with larger swept area to catch more power. Reference [4] suggested that it is possible to achieve a certain rated power output at comparatively lower wind speed than the rated wind speed, only by increasing the swept area. According to [5], future wind turbine research focus should be given on variable swept area to get wind power with reduced turbine size. In fact, large swept areas and wind speed values would involve major fatigue loading and higher manufacturing/installation costs [6]. On the other hand, considering wind speed variation across the rotor plane, the electrical power must be determined through an equivalent wind speed from different wind speed measurements at a set of different heights over such swept area [7], being even necessary to integrate data from multiple sources to accurately characterize the wind profile and thus assess the corresponding wind energy potential [8]. As an extended solution, the wind speed extrapolation can be performed for additional wind energy purposes. However, the most uncertain aspects such as wind speed and direction among others [9] are not commonly modeled in detail and vague results should be obtained. In this way, [10] argued that contemporary guidelines still rely on “idealized” extrapolation methods and “equivalent” wind speed values, which are not accurate enough to characterize all wind variability. Similarly, [11] affirmed that the energy in the profiles varies considerably for the wind speed at the same hub height. Therefore, an accurate conversion of wind speed data to wind speed at hub height strongly depends on a suitable vertical wind profile characterization, among other factors [12]. With this aim, multiple wind characterization contributions focused on evaluating the wind power potential can be found in the specific literature [13]. Nevertheless, [14] affirmed that multiple modeling approaches available in the specific literature lack in describing the influence of several variables on the vertical wind power profiles, such as air density and wind direction.
In terms of remaining useful lifetime (RUL) estimation of wind turbines and corrective/preventive maintenance, wind speed intervenes significantly in the maintenance schedule and influences notably on the RUL determination. Indeed, aerodynamic load on the horizontal axis wind turbine (HAWT) blade is different in the top and bottom positions because the wind speed along the length of the blades is significantly different. The blade operates in different torques and transfers the pulsing vibrations to the hub, which may cause damage and other failures [15]. In addition, it can be assumed an irreversible physical degradation of wind turbines. Reference [16] affirmed that such degradation velocity is not constant over time, depending on a variety of disturbing inputs such as wind speed and orientation, among others. Subsequently, estimated loads by using equivalent wind speed frequency distributions based on extrapolated vertical wind profiles from “idealized” methods are not accepted by [17]-[19], since they neglect some relevant parameters such as vertical variations of wind direction, atmospheric stability, or low-level jets.

From the specific literature, more accurate and subsequently more complex characterization of vertical wind speed profile is required by a variety of topics—maintenance, wind energy resource estimation, collected data in field characterization, etc. These alternative solutions should focus on accounting for wind climate realism and open for further improvement. Moreover, [20] recently affirmed that wind speed measured series usually present relevant complexity and non-linearity, being pattern recognition algorithms based on clustering algorithms, which are robust and suitable candidates to be used for wind speed data clustering and identify well separated and compact clusters. With this aim, we propose an improved vertical wind speed characterization based on agglomerative clustering algorithm to identify the most likely wind speed profile by including both module and direction variation with the height. This work is an improved solution of a previous characterization model addressed in [21], where only wind speed module was considered for wind resource characterization and evaluation. The contributions of this work can then be summarized as follows.

1) An alternative vertical wind speed profile based on module and direction data is proposed and tested against real data corresponding to the Forschungsplattformen in Nord- und Ostsee Nos. 1, 2, 3 (FINO research platforms in the North Sea and Baltic Sea [22]).

2) A clustering considering both wind speed module and wind direction data trajectories is proposed by using Ward’s agglomerative clustering algorithm.

3) The most representative vertical wind speed trajectories are identified for subsequent wind resource evaluation.

The proposed solution can be applied to offshore and onshore wind data evaluations. The rest of this paper is structured as follows. Section II describes the methodology. The case study is given in Section III. Results corresponding to the FINO research platform case study are conducted in Section VI. Finally, Section V provides the conclusions.

II. METHODOLOGY

In line with the specific literature, the clustering is widely used as one of the important steps in the exploratory data analysis. Indeed, clustering algorithms are used to find the useful and unidentified classes of patterns and divide data into groups of similar objects. Depending upon the chosen metric, a data object may belong to a single cluster or more than one cluster. Actually, the choice of selecting the clustering algorithm is a critical step of the process [23], [24]. The optimal number of clusters can be determined by different mathematical criteria aiming to measure and identify some similarities among the data objects. The clustering output gives different groups with a remarkable similarity among their corresponding members. Each group is thus represented by an equivalent profile that is considered as the representative member of such cluster. Actually, the clustering provides a reduction of the initial data set to a set of reduced patterns (i.e., the profiles) that describes the data set.

Clustering, classification, and association rule mining are thus crucial to current data mining. Recent contributions analyzed the challenges associated with the clustering algorithms for two- and high-dimensional databases, and identified such key parametric attributes to evaluate the most appropriate clustering algorithm to be implemented [25]. By considering previous literature contributions, a methodology to characterize vertical wind speed vector profiles is then proposed by considering both wind module and direction. The most likely vertical wind speed vector patterns are then identified including not only wind speed module but also direction for each height. This methodology allows us to evaluate wind resource locations from large amounts of wind speed data gathered by field-measurement campaigns by means of such bi-dimensional pattern identification and clustering. The proposed methodology is also highly useful for online satellite data when wind speed values at specific heights are available to be analyzed.

In this case, the agglomerative clustering algorithm is selected. Indeed, it is considered one of the earliest and the most widely used clustering strategies. According to [26], the biggest advantage of this method is the quality of clusters it produced. It is a bottom-up clustering process where each input object initially forms its own individual cluster. Subsequently, such “closest” clusters are merged, and then one of them remains and involves the rest of “closest” clusters. This process can be defined as a hierarchical clustering process, classifying different clusters from potentially different hierarchy levels [27]. A complete review of algorithms for hierarchical clustering can be found in [28]. By considering both wind speed module and direction values for a group of \( n \) different heights, it is then possible to analyze a bi-dimensional clustering problem with \( n \) data for each sample time \((t_1,t_2,...,t_n)\), or a uni-dimensional clustering problem with \( 2n \) data. Initially, we evaluate both possible approaches, giving the uni-dimensional data approach more consistent results. Moreover, the bi-dimensional configuration provides more dispersion among the results and does not identify correctly the potential groups and patterns. Therefore, a uni-dimensional clustering problem with \( m \times 2n \) data matrix is defined to be characterized. Figure 1 graphically summarizes these proposals.
The Euclidean distance matrix is firstly defined to determine the distance $D_{ij}$ between each pair of points $P_i$ and $P_j$, given as vectors in a $2n$-dimensional space, for $i,j=1,2,\ldots,m$.

$$D_{ij} = \sqrt{\sum_{k=1}^{2n} (p_{ik} - p_{jk})^2}$$  

(1)

where $P_i = [p_{i1}, p_{i2}, \ldots, p_{i2n}]$ is the vector of wind speed module and direction values for $n$ different heights at the $i$th sample time. From a data set of $m$ points, the Euclidean distance among all these points is determined and the corresponding Euclidean distance matrix is constructed. The clustering procedure output gives a list of $m-1$ triples $(a_i, b_j, \delta_i)$, which encodes a step-wise dendrogram. The $i$th triple contains the information of which nodes are joined into a new node in the $i$th step, and what is the cluster dissimilarity between $a_i$ and $b_j$. This information is enough to provide the common graphical representation of the dendrogram as a rooted tree, where each leaf represents the initial nodes, and a branching point at a given height $\delta_i$ represents the joining of nodes $a_i$ and $b_j$ with mutual similarity measure $\delta_i = d(a_i, b_j)$. At each iteration, pairs of clusters that were not previously joined are inspected, and the pair of clusters having the minimum value is joined to form a new cluster [29]. Note that the clustering procedure output is not unique: if more than one pair of nodes has the minimum distance, any of them might be chosen, and this result influences the later step. Many methods have been defined to calculate such distances, and they have a large impact on the resulting hierarchy. A comparative study on different linkage
techniques or methods used to calculate the decision factor for merging of clusters at any level was conducted in [30]. From the specific literature, Table I summarizes these agglomerative clustering distances [31]. The updated expressions for the “centroid”, “ward”, and “median” approaches assume that the input points are given as vectors in Euclidean space with the Euclidean distance (see (1)) as dissimilarity measure.

Table I: Hierarchical Agglomerative Clustering

<table>
<thead>
<tr>
<th>Linkage method</th>
<th>Dissimilarity measure between clusters A and B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single linkage</td>
<td>( \min d(a,b) \quad a \in A, b \in B )</td>
</tr>
<tr>
<td>Complete linkage</td>
<td>( \max d(a,b) \quad a \in A, b \in B )</td>
</tr>
<tr>
<td>Average linkage</td>
<td>( \frac{1}{</td>
</tr>
<tr>
<td>Ward’s linkage</td>
<td>( \frac{2</td>
</tr>
<tr>
<td>Centroid linkage</td>
<td>( |\bar{w}_A - \bar{w}_B|^2 )</td>
</tr>
<tr>
<td>Median linkage</td>
<td>( |\bar{w}_A - \bar{w}_B|^2 )</td>
</tr>
</tbody>
</table>

Note that \( \bar{c}_k \) is the centroid of cluster \( X(X=A,B) \) and \( \bar{w}_X \) is the point defined iteratively and depending on the clustering step order. \( \bar{w}_L \) is determined as \( 0.5(\bar{w}_I + \bar{w}_J) \) assuming that the cluster \( L \) is formed by joining \( I \) and \( J \). Among the different criteria to determine the distance of the data groups, Ward’s linkage method is selected for this case study, as will discussed in Section IV. The Ward’s linkage method is a well-known clustering method based on minimizing the loss associated with each partition \( (S_1, S_2, ..., S_k) \), with \( k \leq m \). With this aim, such loss is represented in an interpretable and quantifiable form. In Ward’s clustering method, each potential merge of clusters must be analyzed, and those two possible clusters are then combined together, whose merger results in the minimum increase in information loss. To define information loss, Ward used sum of square \( ESS \), which is a mathematical technique to find the function which varies least or fits best from the data.

\[
ESS = \sum (X_j - X_{mean})^2 \tag{2}
\]

This criterion \( ESS \) can also be defined as the variance as it measures the deviation of the particular data point \( X_j \) from the mean \( X_{mean} \). An extending Ward’s minimum variance method can be found in [32]. The researchers implemented the methodology by using the statistical programming language R [33] and the function agnes for clustering from package cluster [34]. Other recent solutions and algorithms can also be found in R packages available online. For example, fastcluster includes more efficient alternative algorithms [35]. NbClust package provides 30 indices determining the number of clusters in a data set and providing also the best clustering scheme from different results. In addition, this R package includes a function to perform K-means and hierarchical clustering with different aggregation methods and distance measures [36].

III. Case Study

The FINO research platforms, which belong to the Federal Government of Germany, are used as case study. There are three different platforms (FINO1, FINO2, and FINO3), and their main aim is to determine the environmental conditions for offshore wind power generation in such areas, as well as find potential impacts of the offshore wind power plants on the marine habitat. Figure 2 shows the location of each FINO platform. Several research works have been performed in each FINO platform, including the measurement of wind strength, wind direction, and turbulence; measurement of wave height and wave propagation; and measurement of the strength of sea currents [22].

Fig. 2. Location of FINO platforms.

FINO1 was brought into service in 2003. Data are available since January 2004, including meteorological and oceanographic data, with a total amount of 88 parameters. It is located around 45 km north of the Borkum island. This platform is settled close to wind power plants under operation or under construction: Alpha Ventus, Borkum Riffgrund I, Trianel Borkum, Borkum Riffgrund II, and Merkur. The measured data are sent and transmitted to the Borkum island through a 32 Mb/s directional radio link. Data are fed into the landline system, and transmitted to the German research network. Once the German research network receives such data, they can be processed by the agents of measuring institutes. Most of these results are published in the FINO database, being available to the public. Nowadays, the collected meteorological variables comprise wind speed, wind direction, air temperature, atmospheric pressure, humidity and density, among others. These meteorological variables are measured with a wind measuring mast of 80 m height, being capable of measuring a maximum height of 103 m. The used sensors are balanced to the mast and are located at several heights of the platform [37].

With regard to FINO2, it was completed in 2007 and has been operated by DNV GL since 2010. Data have been available since August 2007. It is around 40 km north-west of the Rügen island, in the border triangle Germany-Denmark-Sweden. In contrast to FINO1, the database of FINO2 only includes meteorological data, considering 32 parameters in total. Such meteorological variables include wind speed, wind direction, temperature, global radiation, humidity and
intensity of the precipitations, among others. These variables are measured at different heights and with several sensors (i.e., wind speed is measured with a cup anemometer and an ultrasonic anemometer, depending on the height) [38].

Finally, FINO3 has published meteorological and oceanographic data since September 2009, involving a total of 71 parameters. It is 80 km west of Sylt, surrounded by three German operating offshore wind power plants (Butendiek, DanTysk, and Sandbank). The meteorology data include wind speed and direction, temperature, humidity, pressure, and precipitation. These data are collected at different heights, by using a 100 m wind measurement mast [39].

IV. Results

From the three different platforms described in Section III, FINO1 and FINO2 are considered for analysis. Indeed, FINO3 is close to FINO1 and thus, the results would be really similar between both platforms. From the available database of FINO1 and FINO2 platforms, the corresponding data characterization is carried out for year 2018, which provides a more complete information for the whole year. An initial collected data of 717851 and 1362240 for FINO1 and FINO2, respectively, are considered with 10-min sample time. Before applying the clustering method described in Section II, data are pre-processed to remove missing and incomplete data. Subsequently, relevant heights for both wind speed module and wind direction collected data are identified. More specifically, 34, 51, 71, and 91 m heights are selected for FINO1 data vector including wind speed and direction consistent data, with a total of 141764 values to be analyzed. Regarding FINO2, the 31, 51, 71, and 91 m heights are identified after such pre-processing stage, accounting for 419824 data to be finally analyzed. As a graphical example of the selected data, Fig. 3 shows the evolution of the wind speed module and direction in FINO1 for a month (April, 2018) and at the specific height (91 m), where the numbers 0, 10, 20, 30 represent the observed frequencies. As can be observed, the south-west direction is the prevailing one. Similar results can be obtained for FINO2 location.

In line with Table I, [40] affirmed that complete, average, weighted, and Ward’s linkage methods are commonly implemented using the nearest-neighbor chain algorithm. An efficient implementation for the centroid and median linkage methods was also developed and included in [40]. Following these contributions, Table II shows the corresponding agglomerative clustering coefficients according to the average, single, complete, and Ward’s linkage methods from the FINO1 data. From these results, Ward’s linkage method is selected. A detailed comparison of Ward’s implementation is provided in [41].

The identification of the “knee” of the agglomerative clustering coefficient indicates the largest magnitude difference between two adjacent points. The Ward’s linkage method was the clustering routines applied. The final number of clusters to be included in the solution was determined by the agglomerative clustering coefficient with the use of the stopping rule. The stopping rule evaluates the changes in the coefficient at each stage of the hierarchical process. The number of clustering groups was deemed appropriate when a continued increase in the number of clusters resulted in a large percentage change in the agglomerative clustering coefficient [42]. From the pre-processing data, the bi-dimensional wind speed values (speed and direction) are then analyzed for each hour, in order to characterize such data and identify their evolution for each specific hour. Subsequently, the most relevant hour for an annual cycle can be then identified. Table III shows the bi-dimensional wind data clustering distribution for each hour.

![Wind Speed Distribution](image_url)

Fig. 3. Evolution of wind speed module and direction for a month. (a) Hour 5. (b) Hour 11. (c) Hour 17. (d) Hour 23.

A total of five differentiated clustering groups (clusters 1-5) are finally identified. Differences between choosing five or eight clustering groups are not significant; and the most representative clustering (about 30% of the trajectories) remains in both distribution, whether five or eight groups are identified. Therefore, five groups simplify the representation of results and optimize the number of such groups. Additionally, the corresponding dendograms for such bi-dimensional data are determined by applying the hierarchical grouping based on the Ward’s linkage method and using the Euclidean distance. Dendrogram allows a visual representation by means of different branches to show the order and relationship in terms of similarity or dissimilarity among trajectories [43]. As an example of these results, four specific hours are selected: hours 5, 11, 17, and 23, during which the corresponding wind vector data characterization is described. Figure 4 shows these dendograms for such specific hours, where the dashed-horizontal line defines the selected cluster number. From this number of clusters, Figs. 5 and 6 summarize a 3D graphical representation of wind speed and wind direction data classification for the identified clusters, corre-
sponding to the specific hours (hours 5, 11, 17, and 23) considered as a result example.

### TABLE II

**Hierarchical Agglomerative Clustering Coefficients with Different Methods**

<table>
<thead>
<tr>
<th>Hour</th>
<th>Hierarchical agglomerative clustering coefficients</th>
<th>Wind data clustering distribution (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>Complete</td>
</tr>
<tr>
<td>0</td>
<td>0.9660</td>
<td>0.9811</td>
</tr>
<tr>
<td>1</td>
<td>0.9686</td>
<td>0.9831</td>
</tr>
<tr>
<td>2</td>
<td>0.9677</td>
<td>0.9820</td>
</tr>
<tr>
<td>3</td>
<td>0.9699</td>
<td>0.9831</td>
</tr>
<tr>
<td>4</td>
<td>0.9594</td>
<td>0.9823</td>
</tr>
<tr>
<td>5</td>
<td>0.9675</td>
<td>0.9832</td>
</tr>
<tr>
<td>6</td>
<td>0.9661</td>
<td>0.9814</td>
</tr>
<tr>
<td>7</td>
<td>0.9664</td>
<td>0.9836</td>
</tr>
<tr>
<td>8</td>
<td>0.9686</td>
<td>0.9835</td>
</tr>
<tr>
<td>9</td>
<td>0.9697</td>
<td>0.9839</td>
</tr>
<tr>
<td>10</td>
<td>0.9706</td>
<td>0.9835</td>
</tr>
<tr>
<td>11</td>
<td>0.9715</td>
<td>0.9838</td>
</tr>
<tr>
<td>12</td>
<td>0.9704</td>
<td>0.9846</td>
</tr>
<tr>
<td>13</td>
<td>0.9648</td>
<td>0.9839</td>
</tr>
<tr>
<td>14</td>
<td>0.9587</td>
<td>0.9823</td>
</tr>
<tr>
<td>15</td>
<td>0.9709</td>
<td>0.9833</td>
</tr>
<tr>
<td>16</td>
<td>0.9689</td>
<td>0.9828</td>
</tr>
<tr>
<td>17</td>
<td>0.9729</td>
<td>0.9836</td>
</tr>
<tr>
<td>18</td>
<td>0.9745</td>
<td>0.9851</td>
</tr>
<tr>
<td>19</td>
<td>0.9703</td>
<td>0.9838</td>
</tr>
<tr>
<td>20</td>
<td>0.9703</td>
<td>0.9827</td>
</tr>
<tr>
<td>21</td>
<td>0.9715</td>
<td>0.9820</td>
</tr>
<tr>
<td>22</td>
<td>0.9650</td>
<td>0.9789</td>
</tr>
<tr>
<td>23</td>
<td>0.9659</td>
<td>0.9798</td>
</tr>
</tbody>
</table>

As an addition result, Figs. 7-10 depict the distribution of wind data divided by height and groups of clusters for the selected hours in polar coordinates, for hours 5, 11, 17, and 23, respectively. From these results, the south-orientation can be identified as the predominant direction, which is over 35% of the total analyzed trajectories and accounting for more than 50% of the total wind trajectories in some hours are in this direction. On the other hand, note the wind direction distribution on each cluster depending on the height, which can affect the estimation of potential power available when the swept areas are increasing more and more. Moreover, these results not only give the most predominant directions depending on the height, but also the wind speed module for each direction and height. These results would allow a more accurate estimation of the potential wind power for each swept area in comparison to wind speed module data at only one height. Furthermore, recent contributions affirm that changes in incoming wind speed along the vertical direction should be considered for large wind turbines [44], [45].

![Fig. 4. Dendrograms of hierarchical agglomerative clustering for selected hours. (a) Hour 5. (b) Hour 11. (c) Hour 17. (d) Hour 23.](image-url)
Fig. 5. 3D graphical representation of wind speed and wind direction data for identified cluster patterns. (a) Hour 5. (b) Hour 11. (c) Hour 17. (d) Hour 23.

Fig. 6. 3D graphical representation of wind speed and wind direction data for identified clusters. (a) Hour 5. (b) Hour 11. (c) Hour 17. (d) Hour 23.
Fig. 7. Wind data clustering distribution and pattern identification (hour 5). (a) Wind data clustering distribution. (b) Wind data clustering pattern.
Fig. 8. Wind data clustering distribution and pattern identification (hour 11). (a) Wind data clustering distribution. (b) Wind data clustering pattern.
Fig. 9. Wind data clustering distribution and pattern identification (hour 17). (a) Wind data clustering distribution. (b) Wind data clustering pattern.
Fig. 10. Wind data clustering distribution and pattern identification (hour 23). (a) Wind data clustering distribution. (b) Wind data clustering pattern.
V. CONCLUSION

A methodology to characterize vertical wind speed patterns from bi-dimensional wind data (wind speed and direction) is described and assessed. The proposed solution is based on Ward’s agglomerative clustering algorithm applied to bi-dimensional data. A 3D representative wind data patterns are then provided for each hour of the day, considering both wind speed module and direction evolution with the height. This characterization allows us a more accurate wind data analysis, and subsequently gives a robust information to determine the potential wind power available for large swept areas. Real wind data-base collected in the FINO research platform is used to assess the methodology. A preliminary pre-processing step is proposed to select the appropriated number of heights and reduce the amount of data. In this case, two locations are selected and around 2080000 wind data are finally analyzed. From both locations, five clustering groups are identified and their corresponding patterns provide the most likely wind speed and direction values according to the height for each hour of the day. The most likely wind speed and direction pattern involves more than 26% of the total bi-dimensional trajectories for the averaged daily wind data, including some hours over 40% of such data. The proposed solution can be applied to other wind data bases, both on-shore and off-shore. In fact, this methodology can be extended to analyze potential wind power plant locations, providing the most likely wind vector data patterns for different sample times.

REFERENCES

M. C. Bueso received the B.S. and the Ph.D. degrees in mathematics from the Universidad de Granada, Granada, Spain, in 1992 and 1996, respectively. She is an Associate Professor with the Department of Applied Mathematics and Statistics, Universidad Politécnica de Cartagena, Cartagena, Spain. Her research interests include space-temporal modeling of stochastic processes, derivation of related inference procedures and sampling strategies, as well as statistical analysis, modeling, and inference of physical-chemical and environmental processes.

A. Molina-Garcia received the electrical engineering degree from the Universidad Politécnica de Valencia, Valencia, Spain, in 1998, and the Ph.D. degree in electrical engineering from the Universidad Politécnica de Cartagena, Cartagena, Spain, in 2003. He is currently a Professor at the Department of Electrical Engineering at the Universidad Politécnica de Cartagena (UPCT), Cartagena, Spain. His research interests include wind power generation, photovoltaic (PV) power plant, energy efficiency, and demand response.

A. P. Ramallo-González received the Ph.D. degree in building physics at the University of Exeter with a scholarship from the Wates Foundation in 2013. He worked as Post-doctoral Researcher on two EPSRC funded projects in the Department of Architecture and Civil Engineer of the University of Bath, Bath, UK, in 2013-2017. He went back to Spain with an excellence program Savedra-Fajardo, and he is now Research Fellow in the Faculty of Computer Science at the University of Murcia. His research interests include big data, energy consumption, and smart power grid.

A. Fernández-Guillamón received the B.S. degree in electrical engineering from the Universidad de Castilla-La Mancha (UCLM), Albacete, Spain, in 2016, and the M.S. degree in renewable energies from the Universidad Politécnica de Cartagena (UPCT), Cartagena, Spain, in 2017. In 2021, she received the Ph.D. degree in renewable energy and energy efficiency from UPCT, with honors. She is currently a Lecturer at the Applied Mechanics and Projects’ Engineering Department at UCLM. Her research interests include renewable energy source integration, power system stability, and optimization.