Technological Forecasting & Social Change 194 (2023) 122748

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Wind energy: Influencing the dynamics of the public opinion formation through the retweet network

Loretta Mastroeni [a,1], Maurizio Naldi [b,1], Pierluigi Vellucci [a,*,1]

[a] Department of Economics, Roma Tre University, Via Silvio D'Amico 77, 00145 Rome, Italy

[b] Department of Law, Economics, Politics and Modern languages, LUMSA University, Via Marcantonio Colonna 19, 00192 Rome, Italy

ARTICLE INFO

Keywords:
Wind power
Renewable energies
Twitter
Opinion formation
Social media

ABSTRACT

Wind power is one of the primary renewable sources that are getting increasing support as a means of addressing climate changes. The debate on its use takes place on social media as a fast and unfiltered forum to express one's opinions. In this paper, we analyse the discussion concerning wind power coming up on Twitter. We measure the influence of opinions (and of the twitterers expressing them) by building a retweet network. A strong concentration of retweets is observed through the use of both the retweet distribution and the Hirschman–Herfindahl Index (HHI): the discussion appears to be driven by a handful of twitterers who are heavily retweeted. We provide a classification of such top influencers by their role in society. A single climate activist is, by far, the top influencer. International and governmental agencies come second, and energy consultants come third. Companies play quite a minor role, on a par with generalist individual twitterers, while scientists are the least-retweeted category. Those top influencers are also constantly present from month to month, while the overwhelming majority of twitterers change from month to month. Leading energy-related events appear to have a short-lived influence on the discussion (two weeks after their taking place).

1. Introduction

The need to reduce greenhouse gas emissions and address global environmental problems is continually growing. International efforts are required to combat climate change, e.g., by adopting policy instruments designed to move towards sustainable, low-carbon, and affordable energy systems. Those may include a new portfolio of electricity generation technologies and a shift in the national energy mix towards renewable energies (Hoffert et al., 2002; De Jesus et al., 2018; Dhakouani et al., 2019; Aleixandre-Tudó et al., 2019). The development and implementation of a wind energy infrastructure is an essential contributor to that energy transition, as shown by Muñoz and Márquez (2018), Stephens et al. (2009), Zhao et al. (2016), Jethani (2016), both in its onshore and offshore implementations as described in Weinzettel et al. (2009), Sun et al. (2012). Countries with high per-capita emissions are taking steps in that direction. Examples are the USA (where 29 states require minimum levels of wind generation through renewable portfolio standards (Lamy et al., 2020)), Switzerland (where citizens approved a national energy strategy in May 2017, and wind energy plays a fundamental role (Vuichard et al., 2019)), and Denmark (where parliament has agreed to promote the establishment of a longer-term goal of satisfying 50% of Denmark's electricity needs through wind power by 2020 (Borch et al., 2020)). At the end of the year 2013, the amount of wind energy capacity in the world was around 318 GW. By the end of 2019, the total was around 650 GW. That represents a compound annual growth rate of 12.6% (Sayigh and Milborrow, 2020), which is helped by steadily falling generation costs and an increase in the size of wind turbines (Sayigh and Milborrow, 2020) as well as a low average construction time (Sayigh and Milborrow, 2020). Recently, the Recovery and Resilience Plan (Piano Nazionale di Ripresa e Resilienza, PNRR) presented by Italy envisages investments and a consistent reform package; it is divided into Missions and Functional Components to achieve the economic and social objectives defined in the Government's strategy. The component devoted to renewable energies aims to increase the share of energy produced from renewable sources and to develop an industrial sector in this area. In particular, a significant contribution will come from offshore wind farms.

To date, however, the deployment of wind energy has been hindered by acceptance-related issues. For example, resistance from people living near such projects may hinder their development (Horbaty et al., 2012; Vuichard et al., 2019). Despite the growing interest in building

* Corresponding author.
E-mail addresses: loretta.mastroeni@uniroma3.it (L. Mastroeni), m.naldi@lumsa.it (M. Naldi), pierluigi.vellucci@uniroma3.it (P. Vellucci).

[1] All authors have contributed equally to the paper.

https://doi.org/10.1016/j.techfore.2023.122748
Received 12 November 2021; Received in revised form 27 January 2023; Accepted 12 July 2023
Available online 26 July 2023

offshore wind farms (which, however, spur signs of conflict in the local communities (Lamy et al., 2020; van der Loos et al., 2020)), onshore wind farms are still the most popular type of wind farm in the world. In landlocked countries or countries with a less developed wind energy sector, the social acceptance of onshore plants continues to be the key challenge facing the governments and industry (Frantál, 2015). Summing up, all renewable energy options have their own set of negative impacts, and wind power is no exception.

For that reason, the analysis of the social perception of wind power is a crucial element in any energy policy debate. Knowing what the stakeholders (which include citizens, scientists, and media) think about wind power and how their opinions form may help governments change policies to make them more socially acceptable or increase acceptance of new power plants.

The literature on the social perception of wind power so far can be subdivided into three major areas according to the focus of their analysis: (a) measurement of perception and identification of driving factors for acceptance; (b) analysis of the impact of wind power plants; (c) policy steering related to social opinions.

In the first group, we find all the papers that aim at measuring the level of acceptance among citizens. Most of them also investigate the socio-demographic and economic factors behind public opinion. The main differences among the papers lie in the population probed on the matter and the particular issues under investigation. In most cases, the sample of interest is made of local residents who live nearby a power plant as in the papers by Firestone and Kempton (2007), Firestone et al. (2012, 2009), Frantál (2015), Swofford and Slattery (2010), Gross (2007), Firestone et al. (2018b), Lamy et al. (2017, 2020), Dimitropoulos and Kontoleon (2009). However, some analyses extend over an entire nation, e.g. Denmark as in Ladenburg (2008), Ladenburg and Dubgaard (2009), and Sovacool and Lakshmi Ratan (2012), the USA in Hoen et al. (2019), Ireland in Sovacool and Lakshmi Ratan (2012), New Zealand in Graham et al. (2009), Ontario in Jami and Walsh (2017), Austria in Sposato and Hampl (2018), Scotland in Warren and McFadyen (2010), Sweden in Ek (2005), Ek and Persson (2014), and Switzerland in Walter (2014), Vuichard et al. (2019), Spiess et al. (2015). In Ladenburg (2010), Landry et al. (2012), Teisl et al. (2018), and Warren and McFadyen (2010), tourists are also considered since the plant may be located in tourist areas. Just a few papers expand their horizon to include also other stakeholders (e.g. landowners, politicians, nature preservation societies, investors) as in Borch (2018), Jami and Walsh (2017) and Sovacool and Lakshmi Ratan (2012). Opinion measurements are often accomplished by administering questionnaires, with some notable exceptions. Borch (2018) conduct a discourse analysis on talks delivered at institutional meetings (e.g., public hearings). Again Borch et al. (2020) perform a textual analysis over a corpus of Facebook pages belonging to Danish wind protest groups. Dehler-Holland et al. (2022) explore the wind power's legitimacy using topic models and sentiment analysis over newspaper coverage of wind power in Germany. Finally, Bjärstig et al. (2022) conduct a frame analysis to explore which national and regional media frames have developed in response to the rapid expansion of large-scale wind farms in Sweden. As to the target of analysis, though most papers consider a dichotomic approach (acceptance vs rejection), the focus is sometimes shifted to the power plant building process itself, as in Firestone et al. (2012), or just the positive side of the story, i.e., the benefits deriving to citizens as in Aitken (2010). The NIMBY effect is studied in Swofford and Slattery (2010), van der Horst (2007), Wolsink (2000), Bell et al. (2005, 2013), Papazu (2017), Jones and Richard Eiser (2010), Zografos and Martínez-Alier (2009), Rand and Hoen (2017), and the related issue of fairness and procedural justice in siting plants is investigated in Firestone et al. (2018a), Walker and Baxter (2017). Some papers focus on the visual impact of wind plants, as in Johansson and Laike (2007), Ladenburg (2009), Hevia-Koch and Ladenburg (2019), and Bishop and Miller (2007), also distinguishing between on-land and offshore plants, as in Ladenburg (2008, 2010).

The second group of papers, which deal with the actual impact of wind plants on residents and tourists, is much slimmer. Several papers conduct visual simulations to assess the impact *before* the plant is built, as in Bishop and Miller (2007) and Jallouli and Moreau (2009). Instead, few papers have assessed the actual impact of plants *after* they have been built. The assessment was accomplished through questionnaires in Hübner et al. (2019) and Katsaprakakis (2012), and through actual noise measurements in Pohl et al. (2018).

The third stream of literature concerns the relationship between public attitude and policymakers. The issues of interest concern, at the same time, how the public perception of wind power is taken into account when setting a policy and how citizens can deliver their opinions to policymakers (or the leaders in charge of the siting and building process). Wolsink (2000) has shown that institutional constraints may be more important than public acceptance in shaping the actual energy policy, which could lead to substantial neglect of public opinions. However, the survey conducted by Langer et al. (2017) has highlighted that citizens wish to be involved in informative and deliberative participation processes, which is a means to have their opinions reach process leaders. According to Wolsink (2007), the best way to facilitate the development of appropriate wind farms is to build institutional capital through collaborative approaches to planning. However, these suggestions have rarely been followed in practice (Slee, 2015; Rydin et al., 2015; Nadaï, 2007; Zárate-Toledo et al., 2019; Walker and Baxter, 2017; Kim et al., 2018) but the price to pay can be very high: attempting to exclude people from the decision-making process may be more likely to promote opposition than overcome it (Bell et al., 2005). The need to interact with people to widen the acceptance of wind power plants is also recognized by Dwyer and Bidwell (2019), who analyse engagement techniques to build a chain of trust in process leaders, the process itself and the outcome of wind power projects.

Though the literature on the social perception of wind power is quite ample, minimal attention has been paid so far to the dynamics of the public opinion formation on the theme, i.e. on how the social actors interact and how each individual may come to form his/her opinion about wind power.

Models have been proposed to understand how people influence each other so that they coalesce around a common opinion as a result of their interaction, e.g. through agent-based models as in Mastroeni et al. (2019c), Guttal and Couzin (2010), Motsch and Tadmor (2014), Tania et al. (2012), Vicsek and Zafeiris (2012), Mastroeni et al. (2019b), Pareschi et al. (2017), Wang et al. (2011), Kolarijani et al. (2020), Proskurnikov et al. (2016), Bandini et al. (2009), Mastroeni et al. (2020, 2019a). However, those are mainly theoretical models and have never been applied to a specific context where wind power is debated.

In order to fill that research gap, in this paper, we wish to analyse how people debating wind power projects influence each other. If the energy policy (specifically that concerning wind power) has to take into account the public attitude, which is what the papers by Langer et al. (2017) and Dwyer and Bidwell (2019) implicitly recognize, it is crucial to know how the public opinion may be influenced.

In order to contribute to such a task, we start by considering a widely used social medium to express one's opinions, which is Twitter. Its wide diffusion (there are 330 million monthly active users and 145 million daily active users on Twitter, whereas 500 million tweets are sent out per day[2] and its limitation to short pieces of text, which place a very small burden on our time to contribute, make it a primary means of interactions. For that reason, we have considered it to start an analysis of social interactions in forming public opinion about wind power. Since Twitter allows a retweet function, where a twitterer can share a tweet with others, we have considered retweets as a proxy for the influence a twitterer can exert over other twitterers: the more a twitterer is retweeted, the more he/she can be considered as influential

[2] https://www.oberlo.com/blog/twitter-statistics

and his/her opinions can influence others. The power of retweets as a means of influence is well established in the literature, as shown, e.g., by Cha et al. (2010), Grover et al. (2019), Panagiotopoulos et al. (2016), Zhang et al. (2015), and Ye and Wu (2010). For that reason, we have employed retweets to build a social network of twitterers (the retweet network) to measure the extent of influence. The importance of social ties in influencing the uptake of technologies has been investigated, e.g., in Bale et al. (2013), McMichael and Shipworth (2013), and Ramirez et al. (2014). Here, we take a step further by considering the most recent place of expression of social interactions, e.g. through social media. Though social media (namely Facebook) have been exploited to study the formation of opinions about wind farms in Borch et al. (2020), the analysis was focussed on the opinion content, i.e. by carrying out a textual analysis; the social network behind the individual Facebook users was not investigated. Similarly, other papers have employed Twitter to investigate the opinions about energy issues, e.g., the perception of clean energy sources in Abdar et al. (2020), the group interactions of consumer behaviour within the UK energy sector (Mogaji et al., 2020), the sentiment on energy issues in Li et al. (2019), Jain and Jain (2019), and Ikoro et al. (2018). In this paper, we do not consider the actual content of those opinions but how they move around and influence citizens; we are interested in the relationships between people.

Our major contributions are:

- the overwhelming majority (from 90 to 96%) of twitterers is made of lone influencers, i.e. influencing just another twitterer and being retweeted just once;
- high influencers, influencing more than 12 other twitterers, represent a fraction lower than what a power law would assume;
- the average twitterer influence just a bit more than one other twitterer;
- the top influencer (the most retweeted twitterer) often exerts a much stronger influence than his/her runner-up;
- climate activists are the overall top-class influencers, gaining almost double the retweets of the runner-up (journalists and scientific journalists);
- among them there seems to be no consensus on climate change and renewables;
- leading international or governmental organizations (including the institutional White House account) rank fifth;
- though there is a large turnover from month to month, the top influencers are quite a steady group, staying for most months during the observation period;
- energy-related world events have a narrow resonance over time.

2. Data and methods

We employ social media data from Twitter to investigate the influence exerted over that social network on wind power topics. We have exploited two Twitter API(s) (Gentry, 2015; Kearney et al., 2022) by searching for all the tweets containing either of the following word combinations:

- *wind* AND *power*;
- *wind* AND *energy*.

Then, we collected all the posts submitted in different time ranges:

- from 2019-11-30 to 2020-03-23 by means of twitteR R package (Gentry, 2015);
- from 2020-04-26 to 2021-03-08 by means of twitteR R package (Gentry, 2015);
- from 2021-03-09 to 2022-08-30 by means of rtweet R package (Kearney et al., 2022).

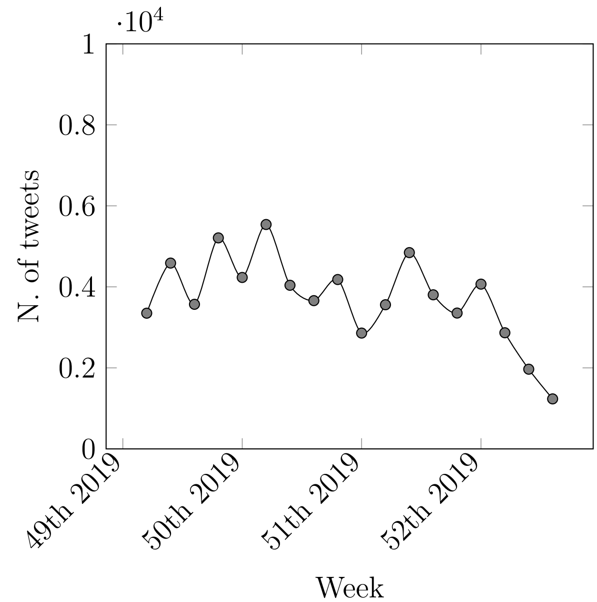

Fig. 1. Average daily number of tweets by week.

The second of these intervals was right after to the declaration of the coronavirus (COVID-19) pandemic, which took place on 11 March 2020. Let us consider indeed Fig. 1. We can spot therein that the average number of tweets reaches its absolute minimum in the 12th week of 2020 (from March 16, 2020, to March 22, 2020), i.e. after the pandemic declaration. This can be explained by considering that the pandemic declaration increased public awareness and increased searches for information on COVID-19, as shown by Jun et al. (2021), probably cutting space to all the other topics of discussion on social networks. This is why we decided to stop collecting tweets for about a month. In the last interval, instead, we decided to change the package for rtweet because it is the only package actively maintained at present. Moreover, the rtweet package provides a few extra features and new conveniences in addition to providing the same basic functionality as the twitteR package. For example, the function *search_fullarchive* provided by Kearney et al. (2022), allows searching for tweets posted within the last 30 days or since the first one was posted in 2006. Other peculiar functionalities of rtweet package allow working with Twitter lists (lists that allow to customize and organize the tweets in the timeline). Users can choose to join lists created by others on Twitter or to create lists of other accounts by group, topic or interest. The functions that in rtweet package provide a tool to work with Twitter lists are *lists_members*, *lists_memberships*, *lists_statuses*, *lists_subscribers*, *lists_subscriptions*, *lists_users*. Another important functionality that characterizes the package rtweet is *tweet_threading*, which returns all the replies from a user to their own tweets (i.e. statuses that are part of a thread).

All tweets are in English but with no geolocation information (latitude and longitude), though the user's browser or device could send this information. Twitter will not show any location information unless the user has opted in and has allowed his/her device or browser to transmit the coordinates to it.[3] As a matter of fact, only a small portion of tweets are geotagged, less than 1% of its users (Hale et al., 2012). However, since it is important to know where a tweet came from in many Twitter studies to investigate regional user behaviour, many approaches have been proposed for the geolocation task. The approaches used are based on text and linguistic attributes of the

[3] See Twitter FAQs: https://help.twitter.com/en/safety-and-security/tweet-location-settings.

tweets (Mishra, 2020; Huang and Carley, 2017; Suwaileh et al., 2020; Paule et al., 2019) or combinations of users data like, e.g., user profile location and text of the tweet (Mahajan and Mansotra, 2021; Chong and Lim, 2019; Gonzalez Paule et al., 2017; Lim et al., 2019; Chong and Lim, 2018). However, this allows for just an estimation of users' actual location, relying on the ground truth obtained by expressly geotagged tweets, which were not available in the dataset we have obtained from Twitter.

We focus particularly on retweets, i.e., posts reposting somebody else's tweet. Reposting is a stronger sign of support for somebody else's opinion than just following him/her: reposting implies an uncritical sharing of his/her opinions. In addition, it shows precise support since it concerns a single message. Being retweeted is then a sign of influence. The relevance of retweeting as a metric of influence, on which other influence measures can be built, has been recognized by Riquelme and González-Cantergiani (2016), who consider the following elementary forms of Twitter relationships: follow-up relationships, retweets, mentions, replies, favourites or likes. However, in our opinion, retweets represent the most expressive representation of support by twitterers for the opinion of another twitterer. Following a twitterer represents an interest in the tweets posted by that twitterer, but not necessarily support of his/her opinions. Mentions and replies may often convey a critical or contrary opinion. Likes are surely supportive of the opinion expressed in the tweet, but with a lower level of engagement, because they do not actively spread that opinion. Before the introduction of retweets, Bakshy et al. (2011) had employed reposts as a measure of influence. For those reasons, we deem that the count of retweets is the most relevant basic metric that should be adopted to measure influence. Riquelme et al. have provided an exhaustive survey of influence measures in Twitter, proposing a classification into the following four categories (Riquelme and González-Cantergiani, 2016): General; Based on metrics or Page Rank, Topical-sensitive; and Predictive.

The class of general measures of influence collects centrality measures defined for the general class of social networks (closeness and betweenness) and the H-index, borrowed from the field of citation analysis in scientific communities. Closeness employs the average distance on Twitter's graph and has been proposed as a measure of influence for social networks in general in Hajian and White (2011). The betweenness measures the capability of a node in a social network to be an intermediary in the relationship between two other nodes, being a passage point on the paths connecting the two nodes (Hajian and White, 2011). Both have been employed in Twitter, e.g., for the directed graph resulting from the twitterer-follower relationship in financial networks by Yang et al. (2015). The H-index can be redefined for Twitter as the maximum value h such that h tweets by the same twitterer have been replied to, retweeted or liked (according to the relationship of choice) at least h times. The H-index has been employed by Razis and Anagnostopoulos (2014) and Romero et al. (2011).

The second category defined by Riquelme and Gonzalez is based on basic metrics and adaptations of the PageRank algorithm. This category comprises 18 metrics. The Retweet impact considers both the number of retweets of the original post and the number of re-twitterers (Pal and Counts, 2011). Similarly, the Mention Impact combines four metrics related to mentions (number of mentions to other users by the author of the original tweet, number of users mentioned by the author, number of mentions to the author by other users, number of users mentioning the author). The number of metrics that are adaptations of PageRank is quite large, including UserRank (Majer and Šimko, 2012) and Influence Rank (Hajian and White, 2011).

Riquelme and Gonzalez also define a set of topical-sensitive measures, which tries to identify twitterers who are influential on a specific topic. Their use implies an analysis of the tweet's contents. They are often used after a preliminary screening of tweets has been carried out, keeping just those tweets concerning the topic of interest.

Finally, the last group of influence measures classified by Riquelme and Gonzalez is the predictive one, which includes just seven measures. The aim of these measures is to predict the most influential twitterers in the future. Their complexity and computational burden are typically higher than the measures of other classes. Examples are the Time Network Influence Model, which uses a probabilistic generative model (Zhaoyun et al., 2013), and the ReachBuzzRank, which employs a Hidden Markov Model (Simmie et al., 2014).

Influence measures have also been proposed for special classes of social networks. Notably, Kempe et al. (2003, 2015) have considered the problem of selecting the most influential nodes for viral marketing strategies. They have introduced the notion of *active node*, where activation is akin to being influenced and is dedicated by the activation status of the neighbour nodes. Leskovec et al. (2006) have instead considered a recommendation network, where influence is recognized if a purchase has taken place.

Though Twitter offers the ability to comment on a post before retweeting it,[4] we have decided to retrieve just the uncommented ones. Retweeting a tweet with no added comments is a sign of full support of the twitterer's opinion, hence an uncritical spread of his/her influence. Hence, we use the number of retweets to measure the twitterer's influence.

Here, we use retweets to measure the influence of somebody's opinion on Twitter on other twitterers. We build a retweet network, designated in Kumar et al. (2014) as a major tool to analyse the influence of twitterers. The use of Twitter influence networks like the one we analyse here is widely supported in the literature; see, e.g. Riquelme and González-Cantergiani (2016), Tinati et al. (2012), Bisconti et al. (2019), Bode and Dalrymple (2016), Simmie et al. (2014). Zhang et al. (2015) underline the tight relationship between retweeting behaviour and social influence. The use of microblogging networks, particularly Twitter, has been recognized by Stieglitz and Dang-Xuan (2012) as an ideal mechanism to spread and reinforce one's political opinions. Anger and Kittl (2011) have examined the number of retweets and the number of followers as indicators of influence on Twitter. In particular, they have concluded that retweets with no comments express compliance (public agreement, with any disagreeing thoughts and opinions being kept to oneself) or internalization (the process of publicly and privately accepting a belief or behaviour), while retweets with comments may be employed to express disagreement. Riquelme and González-Cantergiani (2016) have conducted an exhaustive survey of the measures of influence on Twitter. In particular, the number of retweets ranks first by the number of papers where it is used. In our retweet network, each node represents a twitterer. We draw an edge from node A to node B if A has been retweeted by B. The weight of the edge is the number of retweets. In the end, we obtain a weighted directed network. The out-degree of a node measures the associated twitterer's influence.

In Fig. 2, we show an example of the resulting retweet network for one observation week. In order to avoid excessive garbling, we have arranged it by degree so that the most central nodes are located in the inner core of the graph. We have also removed the edges with weight 1 (i.e., twitterers who are retweeted just once) from the picture. We see that there are very few central nodes and many peripheral ones, i.e. a tiny core of very much retweeted twitterers (influencers) and a much larger number of influenced twitterers.

We must, however, recognize the possibility of including tweets that, despite containing the words *wind* or *power* or *energy*, are not relevant to our actual theme, i.e., the use of wind to get electrical power.

We need to eliminate as many non-relevant tweets as possible. In order to arrive at a set of relevant tweets, we employ a semi-automatic procedure based on hashtags and the co-occurrence principle (Türker and Sulak, 2018; Wang et al., 2016; Yan et al., 2013; Ben-Lhachemi and Nfaoui, 2018). The procedure for the selection of relevant tweets goes through the following steps:

[4] See https://www.digitalinformationworld.com/2020/09/twitter-rebranded-retweets-with-comment-with-quote-tweets-for-all-users.html?m=1.

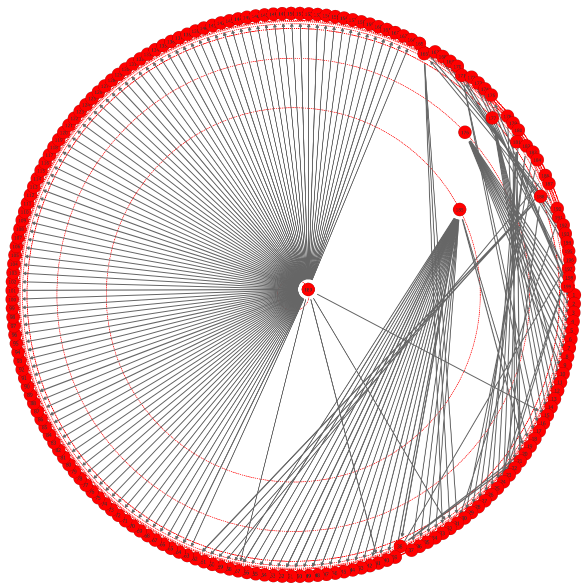

Fig. 2. Retweet network arranged by degree centrality (week ending on January 13, 2020).

(a) Select the k most frequent hashtags in the dataset of interest;
(b) Identify the hashtags that are surely relevant for our topic and form a group with them (say, Group X);
(c) Form a group with all the other hashtags (say Group Y);
(d) Examine all tweets containing Group Y hashtags but not Group X ones, and move their hashtags to Group X if those tweets are relevant;
(e) Assign to Group X all the hashtags co-occurring with Group X hashtags (this is not done iteratively, but just once for each Group X hashtag).

At this point, we have the Group X of relevant hashtags. We can consider a tweet as relevant if it contains any hashtag included in Group X. The number of relevant tweets by month is depicted in Fig. 3, for a total number of 3,875,308 tweets. The total number of tweets collected through twitteR is 1,573,360 whereas the total number of posts collected through rtweet is 2,301,948. Among the latter, 56,236 are quoted tweets (i.e. retweets with an added comment) whereas all the others are simple uncritical posts. The package twitteR, instead, does not allow distinguishing between quoted tweets and simple retweets.

Lastly, we used the R package igraph to build and analyse the retweet networks. In Table 1 we listed the features of the retweet networks month by month.

3. Results

In this section, we discuss the results obtained through the application the social network methodology introduced in previous sections. We consider the following issues, that are related to the research questions described in the Introduction:

- the influence of individual twitterers on the community, by reach and intensity;
- the concentration of influence;
- the composition of influencers, by reach and nature;
- the impact of energy-related events of retweeting activity.

3.1. Influence over the community

The first issue we wish to address is understanding how widespread the influence of any single twitterer is upon the community. As recalled

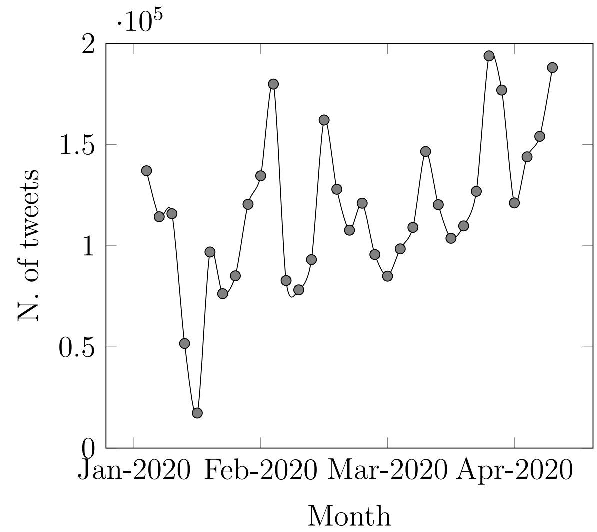

Fig. 3. Number of relevant tweets by month.

Table 1
Number of nodes and edges for each of the networks built month by month.

2019-11	1285	1155
2019-12	77236	91955
2020-01	59663	69716
2020-02	59690	71280
2020-03	26561	29509
2020-05	53133	60934
2020-04	10675	11319
2020-06	38653	43197
2020-07	46264	49718
2020-08	67646	74937
2020-09	77100	86080
2020-10	101797	117613
2020-11	38365	41389
2020-12	35661	40043
2021-01	44248	47993
2021-02	85182	100921
2021-03	58836	68932
2021-04	51101	56949
2021-05	60276	69006
2021-06	43905	48196
2021-07	39957	44497
2021-08	52489	57284
2021-09	52040	60739
2021-10	72659	87606
2021-11	58882	67614
2021-12	49801	56576
2022-01	50544	59575
2022-02	61844	71567
2022-03	88333	111238
2022-04	88336	109381
2022-05	58507	68106
2022-06	74977	91247
2022-07	79756	94487
2022-08	96387	120577

in Section 2, we have adopted the most established way of measuring influence on Twitter, i.e., through retweeting behaviour. It is natural to adopt metrics based on retweets. Riquelme and González-Cantergiani (2016) mentions three metrics associated with retweeting. The third metric is the number of users who have retweeted the author's tweets, which can be assumed to measure the breadth of influence of each twitterer. In our retweet network, that influence is then described by the outdegree of that twitterer. We consider first the twitterers who exert a minimal influence, i.e. those who influence just one other twitterer. In Fig. 4, we report the percentage of twitterers being retweeted just by another twitterer over the 34 months of our investigation. We see

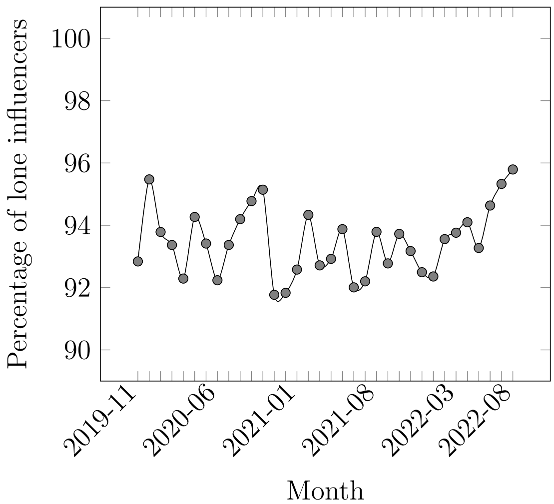

Fig. 4. Percentage of lone influencers by month.

that this percentage is very high (though fluctuating): it is always above 90% with a peak of nearly 96%. The bulk of twitterers influence just another twitterer (*lone influencers*).

Instead, the remaining twitterers exert a wider influence. We now take a look at the overall distribution. In Fig. 5, we report the average cumulative complementary frequency distribution of twitterers (accfd). Precisely, indicating by f_{ij} the relative frequency of the nodes of outdegree j in month i, the accfd is

$$e_j := \frac{1}{34}\sum_{i=1}^{34}\sum_{k\geq j} f_{ik}. \tag{1}$$

We see that the experimental data follow a roughly linear decreasing trend (on a logarithmic scale) for the lowest range of outdegrees but then points markedly downwards for higher values of the outdegree. We can identify two classes of influencers associated with the two trends, depending on the power of the influencers. We name those two classes as medium influencers (influencing roughly up to 12–13 other twitterers) and high influencers. Together with the experimental curve, we show three fitting models that have provided the best fit over 90 models. All three models fit the real data well (exhibiting a correlation coefficient of 0.999), but the Weibull one deviates a bit on the high influencers (large outdegree values). Though the log-logistic and the Hill models rank pretty equal, the former employs three parameters, while the Hill model employs four. Since we prefer more parsimonious models, the log-logistic model appears as the best, being capable of describing the presence of both classes of influencers:

$$\hat{e}_j^{(\text{log-logistic})} = \gamma + \frac{1-\gamma}{1+e^{-\alpha-\beta\ln j}}, \tag{2}$$

with $\alpha = -1.989$, $\beta = -0.9812$, and $\gamma = -6.872 \cdot 10^{-3}$.

What is the net result of the presence of lone influencers, medium influencers, and high influencers? The average outdegree in Fig. 6 tells us that the average twitterer influences between 1 and 1.3 other twitterers on average.

3.2. Influence intensity

In Fig. 5, we have seen how many twitterers a single twitterer may influence. We could call that a measure of *horizontal* influence. We are also interested in measuring the *vertical* influence, i.e., how many times a twitterer is retweeted by a single follower. Again, this is listed by Riquelme and González-Cantergiani (2016) as one of the metrics associated with retweeting, namely the number of retweets accomplished by the author. Here we choose to measure that quantity

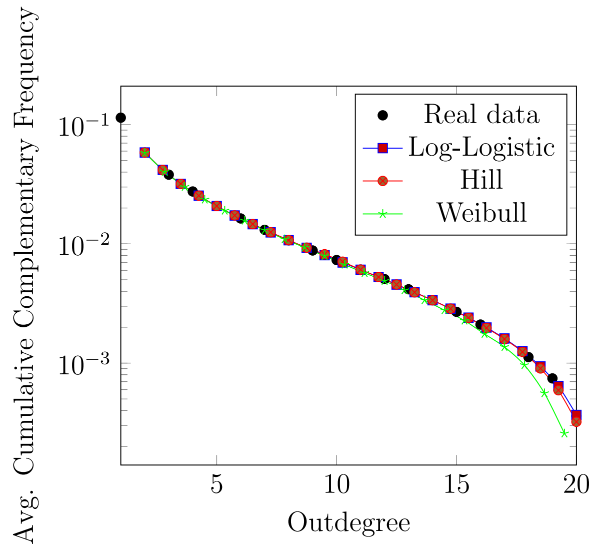

Fig. 5. Complementary cumulative distribution of nodes outdegree.

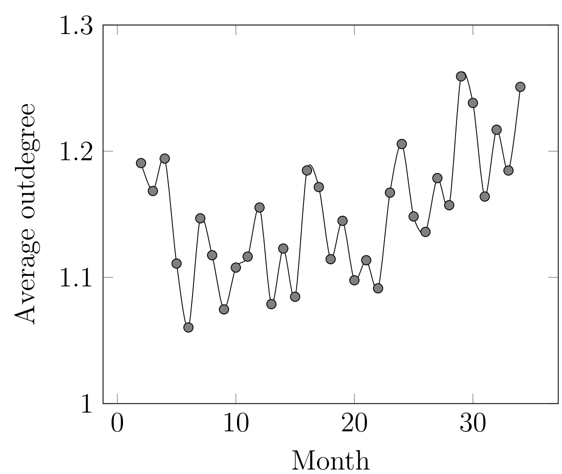

Fig. 6. Average number of influenced twitterers per influencer.

per retwitterer. In our retweet network, that quantity is represented by the weight of edges: a larger weight means a heavier influence. In Fig. 7, we see that most twitterers (91.7% for the entire temporal range) exert minimal influence on others (i.e., the weight of their edges is just 1), though there is a small minority of twitterers who are retweeted more frequently.

However, that small minority of heavy influencers is not enough to tilt the average influence significantly upwards. In Fig. 8, we see that the average influencer is retweeted slightly more than once.

3.3. Concentration and top influencers

Both in Figs. 5 and 7, we have seen that there is a small minority of heavy influencers. We now wish to derive a single index to measure how much the capability of influencing other twitterers is concentrated in the hands of a few influencers. For this purpose, we employ an index that, though born in the domain of industrial economics, has recently been applied to measure concentration phenomena in social networks, namely the Hirschman–Herfindahl Index (HHI) employed, e.g., in Colladon and Naldi (2019), Naldi (2019).

The HHI for the generic month i is defined as

$$\text{HHI}_i := \sum_{k=1}^{n_i}\left(\frac{q_{k,i}}{Q_i}\right)^2 = \sum_{k=1}^{n} r_{k,i}^2 \tag{3}$$

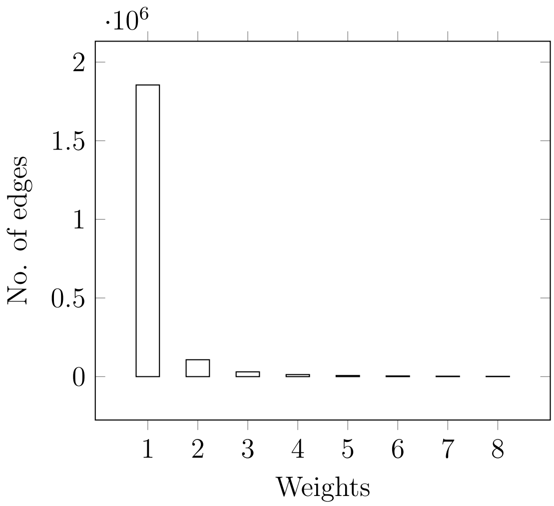

Fig. 7. Distribution of edges by their weight.

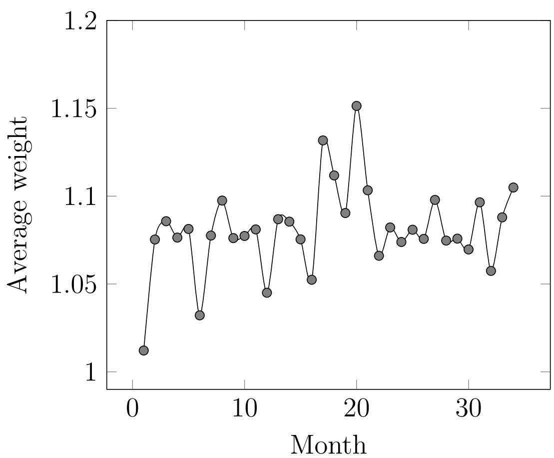

Fig. 8. Average edge weight in the retweet network.

where n_i is the number of retweeted twitterers in month i, q_{ki} is the number of time the influencer k is retweeted, $k = 1, 2, \ldots, n_i$, Q_i is the total volume of the retweets, and $r_{k,i}$ is the share of retweets of the influencer k. For convenience, the frequencies q_{ki} and the relative frequencies $r_{k,i}$ are sorted in decreasing order. The HHI takes values in the $[1/n_i, 1]$ range, with values close to 1 representing scenarios close to a monologue (i.e., just one twitterer being retweeted), and values close to the lower bound representing a more pluralistic discussion. As can be seen in Fig. 9, the degree of concentration fluctuates wildly, but in several months it exhibits a strong concentration (values close to 1 represent a quasi-monopoly). The additive nature of the HHI makes it easy to isolate individual contributions to the index; if we plot the contribution of the top influencer (i.e., r^2_{1i}), we see, in that same picture, that it is actually responsible for the near totality of the HHI value in the presence of strong concentration (and for a substantial proportion of it when the concentration is lower). The concentration peaks are then due to the success of the top influencer alone.

In Table 2, we can see the nicknames of the top 10 influencers over the 34 months and observe how the top influencer got many more retweets than its runner up in the months of larger concentration.

Excluding the first and the last month, where the data collected is only partial because it does not cover the entire month, the peaks in Fig. 9 are achieved in months 6, 11 and 33. If we compare them with the top influencers listed in Table 2, we have a major key to read the

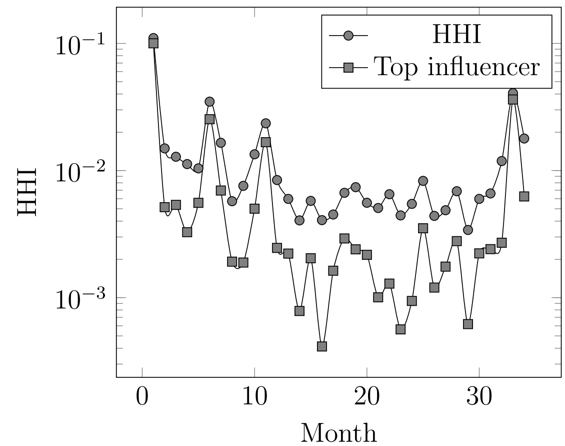

Fig. 9. Herfindahl–Hirschman Index (HHI).

behaviour depicted in Fig. 9. The months 2020-04, 2020-09 and 2022-07 are the months in which the gap between the first and the second is greater (in percentage terms) and most of the other positions in the top 10 are comparable to each other.

3.4. Who is behind top influencers

Among the few very much retweeted twitterers, the Top 10 are reported in Table 2 month by month. But who are they? Are they activists? Or do they work for a company? Or are they scientists? Knowing who is behind their screen names may help us uncover their intentions in writing posts and understand people's preferences. Hereafter we disclose their roles in society, starting with those appearing more often in the Top 10. To accomplish this task, we checked the Twitter bio of each most retweeted user; the Twitter bio of user x can be defined as a summary of x's Twitter profile.[5] Furthermore, in the bio, there may be links to the official websites of the companies or institutions represented on Twitter by the account. By examining the Twitter bio, we can establish whether an account belongs to a company representative or a private person. In particular, we used the information contained in the bio to go back to personal or institutional websites, LinkedIn profiles and even the Wikipedia pages of each user. As we can see in the following list, influencers able to stay in the Top 10 for more than 3 months have non-anonymous accounts and their information are easily retrieved on the web.

- In the Top 10 for 27 months:
  - @MikeHudema is the Twitter account of Mike Hudema, a climate campaigner with Greenpeace Canada, living on Coast Salish Territories (Vancouver).
- In the Top 10 for 15 months:
  - @arikring is the Twitter account of Arik Ring. He is an energy consultant and works on solar and renewable energies in general.
- In the Top 10 for 13 months:
  - @AlexEpstein is the Twitter account of Alexander Epstein, an American author and commentator who advocates for fossil fuels.

[5] See the suggestions by Twitter on https://help.twitter.com/it/managing-your-account/how-to-customize-your-profile.

Table 2
Top 10 influencers (retweets).

2019-11		2019-12		2020-01		2020-02		2020-03		2020-04		2020-05	
names	retweets	names	retweets	names	retweets	names	retweets	names	retweets	names	retweets	names	retweets
CNN	370	MikeHudema	7094	MikeHudema	5545	MikeHudema	4389	MikeHudema	2381	thejessicadore	1859	GovMikeHuckabee	5478
cnni	55	atrupar	4804	CNN	3807	ShellenbergerMD	4138	eastantrimmp	973	EcoSenseNow	695	jwlarrabee	4950
ScienceNews	42	thugsRbadMK	3625	changemation	2859	TrevorSidogi	3006	PaulEDawson	676	lamphieryeg	382	MikeHudema	2297
arikring	32	mmgh_	3244	cnni	2496	AmandaOwen8	2706	ParkerMolloy	606	MikeHudema	372	davidluhnow	1294
ajplus	28	ericswalwell	3076	EcoSenseNow	1271	PaulEDawson	1593	prageru	591	CoryBMorgan	250	lamphieryeg	996
lamphieryeg	28	mmpadellan	2788	latimeralder	1017	OurCoopPower	1076	KeiraSavage00	590	renew_economy	222	MaximeBernier	971
business	26	CNN	2235	arikring	982	dcexaminer	978	coco14391	494	TheBabylonBee	218	LadyVelvet_HFQ	765
MikeHudema	26	matthaig1	2157	rashtrapatibhvn	944	tveitdal	918	arikring	458	DrSimEvans	203	arikring	656
dbirch214	26	IdaAuken	1579	mzjacobson	929	RealMarkLatham	791	Judith_Char	420	NovaTruly	187	beneltham	643
ina_mochiii	25	arikring	1504	IRENA	778	arikring	656	Barbarajdurkin	372	ShellenbergerMD	178	Concealcarrygrl	634

2020-06		2020-07		2020-08		2020-09		2020-10		2020-11		2020-12	
names	retweets	names	retweets	names	retweets	names	retweets	names	retweets	names	retweets	names	retweets
MikeHudema	2077	MikeHudema	2325	LunionSuite	5714	wonderofscience	12027	pbhushan1	6097	SenSanders	2120	MikeHudema	1218
mwarv	1295	tiwarymanoj	2123	ShellenbergerMD	4898	BrianRoemmele	4292	narendramodi	4264	MikeHudema	1519	AskAnshul	784
arikring	1133	tribelaw	1594	davidfrawleyved	3163	MikeHudema	2929	AdamBienkov	4086	arikring	738	CaslerNoel	767
ddale8	879	Jhanzaib_S	1416	DanCrenshawTX	2120	atrupar	2375	thenoelmiller	2834	TechnologyClips	700	BJP4India	668
business	678	UNFCCC	1037	MikeHudema	2009	ddale8	2141	gtconway3d	2785	climate	691	arikring	642
Iberdrola_En	553	funder	839	wef	1223	melanatedmomma	1941	GeorgeMonbiot	1849	mzjacobson	621	AssaadRazzouk	639
ewarren	486	arikring	799	Julez_Norton	1123	MJoelFranklin	1540	drvox	1804	wef	522	mzjacobson	540
tylerwhat16	480	esglaude	561	SpaceCityWX	1035	wef	1444	climate	1524	ZackBornstein	460	prageru	528
elonmusk	480	DanielTurnerPTF	524	IRENA	948	DrGauravGarg4	1423	MikeHudema	1320	prageru	428	wef	480
Reuters	458	SGirardau	467	mkraju	881	DOTA2	1302	KirenRijiju	1262	Greenpeace	418	laurenboebert	450

2021-01		2021-02		2021-03		2021-04		2021-05		2021-06		2021-07	
names	retweets	names	retweets	names	retweets	names	retweets	names	retweets	names	retweets	names	retweets
dcwoodruff	2332	EngineringVids	2158	rssurjewala	3148	laurenboebert	3422	blockfolio	3685	NPC_INDIA_GOV	2586	MikeHudema	1557
MikeHudema	1200	kajalverma0107	1874	MikeHudema	1317	donwill	1203	Windzeit3	2622	PaulEDawson	1224	PaulEDawson	1349
MikeLoychik	1064	AlexEpstein	1619	GretaThunberg	1198	JoshNBCNews	1099	bennyjohnson	1747	AdamSerwer	1151	AlexEpstein	1153
kitextech	986	BjorkBrodern	1602	SecGranholm	979	arikring	1096	reveusehun	1414	Iberdrola_En	839	arikring	927
SenateDems	805	DrEricDing	1453	KateSullivanDC	945	GOPChairwoman	1024	MikeHudema	1364	ShellenbergerMD	828	engineers_feed	817
arikring	743	NPR	1430	kylegriffin1	859	MikeHudema	964	PPathole	1288	gsuberland	796	Iberdrola_En	710
AssaadRazzouk	739	RexChapman	1342	PolitiFact	805	mvmeet	914	DocumentingBTC	1075	milkteus	746	broch101	612
drvolts	737	LisPower1	1319	amitmalviya	790	AlexEpstein	871	GavinNewsom	1013	AlexEpstein	663	PGATOUR	594
wef	653	TexasTribune	1212	ShellenbergerMD	775	helloiammariam	841	arikring	1010	tveitdal	500	KeillerDon	577
mzjacobson	546	ArtiSha10991645	1082	nytimes	755	Quicktake	835	MollyJongFast	912	ScottAdamsSays	487	fgcabezadevaca	529

2021-08		2021-09		2021-10		2021-11		2021-12		2022-01		2022-02	
names	retweets	names	retweets	names	retweets	names	retweets	names	retweets	names	retweets	names	retweets
JackPosobiec	2193	duty2warn	1559	fake_biden	2887	PeterSweden7	4332	johnredwood	2108	johnredwood	2739	mcannonbrookes	4058
AdamBienkov	1844	JavierBlas	1304	AlexEpstein	2766	JohnBasham	3315	ThePlumLineGS	1976	BjornLomborg	1659	bambibaekyoong	1726
zarahsultana	1826	disclosetv	1229	briantylercohen	2165	PeterDClack	1857	DanielAndrewsMP	787	WhiteHouse	1196	Stonekettle	1701
MikeHudema	1553	Nigel_Farage	1219	POTUS	1646	MikeHudema	1189	BetoORourke	771	MikeHudema	1194	engineers_feed	1539
Iberdrola_En	1181	Iberdrola_En	1138	YoukuOfficial	1513	fabre_jaime	950	MikeHudema	687	themetroverse	928	BetoORourke	1310
ReedTimmerAccu	1130	AlexEpstein	1053	WhiteHouse	1344	Iberdrola_En	904	SteveatTH	683	AlexEpstein	821	DrSimEvans	1116
MeghUpdates	859	mattwridley	965	AusIndiMedia	1133	EcoSenseNow	828	BjornLomborg	615	JavierBlas	692	mikegalsworthy	1002
AlexEpstein	686	GBNEWS	838	gautam_adani	1132	Rainmaker1973	565	pleh_mann	612	Iberdrola_En	686	MikeHudema	986
PaulEDawson	686	CMOGuj	812	mattwridley	1098	SecDebHaaland	530	poweroftheseas	547	EcoSenseNow	507	ErikSolheim	860
shen_shiwei	623	JunkScience	741	MikeHudema	996	AlexEpstein	527	Iberdrola_En	534	arikring	503	darrengrimes_	806

2022-03		2022-04		2022-05		2022-06		2022-07		2022-08	
names	retweets	names	retweets	names	retweets	names	retweets	names	retweets	names	retweets
elonmusk	2978	OccupyDemocrats	5524	MikeHudema	3664	POTUS	5017	PeterSweden7	19557	BeckettUnite	10534
RichardJMurphy	1917	joncoopertweets	2920	stats_feed	2548	antonioguterres	4920	michaelholder	3116	PeterSweden7	8160
uk_domain_names	1899	anandmahindra	2593	AlexEpstein	1237	thewire_in	3608	JamesMelville	3053	MikeHudema	6658
BrianGitt	1480	jairbolsonaro	2185	BillGates	1146	pbhushan1	3223	BrianGitt	1736	BrianGitt	5878
ntsafos	1324	ShellenbergerMD	1942	minna_alander	1076	briantylercohen	2907	DanielTurnerPTF	1446	POTUS	2859
RWPUSA	1191	BeckettUnite	1603	antonioguterres	1010	ashoswai	1866	AlexEpstein	1359	ACTBrigitte	2814
joncoopertweets	1101	JohnLeePettim13	1299	briantylercohen	1001	SquizzSTK	1646	WhiteHouse	1318	MetaArcata	2040
AlexEpstein	1083	ToryFibs	1276	JunkScience	968	RepMTG	1504	ProfStrachan	1230	RepMTG	1891
reallovepunk	983	johnredwood	1223	BrianGitt	957	KTRTRS	1437	davenewworld_2	1107	AlexEpstein	1654
johnredwood	955	BrianGitt	1194	shelbywebb	812	BetoORourke	1402	hkakeya	1104	JolyonMaugham	1602

- In the Top 10 for 8 months:
  – @Iberdrola_En is the account of Iberdrola, a world-leading company in renewable energy, with a history of over 170 years. On its Twitter bio, the company declares: *today, we are an international company focused on sustainability*.
- In the Top 10 for 6 months:
  – @ShellenbergerMD is the account of Michael D. Shellenberger, an American author whose Wikipedia page states: *(his) writing has focused on the intersection of climate change, the environment, nuclear power, and politics, and more recently*

Table 3
Who are the Top influencers?

Class	Members	Total no. of retweets
Climate activists	@MikeHudema, @EcoSenseNow, @PeterSweden7	106,858
Journalism	@CNN, @AlexEpstein, @ShellenbergerMD, @briantylercohen	56,779
Energy and financial consultants	@arikring, @BrianGitt, @PaulEDawson	44,045
Politicians	@johnredwood, @BetoORourke, @POTUS	26,164
Leading international or governmental agencies, associations, organizations	@wef, @WhiteHouse	13,758
Companies	@Iberdrola_En	13,602
Academic experts, scientists	@mzjacobson	12,765
Generalist individual twitterers	@lamphieryeg, @prageru	9,212

on how he believes progressivism is linked to homelessness, drug addiction, and mental illness.

- In the Top 10 for 5 months:
  - @wef stands for the *World Economic Forum*, the international organization for public–private cooperation.
  - @BrianGitt is the Twitter account of Brian Gitt. The description given by his web-page introduces him as a financial specialists for investors in the energy sector.
  - @PaulEDawson is the Twitter account of Paul Dawson. He is a writer on climate solutions based in Glasgow. His newsletter and book club, Climate Solutions, provides subscribers information on climate.
- In the Top 10 for 4 months:
  - @mzjacobson is the Twitter account of Prof. Mark Z. Jacobson (Stanford University), an expert in Civil and Environmental Engineering.
  - @EcoSenseNow is the Twitter account of Patrick Moore, former activist, and past president of Greenpeace Canada.
  - @johnredwood is the Twitter account of Sir John Alan Redwood, a British politician member of the Conservative Party.
- In the Top 10 for 3 months:
  - @BetoORourke is the Twitter account of Beto O'Rourke; he is the Democratic nominee for the 2022 Texas gubernatorial election.
  - @briantylercohen is the Twitter account of Brian Tyler Cohen, an American actor, blogger, podcaster and journalist.
  - @CNN is the celebrated multinational cable news channel.
  - @lamphieryeg, @prageru seem to be generalist users
  - @PeterSweden7 is the Twitter account of Peter Sweden, an activist that we could define at least controversial for his conspiratorial positions.
  - @POTUS is the President Biden's account.
  - @WhiteHouse is the Twitter account of White House.

In Table 3 we classified these screen names according to their role, showing the total number of retweets gained by each class. The class of climate activists is the top one and is represented by three twitterers, with an astounding number of retweets. Anyway they do not all seem to be on the same stance on climate change and renewables. The polarization around a small number of different opinions concerning these topics has been recently highlighted in the literature (Iacomini and Vellucci, 2021). Journalists are distant runners-up, with organizations as well as energy and financial consultants being an even more distant set of influencers. Generalist individual twitterers are the least retweeted class.

3.5. Influence turnover

So far, we have assessed the presence of heavy influencers, as measured either by the number of twitterers they influence or by how many retweets they receive. In Table 2, we have seen that some of the top influencers are constantly present. A natural question to answer is then: Is there a core of steady influencers, or do influencers change over time? In order to answer that question, we define some quantities. We denote the set of twitterers at month t by $\mathcal{V}_t$. For the ensemble of n observation months, we introduce the proportion SIR of steady influencers, i.e. the proportion of influencers who are retweeted every month:

$$\mathrm{SIR} = \frac{\left|\bigcap_{t=1}^{n} \mathcal{V}_t\right|}{\left|\bigcup_{t=1}^{n} \mathcal{V}_t\right|}. \tag{4}$$

This ratio ranges between 0 and 1, with values closer to 1 meaning that a strong majority of twitterers are constantly influencing others. Of course, we do not expect it to be very large. Actually, in our case, we have SIR = 0.0001111146, meaning that constant influencers account for 0.01% of the overall set of twitterers.

On the other hand, we can measure how the set of influencers change month by month, as defined by the turnover rate (i.e., the proportion of influencers at month t being retweeted again in the next month $t+1$)

$$\mathrm{TR} = 1 - \frac{\left|\mathcal{V}_t \cap \mathcal{V}_{t+1}\right|}{\left|\mathcal{V}_{t+1}\right|} \tag{5}$$

The monthly behaviour of the turnover is depicted in Fig. 11. We see that the turnover fluctuates wildly; it is always larger than 0.7 (meaning that over 70% of influencers are new) but, removed the first month which is only partial, it can reach values as high as 90% (month 6), which means that just 10% of influencers keep on influencing in the coming month.

3.6. Events

The discussion on Twitter may be fuelled by what goes on in the real world, e.g. some events of particular interest for energy topics. For the sake of simplicity, we decided to focus only on the first 14 weeks of our sample. Here we have considered two major events, namely the World Economic Forum (which is, by the way, one of the most popular contributors to the topic) and COP25 (the 2019 United Nations Climate Change Conference). Those events were held respectively in January 2020 (week 8) and December 2019 (weeks 1 and 2). In order to examine their influence on Twitter, we tracked the number of tweets containing the strings *WEF* or *World Economic Forum* or *COP25* during the weeks following those events. An increase in the number of such tweets would show that those events quite drove the discussion on Twitter. In Fig. 10, we see that both events contributed significantly to the discussion on Twitter. However, while the interest

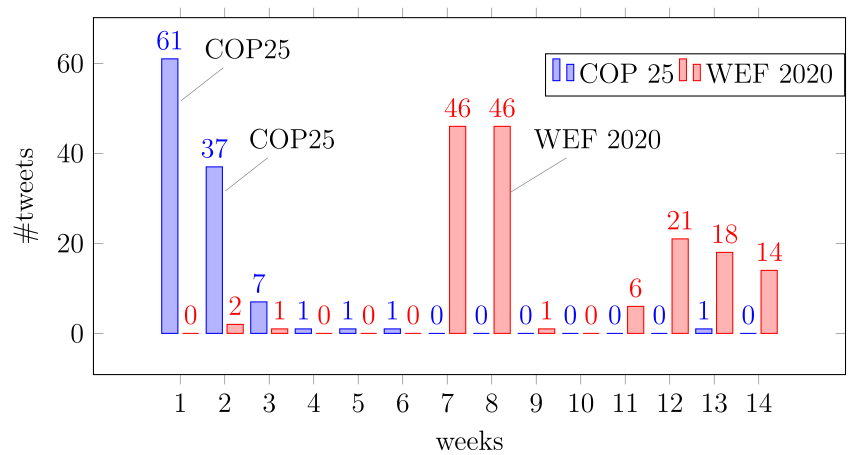

Fig. 10. Interest in major energy-related events.

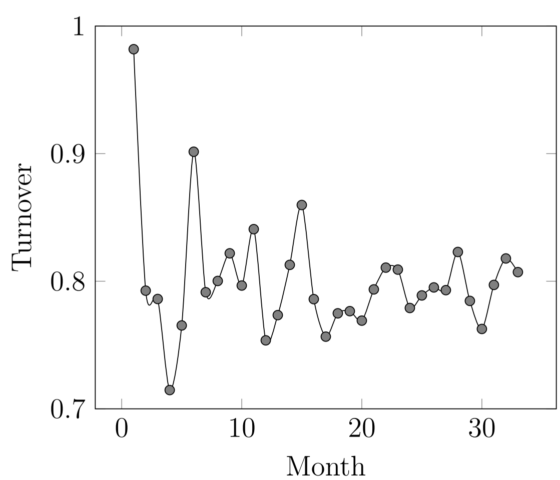

Fig. 11. Turnover.

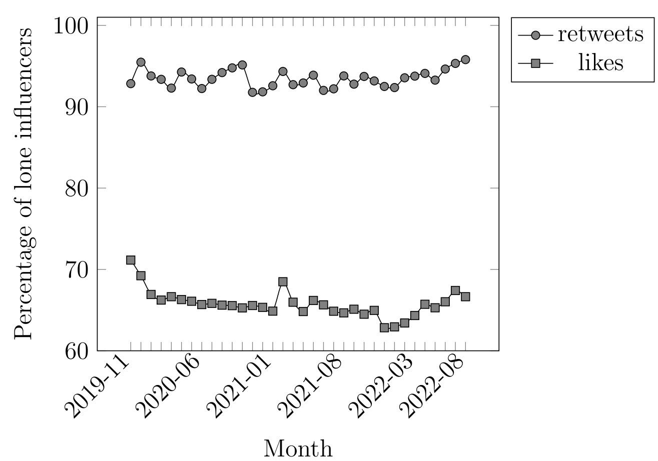

Fig. 12. Likes vs retweets: lone influencers by month.

on COP25 lasted for a couple of weeks, the interest for WEF sprung up again in weeks 1 through 14 after a similar two-week initial period. Many tweets in weeks 7–8 were retweets of a single tweet posted by *@vankapro*, spreading the news that Denmark had obtained almost half of its electrical power from the wind. Tweets concerning WEF published from week 12 to 14 do not concern events related to the last annual meeting in Davos but seem to mention some points discussed in it (, e.g. environment and renewable energies). This suggests a more lasting impact of WEF on public debate about wind energy.

3.7. Likes vs retweets

On Twitter, when someone sees an interesting tweet, they can show they like it by tapping the heart icon. As more people like a tweet, more people will see that sign of appreciation. As we can read on Twitter manual[6]: "Liking a Tweet tells the world and the person who wrote it that you enjoyed, agreed with, or admired it". Likes are then a further sign of influence: the more likes a tweet receives, the more supported the opinion contained in the tweet is.

In this section, we perform some statistical analyses of Twitter users based on the number of likes received, which adds to the influence analysis carried out through retweets. In Table 4, we can see the nicknames of the top 10 influencers over the 34 months based on the likes they have gained. As in Table 2, we observe that some of the top influencers are constantly present.

Despite the presence of much "liked" twitterers, if we look at the number of likes received by each user, we notice that lone influencers (i.e. those who received just one like or no likes at all) still form the bulk of twitterers. In Fig. 12, we can see that the percentage of twitterers who received a maximum of one like over the 34 months of our investigation is quite high. The average number of likes depicted in Fig. 13 tells us that a twitterer receives between 3 and 16 likes on average.

In Fig. 14, we see that most twitterers gain minimal likes from others (i.e., their posts receive just a few likes at most), while a small minority of twitterers receive a large number of likes. In other words, the distribution of likes exhibits concentration as we observed for retweets.

In order to assess the degree of concentration, we can estimate the HHI index (3) over the observation months for likes instead of retweets. Now, n_i is the number of twitterers who gained at least one

[6] https://help.twitter.com/en/resources/twitter-guide/topics/how-to-get-started-with-twitter/how-to-like-a-tweet-on-twitter-twitter-help

Table 4
Top 10 influencers (likes).

month 1		month 2		month 3		month 4		month 5		month 6		month 7	
names	likes	names	likes	names	likes	names	likes	names	likes	names	likes	names	likes
ScienceNews	183	ericswalwell	24701	CNN	16395	ShellenbergerMD	14502	MikeHudema	5230	thejessicadore	8379	GovMikeHuckabee	19737
Brink_Thinker	180	matthaig1	18441	MikeHudema	9887	SenSanders	11778	ParkerMolloy	3394	TheBabylonBee	2096	jwlarrabee	13362
mzjacobson	73	MikeHudema	14618	rashtrapatibhvn	9709	AmandaOwen8	8623	Florent_ATo	2531	CoryBMorgan	978	LadyVelvet_HFQ	8074
NCConservation	62	Iberdrola_En	10348	changemation	9227	MikeHudema	6630	eastantrimmp	1956	lamphieryeg	911	beneltham	4920
sang1983	54	RexHuppke	10044	cnni	7795	TrevorSidogi	4626	prageru	1639	MikeHudema	507	MikeHudema	3940
quea_ali	45	atrupar	8505	ZackBornstein	4768	PaulEDawson	3157	Judith_Char	1434	ShellenbergerMD	495	lamphieryeg	2762
business	40	mmpadellan	8478	EcoSenseNow	2919	dcexaminer	2697	KeiraSavage00	1237	renew_economy	439	iFireMonkey	2345
hardenuppete	39	CNN	8244	MigunaMiguna	2579	RealMarkLatham	2590	PaulEDawson	1106	NovaTruly	360	MaximeBernier	2293
NWSBayArea	38	earlxsweat	7591	thehill	2099	subschneider	1915	HoodHealer	958	Goldwind_Global	334	rananth	2220
AstroCryptoGuru	29	thugsRbadMK	6634	mzjacobson	2019	tveitdal	1608	TheEconomist	918	EdwardJDavey	316	SHREKRAP	2083

month 8		month 9		month 10		month 11		month 12		month 13		month 14	
names	likes	names	likes	names	likes	names	likes	names	likes	names	likes	names	likes
NICKMERCS	9429	tiwarymanoj	7308	davidfrawleyved	14735	wonderofscience	49739	thenoelmiller	27498	SenSanders	19493	CaslerNoel	16739
elonmusk	7217	tribelaw	6075	ShellenbergerMD	12606	BrianRoemmele	13289	gtconway3d	25850	ZackBornstein	4238	AskAnshul	8702
Iberdrola_En	5540	MikeHudema	4755	LunionSuite	9900	ddale8	12858	pbhushan1	20638	MikeHudema	3301	laurenboebert	4761
ddale8	5185	Jhanzaib_S	2900	DanCrenshawTX	9631	atrupar	11933	Minecraft	19702	NewYorker	3110	TheBabylonBee	4530
MikeHudema	3788	funder	2633	siIver_wind	8852	melanatedmomma	8985	hasanthehun	9804	TechnologyClips	2663	siIver_wind	3231
mwarv	3034	esglaude	2535	mkraju	5117	DOTA2	6352	RealJamesWoods	8960	mzjacobson	2517	ChrisCuomo	3029
UberFacts	2386	UNFCCC	2337	engineers_feed	4119	MikeHudema	5730	JeffreeStar	8018	prageru	2228	prageru	2853
ewarren	2158	Total	2071	MattWalshBlog	3825	MaryHeglar	4260	ZacksJerryRig	7546	climate	2005	MikeHudema	2590
ashokgehlot51	1959	TheRaDR	2043	MusaliaMudavadi	3530	wef	3923	DeAnna4Congress	7405	JoelSsenyonyi	1708	BJP4India	2371
business	1888	DanielTurnerPTF	1977	wef	3212	Goldwind_Global	3074	KirenRijiju	6883	RealKevinNash	1595	Goldwind_Global	2115

month 15		month 16		month 17		month 18		month 19		month 20		month 21	
names	likes	names	likes	names	likes	names	likes	names	likes	names	likes	names	likes
dcwoodruff	21590	EngineringVids	10546	rssurjewala	10182	laurenboebert	11620	blockfolio	41101	Iberdrola_En	10829	Iberdrola_En	11456
EngineringVids	9995	RexChapman	9415	Merryweatherey	5936	Iberdrola_En	4564	PPathole	12093	AdamSerwer	4488	PGATOUR	11438
drvolts	3224	BjorkBrodern	7847	KateSullivanDC	5589	GOPChairwoman	3734	Iberdrola_En	6792	ScottAdamsSays	4359	engineers_feed	5714
MikeLoychik	3007	JasonMillerinDC	6063	elonmusk	5443	moonahoshinova	3159	MollyJongFast	6655	bunsenbernerbmd	3556	AlexEpstein	4420
MikeHudema	2781	LisPower1	5999	GretaThunberg	5309	shintiyahwijaya	2917	GavinNewsom	6590	AlexEpstein	2741	UberFacts	2771
SenateDems	2669	DrEricDing	5718	SecGranholm	4871	Quicktake	2879	VP	6203	HipHopNumbers	2651	MikeHudema	2677
JesseBWatters	2575	elonmusk	5393	kylegriffin1	4668	AlexEpstein	2682	bennyjohnson	5294	PaulEDawson	2071	PaulEDawson	2242
mcannonbrookes	2517	NPR	5250	nytimes	3993	donwill	2635	DocumentingBTC	4781	ShellenbergerMD	1803	electricalvides	2223
scogq	2271	chamath	3891	prageru	2824	ShashiTharoor	2514	engineers_feed	4657	milkteus	1683	shaun_vids	2046
deepolice12	1896	AlexEpstein	3871	Haggis_UK	2747	mvmeet	2266	BobPearce52	4509	gsuberland	1664	AlanKohler	1363

month 22		month 23		month 24		month 25		month 26		month 27		month 28	
names	likes	names	likes	names	likes	names	likes	names	likes	names	likes	names	likes
Iberdrola_En	10525	Iberdrola_En	16987	Iberdrola_En	13220	Iberdrola_En	16402	johnredwood	6847	johnredwood	12290	mcannonbrookes	21594
JackPosobiec	8019	Nigel_Farage	5817	gautam_adani	12619	PeterSweden7	11639	Iberdrola_En	6435	poweroftheseas	9624	engineers_feed	19033
zarahsultana	7050	duty2warn	4163	fake_biden	12458	vinniehacker	8139	poweroftheseas	6271	Renewables4ever	8599	windflowerlia	9782
MeghUpdates	5258	JavierBlas	4123	POTUS	12169	JohnBasham	6756	ThePlumLineGS	5641	WhiteHouse	6689	Stonekettle	8917
ReedTimmerAccu	3483	johnredwood	4002	AlexEpstein	8186	fabre_jaime	5138	DanielAndrewsMP	5271	BjornLomborg	3893	bambibaekyoong	7756
MikeHudema	2607	GBNEWS	3952	WhiteHouse	8185	PeterDClack	3846	BetoORourke	3329	AlexEpstein	2738	BetoORourke	7619
AlexEpstein	2191	AlexEpstein	3435	mattwridley	6603	BitcoinMagazine	3454	cleantechnica	3096	MikeHudema	2340	AyoCaesar	7217
poetastrologers	1854	DanCrenshawTX	3419	ImSpeaking13	5709	DivineHealer777	3238	marinebharat	2494	JavierBlas	2060	Iberdrola_En	5916
KetanJ0	1841	craigclemens	3301	briantylercohen	5474	Rainmaker1973	3111	BjornLomborg	2384	themetroverse	1864	mikegalsworthy	5258
AdamBienkov	1803	disclosetv	3067	AusIndiMedia	4699	alex_avoigt	3060	afneil	1839	Iberdrola_En	1818	darrengrimes_	4842

month 29		month 30		month 31		month 32		month 33		month 34	
names	likes	names	likes	names	likes	names	likes	names	likes	names	likes
elonmusk	78480	anandmahindra	43423	stats_feed	23233	briantylercohen	19530	PeterSweden7	69277	BeckettUnite	41972
ntsafos	11278	OccupyDemocrats	18490	minna_alander	15290	antonioguterres	18830	buitengebieden	11965	MikeHudema	19697
reallovepunk	9153	joncoopertweets	14045	MikeHudema	9707	POTUS	18109	michaelholder	11933	BrianGitt	17386
uk_domain_names	9066	Iberdrola_En	13792	stevenmarkryan	7024	pbhushan1	8560	WhiteHouse	7629	ACTBrigitte	16936
RichardJMurphy	6155	jairbolsonaro	7313	briantylercohen	6960	Iberdrola_En	8026	JamesMelville	7045	FastestPitStop	15727
biggestjoel	5714	johnredwood	6326	Iberdrola_En	4758	RepMTG	7850	Iberdrola_En	7016	POTUS	15312
RWPUSA	5525	hankgreen	5738	AlexEpstein	4694	SquizzSTK	7580	BrianGitt	5797	PeterSweden7	12534
BrianGitt	5504	RachelConnoll14	5648	italienby	3852	thewire_in	7030	AlexEpstein	5463	RepMTG	11106
darrengrimes_	5268	ShellenbergerMD	5505	antonioguterres	3446	KTRTRS	6571	DanielTurnerPTF	5068	elonmusk	11093
ianbremmer	4939	GitanasNauseda	5409	BrianGitt	3350	BetoORourke	6278	afneil	4663	NBSaphierMD	9536

like in month i, q_{ki} is the number of likes gained by the influencer k, $k = 1, 2, \dots, n_i$, Q_i is the total volume of the likes, and $r_{k,i}$ is the share of likes of the influencer k. For convenience, the frequencies q_{ki} and the relative frequencies $r_{k,i}$ are sorted in decreasing order. The HHI takes values in the $[1/n_i, 1]$ range, with values close to 1 representing scenarios with just one twitterer being liked, and values close to the lower bound a discussion where more people are admired for what they write. As can be seen in Fig. 15, the degree of concentration of likes is similar to that of retweets.

4. Conclusions and policy implications

Our analysis of the influence of the different stakeholders in a social medium like Twitter allows us to see who is leading the discussion on wind energy. By far and large, the most followed class

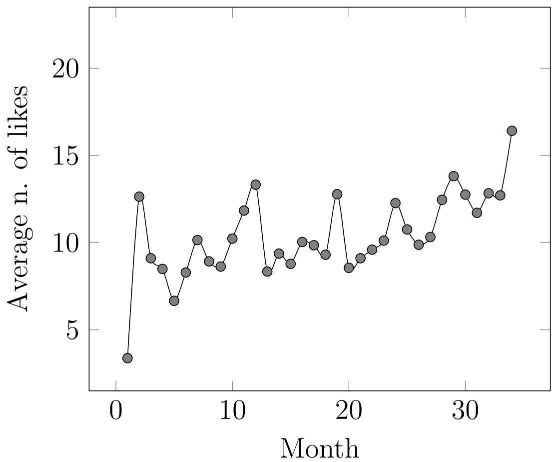

Fig. 13. Average number of likes per month.

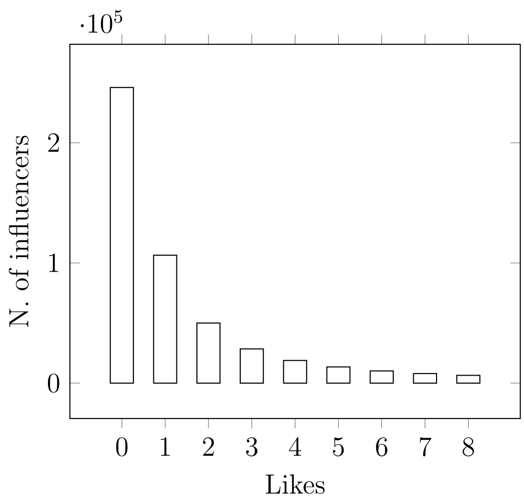

Fig. 14. Distribution of influencers by their achieved number of likes over the entire time span.

of opinion leaders is the climate activists, whose tweets have been retweeted nearly two times as much as the whole class of their runner-ups (journalists and scientific journalists). Companies exert a much lower influence, nearly on a par with generalist individual twitterers. Despite the major weight that the appraisal of economic benefits plays in the acceptance of wind turbines, as proven in Frantál (2015), the climate-driven opinions pushed forward by activists seem to prevail on Twitter. The rise of green influencers (*greenfluencers*) in promoting activism on sustainability issues through their posts on social media had already been recognized by Knupfer et al. (2022). However, the comparison between categories of influencers on Twitter on renewable energy issues recently carried out by Walter and Hanke (2020) had shown a different picture. News outlets and political organizations led the ranking by the number of their followers (respectively with 59% and 21%), while environmental organizations exhibited a share of just 4%. We note that the number of followers may reflect the general level of influence rather than that related to energy issues only. We claim that our approach more precisely reflects the level of influence on the specific topic at hand. Our findings reverse the rankings reported by Walter and Hanke (2020), though they are in line with the general feeling that activists exert a significant influence.

Aside from the sheer evidence of facts, this may be due to either of two direct factors (or both of them): either the other stakeholders are not making their voices heard enough (i.e., they are not steadily present on Twitter, voicing their opinion) or they do not capture the attention and the consensus of the people of Twitter.

Though institutions can have a crucial influence on local attitudes towards wind energy projects, as shown in several papers by Toke (2002, 2005), Langer et al. (2017), this does not show through on Twitter. The presence of institutions on Twitter must increase if they want to develop more effective communications with citizens. This is especially true when financial incentives can be granted by governments, local policy-makers or government agencies since those incentives are often a driver for purchasing many green products. This has been shown in Higueras-Castillo et al. (2020) for the adoption of electric and hybrid vehicles, but it also applies to investments in wind farm projects. Different combinations of variables can help bring forward investments in wind generation. One-off policies, e.g., a transitory initial subsidy, seem to have a more substantial effect than a fixed premium per MWh produced (Abadie and Chamorro, 2014). The economic factor is also remarkable for its absence: the lack of economic benefits is also one of the most frequent reasons for rejecting wind energy projects (Frantál, 2015; Slattery et al., 2012; Katsaprakakis, 2012; Clausen and Rudolph, 2019). Among those who disagreed on the development of a wind project, a large part of them admitted that they would have supported the project if they or their household had received some direct financial benefit from it (e.g. individual financial compensation and cheaper electricity).

If we look at the entire time span, we can observe that the discussion on wind energy shows an increasing trend in users' activities. We refer in particular to statistics like, e.g., the number of relevant tweets and the average number of influenced twitterers per influencer (via both retweets and likes). The average number of retweets and likes have recorded a marked increment during the 2021–present global energy crisis; this can be explained by assuming that the crisis pushes users to discuss energy-related topics more often than in more stable periods.

Anyway, all the influencers do not seem to share the same stance on climate change and renewables. The polarization around a small number of different opinions concerning these topics has been recently highlighted in the literature. This polarization seems to concern mainly the two most influential categories of influencers (according to the number of retweets gained from them): climate activists and journalists. To be convinced of this, it is enough to observe the personal web pages or Wikipedia pages of influencers who fall into these two categories. This polarization may have helped push up the number of retweets earned by the two categories.

We must recognize some limitations in our current work, which we hope to remove in our further research.

Though Tweet is an extremely popular means to voice one's opinions, due to its ease of use, diffusion, and shortness of texts (as documented by its figures, briefly recalled in the Introduction), it is by no means the only place where people discuss energy issues. We plan to examine a wide variety of social media in the future, including specialized forums.

A further limitation is due to our choice to collect only tweets in English. Twitterers indeed prefer to post tweets in the dominant language of their country, as reported in the analysis conducted by Mocanu et al. (2013). However, English is the most used language, and even non-native English speakers may prefer to post tweets in English to reach a broader audience.

In order to continue our investigation into the opinions about wind energy, we envisage broadening our scope beyond Twitter and examining both the opinions voiced on discussion forums (which may exhibit a different degree of regulation than Twitter) and the communication strategies of institutional stakeholders, which may find their way through different media. Also, we plan to identify the mechanisms of consensus push and propagation on social media, which may help us understand how forceful the communications strategies of different stakeholders are.

Data availability

Data will be made available on request.

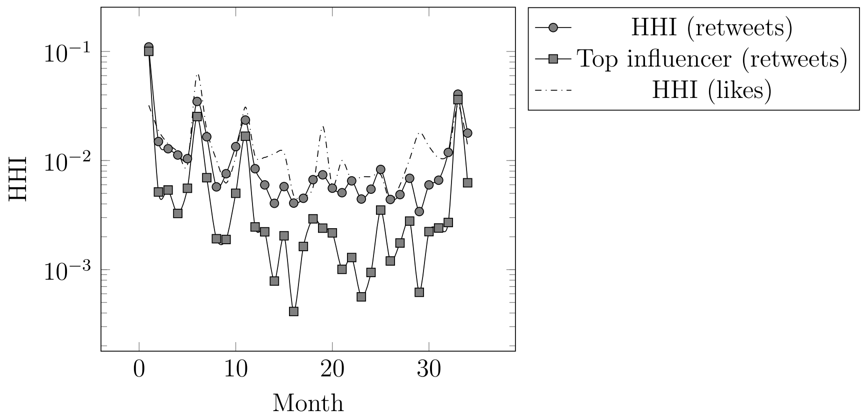

Fig. 15. Likes vs retweets: Herfindahl–Hirschman Index (HHI).

References

Abadie, L.M., Chamorro, J.M., 2014. Valuation of wind energy projects: A real options approach. Energies 7 (5), 3218–3255.
Abdar, M., Basiri, M.E., Yin, J., Habibnezhad, M., Chi, G., Nemati, S., Asadi, S., 2020. Energy choices in Alaska: Mining people's perception and attitudes from geotagged tweets. Renew. Sustain. Energy Rev. 124, 109781.
Aitken, M., 2010. Wind power and community benefits: Challenges and opportunities. Energy Policy 38 (10), 6066–6075.
Aleixandre-Tudó, J.L., Castelló-Cogollos, L., Aleixandre, J.L., Aleixandre-Benavent, R., 2019. Renewable energies: Worldwide trends in research, funding and international collaboration. Renew. Energy 139, 268–278.
Anger, I., Kittl, C., 2011. Measuring influence on Twitter. In: Proceedings of the 11th International Conference on Knowledge Management and Knowledge Technologies. pp. 1–4.
Bakshy, E., Hofman, J.M., Mason, W.A., Watts, D.J., 2011. Everyone's an influencer: quantifying influence on twitter. In: Proceedings of the Fourth ACM International Conference on Web Search and Data Mining. pp. 65–74.
Bale, C.S., McCullen, N.J., Foxon, T.J., Rucklidge, A.M., Gale, W.F., 2013. Harnessing social networks for promoting adoption of energy technologies in the domestic sector. Energy Policy 63, 833–844.
Bandini, S., Manzoni, S., Vizzari, G., 2009. Agent based modeling and simulation: an informatics perspective. J. Artif. Soc. Soc. Simul. 12 (4), 4.
Bell, D., Gray, T., Haggett, C., 2005. The 'social gap' in wind farm siting decisions: Explanations and policy responses. Environ. Politics 14 (4), 460–477.
Bell, D., Gray, T., Haggett, C., Swaffield, J., 2013. Re-visiting the 'social gap': public opinion and relations of power in the local politics of wind energy. Environ. Politics 22 (1), 115–135.
Ben-Lhachemi, N., Nfaoui, E.H., 2018. Using tweets embeddings for hashtag recommendation in Twitter. Procedia Comput. Sci. 127, 7–15.
Bisconti, C., Corallo, A., Fortunato, L., Spennato, A., 2019. Influence parameters correlation in a Twitter event network. Int. J. Entrepreneurship Small Bus. 37 (4), 513–529.
Bishop, I.D., Miller, D.R., 2007. Visual assessment of off-shore wind turbines: The influence of distance, contrast, movement and social variables. Renew. Energy 32 (5), 814–831.
Bjärstig, T., Mancheva, I., Zachrisson, A., Neumann, W., Svensson, J., 2022. Is large-scale wind power a problem, solution, or victim? A frame analysis of the debate in Swedish media. Energy Res. Soc. Sci. 83, 102337.
Bode, L., Dalrymple, K.E., 2016. Politics in 140 characters or less: Campaign communication, network interaction, and political participation on Twitter. J. Political Mark. 15 (4), 311–332.
Borch, K., 2018. Mapping value perspectives on wind power projects: The case of the danish test centre for large wind turbines. Energy Policy 123, 251–258.
Borch, K., Munk, A.K., Dahlgaard, V., 2020. Mapping wind-power controversies on social media: Facebook as a powerful mobilizer of local resistance. Energy Policy 138, 111223.
Cha, M., Haddadi, H., Benevenuto, F., Gummadi, P.K., et al., 2010. Measuring user influence in twitter: The million follower fallacy. Icwsm 10 (10–17), 30.
Chong, W.H., Lim, E.P., 2018. Exploiting user and venue characteristics for fine-grained tweet geolocation. ACM Trans. Inf. Syst. (TOIS) 36 (3), 1–34.
Chong, W.H., Lim, E.P., 2019. Fine-grained geolocation of tweets in temporal proximity. ACM Trans. Inf. Syst. 37 (2).
Clausen, L.T., Rudolph, D., 2019. (Dis) Embedding the wind-on people-climate reconciliation in danish wind power planning. J. Transdiscipl. Environ. Stud. 17 (1).
Colladon, A.F., Naldi, M., 2019. Predicting the performance of TV series through textual and network analysis: The case of big bang theory. PLoS One 14 (11).
De Jesus, A., Antunes, P., Santos, R., Mendonça, S., 2018. Eco-innovation in the transition to a circular economy: An analytical literature review. J. Clean. Prod. 172, 2999–3018.
Dehler-Holland, J., Okoh, M., Keles, D., 2022. Assessing technology legitimacy with topic models and sentiment analysis – The case of wind power in Germany. Technol. Forecast. Soc. Change 175, 121354.
Dhakouani, A., Znouda, E., Bouden, C., 2019. Impacts of energy efficiency policies on the integration of renewable energy. Energy Policy 133, 110922.
Dimitropoulos, A., Kontoleon, A., 2009. Assessing the determinants of local acceptability of wind-farm investment: A choice experiment in the Greek Aegean Islands. Energy Policy 37 (5), 1842–1854.
Dwyer, J., Bidwell, D., 2019. Chains of trust: Energy justice, public engagement, and the first offshore wind farm in the United States. Energy Res. Soc. Sci. 47, 166–176.
Ek, K., 2005. Public and private attitudes towards "green" electricity: the case of Swedish wind power. Energy Policy 33 (13), 1677–1689.
Ek, K., Persson, L., 2014. Wind farms — Where and how to place them? A choice experiment approach to measure consumer preferences for characteristics of wind farm establishments in Sweden. Ecol. Econom. 105, 193–203.
Firestone, J., Bidwell, D., Gardner, M., Knapp, L., 2018a. Wind in the sails or choppy seas?: People-place relations, aesthetics and public support for the United States' first offshore wind project. Energy Res. Soc. Sci. 40, 232–243.
Firestone, J., Hoen, B., Rand, J., Elliott, D., Hübner, G., Pohl, J., 2018b. Reconsidering barriers to wind power projects: community engagement, developer transparency and place. J. Environ. Policy Plan. 20 (3), 370–386.
Firestone, J., Kempton, W., 2007. Public opinion about large offshore wind power: Underlying factors. Energy Policy 35 (3), 1584–1598.
Firestone, J., Kempton, W., Krueger, A., 2009. Public acceptance of offshore wind power projects in the USA. Wind Energy 12 (2), 183–202.
Firestone, J., Kempton, W., Lilley, M.B., Samoteskul, K., 2012. Public acceptance of offshore wind power: does perceived fairness of process matter? J. Environ. Plan. Manag. 55 (10), 1387–1402.
Frantál, B., 2015. Have local government and public expectations of wind energy project benefits been met? Implications for repowering schemes. J. Environ. Policy Plan. 17 (2), 217–236.
Gentry, J., 2015. twitteR: R based Twitter client. URL: https://CRAN.R-project.org/package=twitteR, R package version 1.1.9.
Gonzalez Paule, J.D., Moshfeghi, Y., Jose, J.M., Thakuriah, P., 2017. On fine-grained geolocalisation of tweets. In: Proceedings of the ACM SIGIR International Conference on Theory of Information Retrieval. pp. 313–316.
Graham, J.B., Stephenson, J.R., Smith, I.J., 2009. Public perceptions of wind energy developments: Case studies from New Zealand. Energy Policy 37 (9), 3348–3357.
Gross, C., 2007. Community perspectives of wind energy in Australia: The application of a justice and community fairness framework to increase social acceptance. Energy Policy 35 (5), 2727–2736.
Grover, P., Kar, A.K., Dwivedi, Y.K., Janssen, M., 2019. Polarization and acculturation in US election 2016 outcomes – Can twitter analytics predict changes in voting preferences. Technol. Forecast. Soc. Change 145, 438–460.
Guttal, V., Couzin, I.D., 2010. Social interactions, information use, and the evolution of collective migration. Proc. Natl. Acad. Sci. 107 (37), 16172–16177.
Hajian, B., White, T., 2011. Modelling influence in a social network: Metrics and evaluation. In: 2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing. IEEE, pp. 497–500.
Hale, S., Gaffney, D., Graham, M., 2012. Where in the world are you? Geolocation and language identification in Twitter. Proc. ICWSM 12, 518–521.
Hevia-Koch, P., Ladenburg, J., 2019. Where should wind energy be located? A review of preferences and visualisation approaches for wind turbine locations. Energy Res. Soc. Sci. 53, 23–33.

Higueras-Castillo, E., Kalinic, Z., Marinkovic, V., Liébana-Cabanillas, F.J., 2020. A mixed analysis of perceptions of electric and hybrid vehicles. Energy Policy 136, 111076.
Hoen, B., Firestone, J., Rand, J., Elliot, D., Hübner, G., Pohl, J., Wiser, R., Lantz, E., Haac, T.R., Kaliski, K., 2019. Attitudes of U.S. wind turbine neighbors: Analysis of a nationwide survey. Energy Policy 134, 110981.
Hoffert, M., Caldeira, K., Benford, G., Criswell, D., Green, C., Herzog, H., Jain, A., Kheshgi, H., Lackner, K., Lewis, J., Lightfoot, H., Manheimer, W., Mankins, J., Mauel, M., Perkins, L., Schlesinger, M., Volk, T., Wigley, T., 2002. Engineering: Advanced technology paths to global climate stability: Energy for a greenhouse planet. Science 298 (5595), 981–987.
Horbaty, R., Huber, S., Ellis, G., 2012. Large-scale wind deployment, social acceptance. WIREs Energy Environ. 1 (2), 194–205.
Huang, B., Carley, K.M., 2017. On predicting geolocation of tweets using convolutional neural networks. In: Lee, D., Lin, Y.R., Osgood, N., Thomson, R. (Eds.), Social, Cultural, and Behavioral Modeling. Springer International Publishing, Cham, pp. 281–291.
Hübner, G., Pohl, J., Hoen, B., Firestone, J., Rand, J., Elliott, D., Haac, R., 2019. Monitoring annoyance and stress effects of wind turbines on nearby residents: A comparison of U.S. and European samples. Environ. Int. 132, 105090.
Iacomini, E., Vellucci, P., 2021. Contrarian effect in opinion forming: insights from greta thunberg phenomenon. J. Math. Sociol. 1–47.
Ikoro, V., Sharmina, M., Malik, K., Batista-Navarro, R., 2018. Analyzing sentiments expressed on Twitter by UK energy company consumers. In: 2018 Fifth International Conference on Social Networks Analysis, Management and Security. SNAMS, pp. 95–98.
Jain, A., Jain, V., 2019. Sentiment classification of twitter data belonging to renewable energy using machine learning. J. Inf. Optim. Sci. 40 (2), 521–533.
Jallouli, J., Moreau, G., 2009. An immersive path-based study of wind turbines' landscape: A French case in Plouguin. Renew. Energy 34 (3), 597–607.
Jami, A.A., Walsh, P.R., 2017. From consultation to collaboration: A participatory framework for positive community engagement with wind energy projects in Ontario, Canada. Energy Res. Soc. Sci. 27, 14–24.
Jethani, J., 2016. Wind power policy in India. World 6000, 5358.
Johansson, M., Laike, T., 2007. Intention to respond to local wind turbines: the role of attitudes and visual perception. Wind Energy 10 (5), 435–451.
Jones, C.R., Richard Eiser, J., 2010. Understanding 'local' opposition to wind development in the UK: How big is a backyard? Energy Policy 38 (6), 3106–3117.
Jun, S.P., Yoo, H.S., Lee, J.S., 2021. The impact of the pandemic declaration on public awareness and behavior: Focusing on COVID-19 google searches. Technol. Forecast. Soc. Change 166, 120592.
Katsaprakakis, D.A., 2012. A review of the environmental and human impacts from wind parks. A case study for the Prefecture of Lasithi, Crete. Renew. Sustain. Energy Rev. 16 (5), 2850–2863.
Kearney, M.W., Heiss, A., Briatte, F., 2022. rtweet: Collecting Twitter data. URL: https://cran.r-project.org/web/packages/rtweet/index.html, R package version 1.0.2.
Kempe, D., Kleinberg, J., Tardos, É., 2003. Maximizing the spread of influence through a social network. In: Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 137–146.
Kempe, D., Kleinberg, J., Tardos, É., 2015. Maximizing the spread of influence through a social network. Theory Comput. 11 (4), 105–147.
Kim, E.S., Chung, J.B., Seo, Y., 2018. Korean traditional beliefs and renewable energy transitions: Pungsu, shamanism, and the local perception of wind turbines. Energy Res. Soc. Sci. 46, 262–273.
Knupfer, H., Neureiter, A., Matthes, J., 2022. From social media diet to public riot? Engagement with "greenfluencers" and young social media users' environmental activism. Comput. Hum. Behav. 107527.
Kolarijani, M.A.S., Proskurnikov, A.V., Esfahani, P.M., 2020. Macroscopic noisy bounded confidence models with distributed radical opinions. IEEE Trans. Automat. Control 1.
Kumar, S., Morstatter, F., Liu, H., 2014. Twitter Data Analytics. Springer.
Ladenburg, J., 2008. Attitudes towards on-land and offshore wind power development in Denmark; choice of development strategy. Renew. Energy 33 (1), 111–118.
Ladenburg, J., 2009. Visual impact assessment of offshore wind farms and prior experience. Appl. Energy 86 (3), 380–387.
Ladenburg, J., 2010. Attitudes towards offshore wind farms—The role of beach visits on attitude and demographic and attitude relations. Energy Policy 38 (3), 1297–1304.
Ladenburg, J., Dubgaard, A., 2009. Preferences of coastal zone user groups regarding the siting of offshore wind farms. Ocean & Coastal Management 52 (5), 233–242.
Lamy, J., Azevedo, I.M., Bruine de Bruin, W., Morgan, M.G., 2017. Perceptions of wind energy projects in two coastal massachusetts communities. Electr. J. 30 (7), 31–42.
Lamy, J., de Bruin, W.B., Azevedo, I.M., Morgan, M.G., 2020. Keep wind projects close? A case study of distance, culture, and cost in offshore and onshore wind energy siting. Energy Res. Soc. Sci. 63, 101377.
Landry, C.E., Allen, T., Cherry, T., Whitehead, J.C., 2012. Wind turbines and coastal recreation demand. Resour. Energy Econ. 34 (1), 93–111.
Langer, K., Decker, T., Menrad, K., 2017. Public participation in wind energy projects located in Germany: Which form of participation is the key to acceptance? Renew. Energy 112, 63–73.
Leskovec, J., Singh, A., Kleinberg, J., 2006. Patterns of influence in a recommendation network. In: Pacific-Asia Conference on Knowledge Discovery and Data Mining. Springer, pp. 380–389.
Li, R., Crowe, J., Leifer, D., Zou, L., Schoof, J., 2019. Beyond big data: Social media challenges and opportunities for understanding social perception of energy. Energy Res. Soc. Sci. 56, 101217.
Lim, K.H., Karunasekera, S., Harwood, A., George, Y., 2019. Geotagging tweets to landmarks using convolutional neural networks with text and posting time. In: Proceedings of the 24th International Conference on Intelligent User Interfaces: Companion. pp. 61–62.
Mahajan, R., Mansotra, V., 2021. Predicting geolocation of tweets: Using combination of CNN and BiLSTM. Data Sci. Eng. 1–9.
Majer, T., Šimko, M., 2012. Leveraging microblogs for resource ranking. In: International Conference on Current Trends in Theory and Practice of Computer Science. Springer, pp. 518–529.
Mastroeni, L., Naldi, M., Vellucci, P., 2019a. An agent-based model on scale-free networks for personal finance decisions. In: Proceedings of the 20th Workshop "from Objects To Agents".
Mastroeni, L., Naldi, M., Vellucci, P., 2019b. Opinion dynamics in multi-agent systems under proportional updating and any-to-any influence. In: Advances in Optimization and Decision Science for Society, Services and Enterprises. In: AIRO Springer Series, vol. 3, Springer Nature Switzerland, pp. 279–290.
Mastroeni, L., Naldi, M., Vellucci, P., 2020. Calibration of an agent-based model for opinion formation through a retweet social network. In: Proceedings of the 21th Workshop "from Objects To Agents".
Mastroeni, L., Vellucci, P., Naldi, M., 2019c. Agent-based models for opinion formation: A bibliographic survey. IEEE Access 7, 58836–58848.
McMichael, M., Shipworth, D., 2013. The value of social networks in the diffusion of energy-efficiency innovations in UK households. Energy Policy 53, 159–168.
Mishra, P., 2020. Geolocation of tweets with a BiLSTM regression model. In: Proceedings of the 7th Workshop on NLP for Similar Languages, Varieties and Dialects. Barcelona, Spain (Online), pp. 283–289.
Mocanu, D., Baronchelli, A., Perra, N., Gonçalves, B., Zhang, Q., Vespignani, A., 2013. The twitter of babel: Mapping world languages through microblogging platforms. PLoS One 8 (4), e61981.
Mogaji, E., Balakrishnan, J., Kieu, T.A., 2020. Examining consumer behaviour in the UK energy sector through the sentimental and thematic analysis of tweets. J. Consum. Behav.
Motsch, S., Tadmor, E., 2014. Heterophilious dynamics enhances consensus. SIAM Rev. 56 (4), 577–621.
Muñoz, C.Q.G., Márquez, F.P.G., 2018. Wind energy power prospective. In: Renewable Energies. Springer, pp. 83–95.
Nadaï, A., 2007. "Planning", "siting" and the local acceptance of wind power: Some lessons from the French case. Energy Policy 35 (5), 2715–2726.
Naldi, M., 2019. Interactions and sentiment in personal finance forums: An exploratory analysis. Information 10 (7), 237.
Pal, A., Counts, S., 2011. Identifying topical authorities in microblogs. In: Proceedings of the Fourth ACM International Conference on Web Search and Data Mining. pp. 45–54.
Panagiotopoulos, P., Barnett, J., Bigdeli, A.Z., Sams, S., 2016. Social media in emergency management: Twitter as a tool for communicating risks to the public. Technol. Forecast. Soc. Change 111, 86–96.
Papazu, I., 2017. Nearshore wind resistance on Denmark's renewable energy island: Not another NIMBY story. Sci. Technol. Stud. 30 (1), 4–24.
Pareschi, L., Vellucci, P., Zanella, M., 2017. Kinetic models of collective decision-making in the presence of equality bias. Physica A 467, 201–217.
Paule, J.D.G., Sun, Y., Moshfeghi, Y., 2019. On fine-grained geolocalisation of tweets and real-time traffic incident detection. Inf. Process. Manage. 56 (3), 1119–1132.
Pohl, J., Gabriel, J., Hübner, G., 2018. Understanding stress effects of wind turbine noise – The integrated approach. Energy Policy 112, 119–128.
Proskurnikov, A.V., Matveev, A.S., Cao, M., 2016. Opinion dynamics in social networks with hostile camps: Consensus vs. polarization. IEEE Trans. Automat. Control 61 (6), 1524–1536.
Ramirez, S., Dwivedi, P., Ghilardi, A., Bailis, R., 2014. Diffusion of non-traditional cookstoves across western Honduras: A social network analysis. Energy Policy 66, 379–389.
Rand, J., Hoen, B., 2017. Thirty years of North American wind energy acceptance research: What have we learned? Energy Res. Soc. Sci. 29, 135–148.
Razis, G., Anagnostopoulos, I., 2014. InfluenceTracker: Rating the impact of a Twitter account. In: IFIP International Conference on Artificial Intelligence Applications and Innovations. Springer, pp. 184–195.
Riquelme, F., González-Cantergiani, P., 2016. Measuring user influence on Twitter: A survey. Inf. Process. Manage. 52 (5), 949–975.
Romero, D.M., Galuba, W., Asur, S., Huberman, B.A., 2011. Influence and passivity in social media. In: Joint European Conference on Machine Learning and Knowledge Discovery in Databases. Springer, pp. 18–33.
Rydin, Y., Lee, M., Lock, S.J., 2015. Public engagement in decision-making on major wind energy projects. J. Environ. Law 27 (1), 139–150.
Sayigh, A., Milborrow, D., 2020. The Age of Wind Energy: Progress and Future Directions from a Global Perspective, first ed. In: Innovative Renewable Energy, Springer International Publishing.
Simmie, D., Vigliotti, M.G., Hankin, C., 2014. Ranking twitter influence by combining network centrality and influence observables in an evolutionary model. J. Complex Netw. 2 (4), 495–517.

Slattery, M.C., Johnson, B.L., Swofford, J.A., Pasqualetti, M.J., 2012. The predominance of economic development in the support for large-scale wind farms in the U.S. Great Plains. Renew. Sustain. Energy Rev. 16 (6), 3690–3701.
Slee, B., 2015. Is there a case for community-based equity participation in scottish on-shore wind energy production? Gaps in evidence and research needs. Renew. Sustain. Energy Rev. 41, 540–549.
Sovacool, B.K., Lakshmi Ratan, P., 2012. Conceptualizing the acceptance of wind and solar electricity. Renew. Sustain. Energy Rev. 16 (7), 5268–5279.
Spiess, H., Lobsiger-Kägi, E., Carabias-Hütter, V., Marcolla, A., 2015. Future acceptance of wind energy production: Exploring future local acceptance of wind energy production in a Swiss alpine region. Technol. Forecast. Soc. Change 101, 263–274.
Sposato, R.G., Hampl, N., 2018. Worldviews as predictors of wind and solar energy support in Austria: Bridging social acceptance and risk perception research. Energy Res. Soc. Sci. 42, 237–246.
Stephens, J.C., Rand, G.M., Melnick, L.L., 2009. Wind energy in US media: a comparative state-level analysis of a critical climate change mitigation technology. Environ. Commun. 3 (2), 168–190.
Stieglitz, S., Dang-Xuan, L., 2012. Political communication and influence through microblogging–An empirical analysis of sentiment in Twitter messages and retweet behavior. In: 2012 45th Hawaii International Conference on System Sciences. IEEE, pp. 3500–3509.
Sun, X., Huang, D., Wu, G., 2012. The current state of offshore wind energy technology development. Energy 41 (1), 298–312.
Suwaileh, R., Imran, M., Elsayed, T., Sajjad, H., 2020. Are we ready for this disaster? Towards location mention recognition from crisis tweets. In: Proceedings of the 28th International Conference on Computational Linguistics. pp. 6252–6263.
Swofford, J., Slattery, M., 2010. Public attitudes of wind energy in Texas: Local communities in close proximity to wind farms and their effect on decision-making. Energy Policy 38 (5), 2508–2519.
Tania, N., Vanderlei, B., Heath, J.P., Edelstein-Keshet, L., 2012. Role of social interactions in dynamic patterns of resource patches and forager aggregation. Proc. Natl. Acad. Sci. 109 (28), 11228–11233.
Teisl, M.F., Noblet, C.L., Corey, R.R., Giudice, N.A., 2018. Seeing clearly in a virtual reality: Tourist reactions to an offshore wind project. Energy Policy 122, 601–611.
Tinati, R., Carr, L., Hall, W., Bentwood, J., 2012. Identifying communicator roles in Twitter. In: Proceedings of the 21st International Conference on World Wide Web. In: WWW '12 Companion, Association for Computing Machinery, New York, NY, USA, pp. 1161–1168.
Toke, D., 2002. Wind power in UK and Denmark: Can rational choice help explain different outcomes? Environ. Politics 11 (4), 83–100.
Toke, D., 2005. Explaining wind power planning outcomes:: some findings from a study in England and Wales. Energy Policy 33 (12), 1527–1539.
Türker, I., Sulak, E.E., 2018. A multilayer network analysis of hashtags in Twitter via co-occurrence and semantic links. Internat. J. Modern Phys. B 32 (04), 1850029.
van der Horst, D., 2007. NIMBY or not? Exploring the relevance of location and the politics of voiced opinions in renewable energy siting controversies. Energy Policy 35 (5), 2705–2714.
van der Loos, H.A., Negro, S.O., Hekkert, M.P., 2020. Low-carbon lock-in? Exploring transformative innovation policy and offshore wind energy pathways in the Netherlands. Energy Res. Soc. Sci. 69, 101640.
Vicsek, T., Zafeiris, A., 2012. Collective motion. Phys. Rep. 517 (3), 71–140.
Vuichard, P., Stauch, A., Dällenbach, N., 2019. Individual or collective? Community investment, local taxes, and the social acceptance of wind energy in Switzerland. Energy Res. Soc. Sci. 58, 101275.
Walker, C., Baxter, J., 2017. Procedural justice in Canadian wind energy development: A comparison of community-based and technocratic siting processes. Energy Res. Soc. Sci. 29, 160–169.
Walter, G., 2014. Determining the local acceptance of wind energy projects in Switzerland: The importance of general attitudes and project characteristics. Energy Res. Soc. Sci. 4, 78–88.
Walter, S., Hanke, K.J., 2020. Opinion leaders in the digital age–social network analysis for renewable energies on Twitter. Min. Rep. 156 (6).
Wang, R., Liu, W., Gao, S., 2016. Hashtags and information virality in networked social movement. Online Inf. Rev.
Wang, L., Markdahl, J., Hu, X., 2011. Distributed attitude control of multi-agent formations*. IFAC Proc. Vol. 44 (1), 4513–4518.
Warren, C.R., McFadyen, M., 2010. Does community ownership affect public attitudes to wind energy? A case study from south-west Scotland. Land Use Policy 27 (2), 204–213.
Weinzettel, J., Reenaas, M., Solli, C., Hertwich, E.G., 2009. Life cycle assessment of a floating offshore wind turbine. Renew. Energy 34 (3), 742–747.
Wolsink, M., 2000. Wind power and the NIMBY-myth: institutional capacity and the limited significance of public support. Renew. Energy 21 (1), 49–64.
Wolsink, M., 2007. Wind power implementation: The nature of public attitudes: Equity and fairness instead of 'backyard motives'. Renew. Sustain. Energy Rev. 11 (6), 1188–1207.
Yan, X., Guo, J., Lan, Y., Cheng, X., 2013. A Biterm topic model for short texts. In: Proceedings of the 22nd International Conference on World Wide Web. WWW '13, Association for Computing Machinery, New York, NY, USA, pp. 1445–1456.
Yang, S.Y., Mo, S.Y.K., Liu, A., 2015. Twitter financial community sentiment and its predictive relationship to stock market movement. Quant. Finance 15 (10), 1637–1656.
Ye, S., Wu, S.F., 2010. Measuring message propagation and social influence on Twitter. com. In: International Conference on Social Informatics. Springer, pp. 216–231.
Zárate-Toledo, E., Patiño, R., Fraga, J., 2019. Justice, social exclusion and indigenous opposition: A case study of wind energy development on the Isthmus of Tehuantepec, Mexico. Energy Res. Soc. Sci. 54, 1–11.
Zhang, J., Tang, J., Li, J., Liu, Y., Xing, C., 2015. Who influenced you? predicting retweet via social influence locality. ACM Trans. Knowl. Discov. Data (TKDD) 9 (3), 1–26.
Zhao, X., Li, S., Zhang, S., Yang, R., Liu, S., 2016. The effectiveness of China's wind power policy: An empirical analysis. Energy Policy 95, 269–279.
Zhaoyun, D., Yan, J., Bin, Z., Yi, H., 2013. Mining topical influencers based on the multi-relational network in micro-blogging sites. China Commun. 10 (1), 93–104.
Zografos, C., Martínez-Alier, J., 2009. The politics of landscape value: A case study of wind farm conflict in rural catalonia. Environ. Plan. A Econ. Space 41 (7), 1726–1744.

Loretta Mastroeni is Associate Professor at the Department of Economics of Roma Tre University. She holds a M.Sc. degree magna cum laude in Mathematics and attended the National Institute of High Mathematics in Rome. Her main research interests focus on energy and commodity finance, pricing models and risk management in finance and in telecommunications. She is the author of many papers published in peer-reviewed journals. She acts as an expert evaluator of European Union projects and as a referee for a number of peer-reviewed international journals.

Maurizio Naldi is a Full Professor of Computer Science at LUMSA University in Rome. He holds an M.Sc. degree magna cum laude in Electronic Engineering and a Ph.D. in Telecommunications Engineering. He was with the University of Rome Tor Vergata in 2000–2019. Prior to 2000, he worked in the R&D departments of several telecom companies and represented Italy in major telecommunications standardization bodies (ETSI and ITU). He is presently Co-Editor of Electronic Commerce Research and Applications. His current research interests lie in ICT risk analysis, network economics, privacy-enhancing technologies, and sentiment analysis.

Pierluigi Vellucci received his M.Sc. in Electronic Engineering magna cum laude from the Sapienza University of Rome in 2013, and his Ph.D. in Mathematical Models for Engineering, Electromagnetism, and Nanosciences in 2017 from the Sapienza University of Rome. From 2016 to 2018, he had a postdoctoral position at the Department of Economics at Roma Tre University, where he is now an Assistant Professor in Mathematics. He works in several interdisciplinary applications of Mathematics, but primarily in waveform dictionaries and Gabor/ wavelet expansions in energy economics.