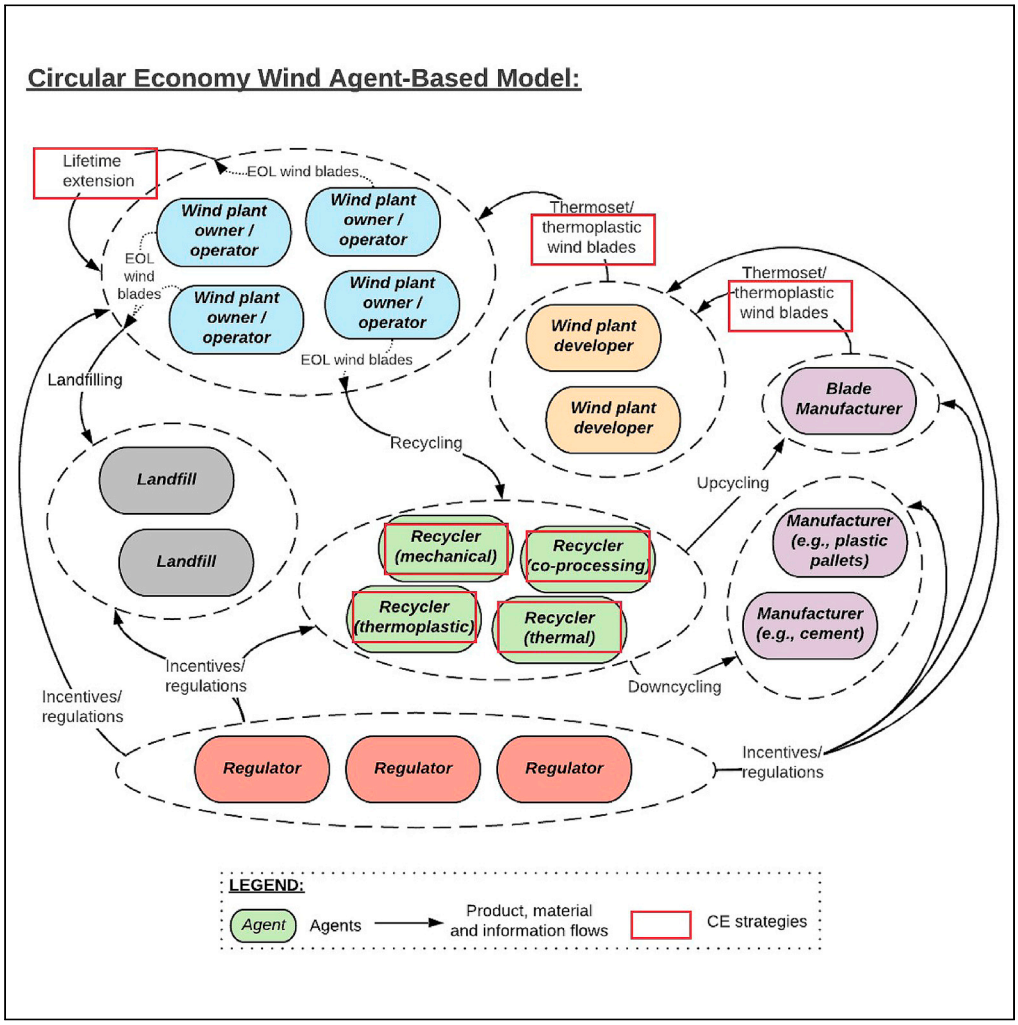
iScience

CellPress
OPEN ACCESS

Article

Regional representation of wind stakeholders' end-of-life behaviors and their impact on wind blade circularity



Julien Walzberg, Aubryn Cooperman, Liam Watts, Annika L. Eberle, Alberta Carpenter, Garvin A. Heath

julien.walzberg@nrel.gov

Highlights

Spatial agent-based model adds behavioral factors to wind blades circularity study

Logistical barriers and transportation costs significantly affect the results

Recycling early adopters incite new social norms speeding up circularity transition

Walzberg et al., iScience 25, 104734
August 19, 2022
https://doi.org/10.1016/j.isci.2022.104734

iScience

CellPress
OPEN ACCESS

Article

Regional representation of wind stakeholders' end-of-life behaviors and their impact on wind blade circularity

Julien Walzberg,[1,3,*] Aubryn Cooperman,[1] Liam Watts,[1] Annika L. Eberle,[1] Alberta Carpenter,[1] and Garvin A. Heath[1,2]

SUMMARY

The growing number of end-of-life (EOL) wind blades could further strain US landfills or be a valuable composite materials source, depending on stakeholders' behaviors. Technical solutions based on circular economy (CE) principles have been proposed but are not guaranteed to solve the issue of EOL management. Transitioning to CE implies changing how business models, supply chains, and behaviors deal with products and waste. A spatially resolved agent-based modeling combined with a machine-learning metamodel shows that including behavioral factors is crucial to designing effective policies. Logistical barriers and transportation costs significantly affect the results: lowering blade shredding costs by a third before transportation makes EOL blades a source of valuable materials, decreasing the 2050 cumulative landfill rate below 50%. In another scenario, parameter settings simulating policy interventions aiming at boosting early adoption incites new social norms favorable to recycling, lowering the cumulative landfill rate below 10%.

INTRODUCTION

Wind power is one of the world's fastest-growing sources of renewable electricity generation. In the United States (US), wind turbines comprised 122 GW of installed capacity and produced 8% of global electricity in 2020, the highest share for renewables (EIA, 2022; Wiser et al., 2021). Although most US wind plants are still far from reaching their end of life (EOL) (more than 90% of currently installed wind plant capacity in the US was constructed within the last decade), a significant amount of EOL materials will be generated by 2040 (e.g., between 10,000 and 20,000 EOL blades annually between 2025 and 2040) (Cooperman et al., 2021). Therefore, wind plant owners will be increasingly faced with EOL management decisions, such as life extension and decommissioning, followed (or not) by recycling of salvaged materials.

Wind turbines are composed of four main components: foundations, towers, nacelles, and blades (Sakellariou, 2018) and typically have a lifespan of 20 years (Cooperman et al., 2021). Usually, foundations are composed of concrete and steel, towers are made of steel, nacelles mainly contain steel, iron, aluminum, and plastics, and blades are primarily made of composites. Materials from the foundation, tower, and nacelle are recycled at EOL using mature technologies (Cooperman et al., 2021; Jensen and Skelton, 2018). However, wind blades are more complicated to recycle, and most blades are currently land-filled (although there are exceptions, including a landfill ban in Germany (Nagle et al., 2020)); if current trends continue, about 235,000 wind blades will have been decommissioned in the US by 2050 (Cooperman et al., 2021). Aside from discarding valuable composite materials and potentially tarnishing the reputation of wind power as a clean energy technology, EOL wind blades could, in some landfills, add a significant volume of waste (e.g., although for the whole US, EOL wind blades would only comprise 1% of landfill capacity in 2050, they could represent up to 30% of North Dakota's landfill capacity) (Cooperman et al., 2021). This challenge motivates the analysis of circular economy (CE) strategies to mitigate the impact of EOL wind blades.

Wind blades are generally composed (by mass) of about 5% steel, 9% of either polyethylene terephthalate (PET) or polyvinyl chloride (PVC), 86% composite materials, and a small percentage of lacquers and adhesives (Nagle et al., 2020; Tazi et al., 2019). The composite materials are either glass-fiber-reinforced

[1]National Renewable Energy Laboratory, 15013 Denver West Parkway, Golden, CO 80401, USA

[2]Joint Institute for Strategic Energy Analysis, 15013 Denver West Parkway Golden, CO 80401, USA

[3]Lead contact

*Correspondence: julien.walzberg@nrel.gov

https://doi.org/10.1016/j.isci.2022.104734

polymers (GFRP) or carbon-fiber-reinforced polymers (CFRP), usually comprised 30%–40% of an epoxy matrix and 60%–70% of glass or carbon fibers (Nagle et al., 2020; Ramôa Correia, 2013). Most wind blades in use today only use GFRP composites. However, the material breakdown of wind blades may change as blade technologies evolve. For example, researchers are studying materials that are more recyclable, such as alternative thermoplastic resins, instead of epoxy resins (Murray et al., 2019; Sakellariou, 2018). Some specific thermoplastics, such as polymethyl methacrylate, could replace epoxy while requiring minimal changes to blade manufacturing processes (simply referred to as thermoplastic blades in the following). A practical example is the Elium® resin developed by Arkema (2022).

Contrary to today's predominantly linear economy—where resources are extracted to manufacture goods that are later discarded—the CE model could alleviate EOL (Stahel, 2016) issues by encouraging dematerialization and the recovery and reuse of products and materials (Linder et al., 2017; Stahel, 2016). There are several CE strategies for wind blades, including EOL pathways and options at the beginning of life. These CE strategies include designing wind blades with less or different materials, extending their lifetimes, reusing and repurposing sections of blades (e.g., to build bridges), and implementing various recycling options (e.g., pyrolysis, mechanical recycling, solvolysis) (Cooperman et al., 2021).

However, behavioral traits often undermine the viability of technical solutions (Khan et al., 2020; Moraga et al., 2019; Salim et al., 2019; Sovacool and Griffiths, 2020). For instance, a lack of trust or dissonance with cultural identity caused by a newly introduced technology may cause its failure to reach full market potential (Sovacool and Griffiths, 2020; Walzberg et al., 2022). Thus, it is critical to understand how wind power industry stakeholders' behavioral decisions will affect wind blades' circularity (Walzberg et al., 2021a, 2021b). Several regional and behavioral factors, such as the regulatory context, current practices, and logistical constraints (other than those reflected in transportation costs) could affect wind blade circularity (Hanes et al., 2021). Transportation costs, various transportation regulations, and remaining landfill capacities across the US further complicate the problem. It is therefore relevant to incorporate behavioral factors and include regional particularities in CE studies of wind blades. However, current studies of wind blade circularity usually do not account for stakeholders' behaviors (Cooperman et al., 2021; Hanes et al., 2021; Jensen, 2019; Jensen and Skelton, 2018; Nagle et al., 2020) and their regional specificities, which may compromise the design of effective policies. The circular economy wind agent-based model (CE wind ABM, (Walzberg et al., 2021c)) presented in this study bridges the gap in the literature identified above by representing wind stakeholders' heterogeneity and behavioral factors affecting circularity.

The CE wind ABM builds on two detailed, spatially resolved databases of wind plant projects and landfills in the US (Rand et al., 2020; Waste Business Journal, 2020). The Theory of Planned Behavior (TPB), a social-psychology model (Ajzen, 1991; Gainforth et al., 2015), is used to represent agents' decisions. We also build a machine-learning (ML) metamodel of the ABM to study the effect of varying some of the model's input variables in more detail (i.e., the ABM is used to generate a training dataset for a machine learning algorithm, greatly reducing computational requirements (R. Vahdati et al., 2019)). We then use the model to investigate wind blade EOL management, an aspect of sustainable energy often overlooked (Cantzler et al., 2020).

Integrating factors beyond costs into the agents' decisions allows for a more accurate assessment of the potential effectiveness of CE interventions (e.g., by accounting for the regulatory context and logistical constraints). In addition, the ABM enables accounting for agents' heterogeneity (e.g., various wind projects' capacities or geolocation of landfills). The model also allows for a detailed account of transportation distances, a crucial factor affecting wind blade circularity.

RESULTS

Modeling using historical trends indicates that 78% of blades will be landfilled by 2050

The ABM used in this study builds on previous work (Walzberg et al., 2021b, 2022). This model defines six types of agents (wind plant owners, wind plant developers, recyclers, original equipment manufacturers [OEMs], landfills, and regulators), five EOL pathways (lifetime extension, mechanical recycling, pyrolysis recycling, cement co-processing, and landfilling), and two design options (thermoset and thermoplastic blades) (Figure S1). This selection of EOL pathways and design options allows the study to focus on relatively mature technologies (GE, 2020; Murray et al., 2019; Piel et al., 2019; Rybicka et al., 2016) that are already used or could soon be adopted in the US. Furthermore, given their current predominance, only onshore wind turbines in the contiguous US are included in our analysis.

In the ABM, the adoption of CE strategies (i.e., thermoplastic blade design, lifetime extension, recycling) is simulated from the agents' behavioral rules. For instance, during the simulations, the wind plant owners adopt a particular EOL behavior according to an extended version of the TPB (Khan et al., 2020) (Equation 1).

$$BI_{ij}^{t} = w_{bi}\left(w_A A_{ij} + w_{SN} SN_{ij}^{t} + w_{PBC} PBC_{ij}^{t}\right) + w_{dPBC} PBC_{ij}^{t} + w_P P_{ij}^{t} + w_{BA} BA_{ij} \quad \text{(Equation 1)}$$

For agent i and behavior j at time t, BI_{ij}^{t} is the behavioral intention of performing the behavior, A_{ij} is the attitude toward the behavior (describing agents affinity with CE concepts), SN_{ij}^{t} are subjective norms, PBC_{ij}^{t} is the perceived behavioral control over (or cost of) the behavior, P_{ij}^{t} is the perceived pressure on organizations from regulatory bodies to perform the behavior, BA_{ij} are the perceived barriers to adopting the behavior.

The TPB is one of the most popular theories to explain and model human decision processes (Gainforth et al., 2015; Khan et al., 2020). The use of this theory has been growing in industrial ecology, primarily to explain pro-environmental and circular behaviors (Yuriev et al., 2020). According to the theory, the intention of an individual or an organization to perform a behavior (and thus, to a certain extent, the actual behavior) is mediated by three main factors: attitude, subjective norm, and perceived behavioral control (Ajzen, 1991). Subjective norms mean that each agent's decisions affect the decisions of neighboring agents within their social network. In the extended version of the TPB used in this ABM, regulatory context and logistical barriers also affect EOL behaviors. Details are presented in the STAR Methods and supplemental methods.

The ABM is stochastic, and, if not indicated otherwise, results for each scenario are presented for 20 simulations. In the simulations, a time step represents one year, and simulations run from 2020 through 2050, when many existing wind plants will reach their EOL (Cooperman et al., 2021). The ABM differs from current literature on wind blade EOL management because it does not assume homogeneity of wind blade stakeholders (each agent is spatially resolved and possesses its own characteristics) and because it includes behavioral aspects that may hinder or boost adoption of CE strategies (see Equation 1).

The current state of wind blade EOL management (regulators' emerging awareness of the issue, difficulty of recycling, high volume in landfills) seems reminiscent of the case of rubber tires. Although certain aspects differ (e.g., environmental concerns in the case of illegally burning rubber tires), we chose to calibrate our model baseline to reproduce similar recycling trends as rubber tire recycling. Rubber tire EOL management was first identified as a problem around the 1970s (Chang, 2008; Purcell, 1978). According to data from the US Environmental Protection Agency, the annual landfill rate of rubber tires has decreased from about 95% in 1970 to about 20% in 2010 (EPA, 2021), partly because of the enactment of regulations across the US (EPA, 1999). In calibrating the model (by varying the unknown wind plant owners' attitudes toward circular pathways), similar legislation for wind blades as for rubber tires was assumed in the baseline (Figure S2).

Figure 1A presents the adoption rate of EOL behaviors in the baseline. Because of adoption dynamics, most blades end up being landfilled during the simulations (in some cases after their lifetimes are extended). Moreover, because mechanical recycling is less expensive than pyrolysis recycling and has more facilities across the US (including one in Texas, which accounts for 14% of the cumulative wind power capacity in 2050), this option accounts for the second-highest mass of cumulative EOL wind blades, after landfill. The percentages of the cumulative EOL wind blade mass going to landfill, mechanical recycling, pyrolysis recycling, and cement co-processing by 2050 are 78 $\pm$ 5%, 14 $\pm$ 3%, 6 $\pm$ 2%, and 2 $\pm$ 1%, respectively. The landfill and recycling rates vary significantly by state (Figure S3). Lifetime extension (5–15 years (Hutton and Soulier, 2020)) avoids the disposal of almost half a million metric tons of EOL wind blades during the studied period. However, even when blades' lifetimes are extended, they need to be disposed of eventually. Thus, solutions to improve EOL management through recycling are presented next.

Increased recycling rates in low cost transportation scenarios

Transportation costs and logistical barriers are likely to constrain the diversion of EOL wind blades from landfills (Cooperman et al., 2021; Hanes et al., 2021). The Electric Power Research Institute evaluated transportation costs to be about \$0.20/metric ton-mile for a 10-ton load of blade materials (EPRI, 2020), whereas James and Goodrich's (EPRI, 2020; James and Goodrich, 2013) estimation is \$14–\$22/mile or

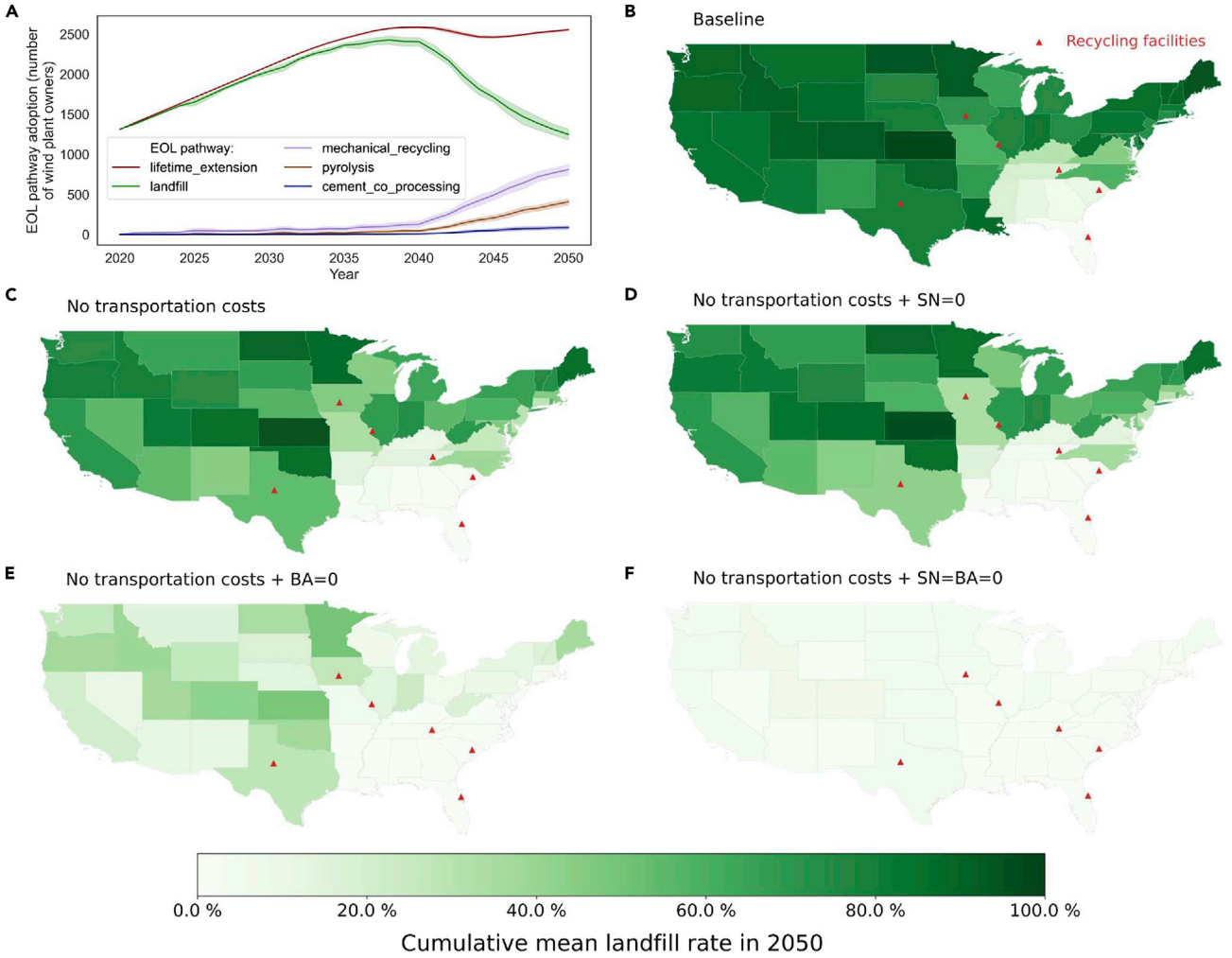


Figure 1. Regional cumulative mean landfill rates according to different transportation costs and TPB factor assumptions (SN = subjective norms, BA = barriers)

Transportation costs include both preprocessing and transport costs.

Panels A and B show results for the baseline. The "no transportation costs" assumption (panels C, D, E, and F) applies only to EOL wind blades that are recycled (i.e., assumes subsidies to encourage recycling); in other words, if blades are landfilled under this assumption, wind plant owners bear transportation costs. SN/BA = 0 means that the factor has been removed from the TPB model (i.e., the factor no longer affects the wind plant owner agents' decisions), whereas SN/BA = 1 means that the factor is present in the TPB model (as in the baseline).

$3.7–$4.4/metric ton-mile for 40–45-meter blades. The higher costs of transporting whole blades or large segments include expenses for logistical requirements, such as specialized equipment, oversize permits, or temporary road closures. Therefore, transportation costs from wind turbine sites to recycling facilities could be essential to recycling competitiveness. Above a certain distance threshold, it may become more economical to transport wind blades to a local landfill than to a recycling site (Global Fiberglass Solutions, 2020). Furthermore, because of subjective norms and without appropriate incentives or regulations, a lock-in scenario could develop (i.e., the first accepted practice retains most of the market) (Korhonen et al., 2018; Walzberg et al., 2022). The following sections analyze such scenarios and the factors affecting them.

Quantifying the effect of TPB factors

Figure 1 and Table S1 show the quantity of EOL blades landfilled or recycled under different transportation costs and TPB factors. As shown in Table S1, factors hindering recycling are subjective norms, barriers, and high transportation costs. Regulatory pressures and attitudes toward recycling both exert a positive effect

on the recycling rate. Figure 1 further investigates the role of subjective norms and barriers on the landfill rate.

The TPB's barriers factor is used to represent the logistical hurdles of transporting EOL blades from the turbine sites to the recycling or disposal sites. A detailed representation of logistical hurdles would be challenging because of their variability. For example, it would require representing all applicable transportation regulations in the different states en route from the turbine site to the recycling or landfill site (e.g., when an oversize/overweight permit is required). Indeed, a short review of transportation requirements in six states—California, Texas, Wyoming, Iowa, Missouri, and New York—found that such requirements vary significantly between states (Table S2). As such, the TPB's barriers factor represents logistical barriers as a function of the required transportation distance.

Transporting blades as shreds rather than segments may decrease the perceived barriers for wind plant owners, as smaller trucks can be used, reducing the potential need for oversize/overweight permits. To contextualize the impact of the barriers factor, Figure 1 shows the effect of reducing the strength of the barriers factor on the landfill rate. For example, if on-site shredding of blades completely removed perceived barriers, the landfill rate would decrease by 42 $\pm$ 5%. In addition, fully subsidizing the preprocessing of EOL wind blades (i.e., on-site shredding) further reduces the landfill rate by 43 $\pm$ 6% (Figure S4).

Subjective norms have ambiguous effects. When most wind plant owners are landfilling, subjective norms reinforce that behavior. However, once enough agents have adopted recycling behaviors, subjective norms further push other agents to recycle. Overall, Figure 1 shows that subjective norms hinder recycling in the cases studied here because of a high initial landfilling rate.

Another interesting insight from Figure 1 is that the absence of nearby recycling facilities appears to be the most significant factor in the decisions of West Coast wind plant owners to landfill EOL wind blades. For those agents, transporting blades to a nearby landfill and paying the landfill fee is the preferred option, even when accounting for possible regulatory pressures, lower gate fees from recycling facilities, and a generally positive attitude toward recycling. On the other hand, even in states with recycling facilities (e.g., Texas), the landfill rate may be higher than expected, as landfills (including those in neighboring states) may still have lower transportation distances and gate fees than recycling facilities. In Figure S5, additional recycling facilities located closer to some of the biggest US wind plant projects decrease the landfill rate by 15%.

Finally, the "no transportation costs" scenarios in Figure 1 assume that transportation costs are subsidized only when blades are recycled. However, even if free transportation is provided for both landfilled and recycled blades, the percentage points in cumulative 2050 landfill rates are 9 $\pm$ 6, 11 $\pm$ 6, 6 $\pm$ 1, and 7 $\pm$ 1 for the scenarios presented in Figures 1C–1F, respectively, demonstrating that recycling is a competitive option because of the potentially lower gate fees (as recycling can provide revenues from material recovery).

Next, given the uncertainty surrounding how strongly logistical barriers hinder recycling and the potential of transporting shredded blades to alleviate those barriers, Figure 2 presents a sensitivity analysis of the landfill rate to the preprocessing costs required to shred or cut EOL wind blades and the weight of the barriers factors in the wind plant owners' EOL decisions. The sensitivity analysis was performed with a ML metamodel trained on thousands of ABM simulations (varying input parameters). Figure 2 also presents the 2050 cumulative revenues from recycling.

Figures 2A and 2C show that when EOL wind blades are transported as segments, the landfill rate and national recycling revenues vary little with both preprocessing costs (i.e., costs associated with cutting blades into 30-m segments) and barriers. Although logistical barriers seem to be the main obstacle between the two factors studied (as lines are mainly vertical), the landfill rate stays above 65% regardless of the strength of the barriers factor or the preprocessing costs. This result is explained by the prohibitive transport costs ($3.7–$4.4/metric ton-mile), which deter wind plant owners from sending EOL blades to recycling facilities (which, for the most part, are more distant than landfill sites).

Conversely, Figure 2B shows that when EOL wind blades are transported as shreds (for $0.05–$0.12/metric ton-mile), removing either logistical barriers or costs associated with blade preprocessing (i.e., shredding)

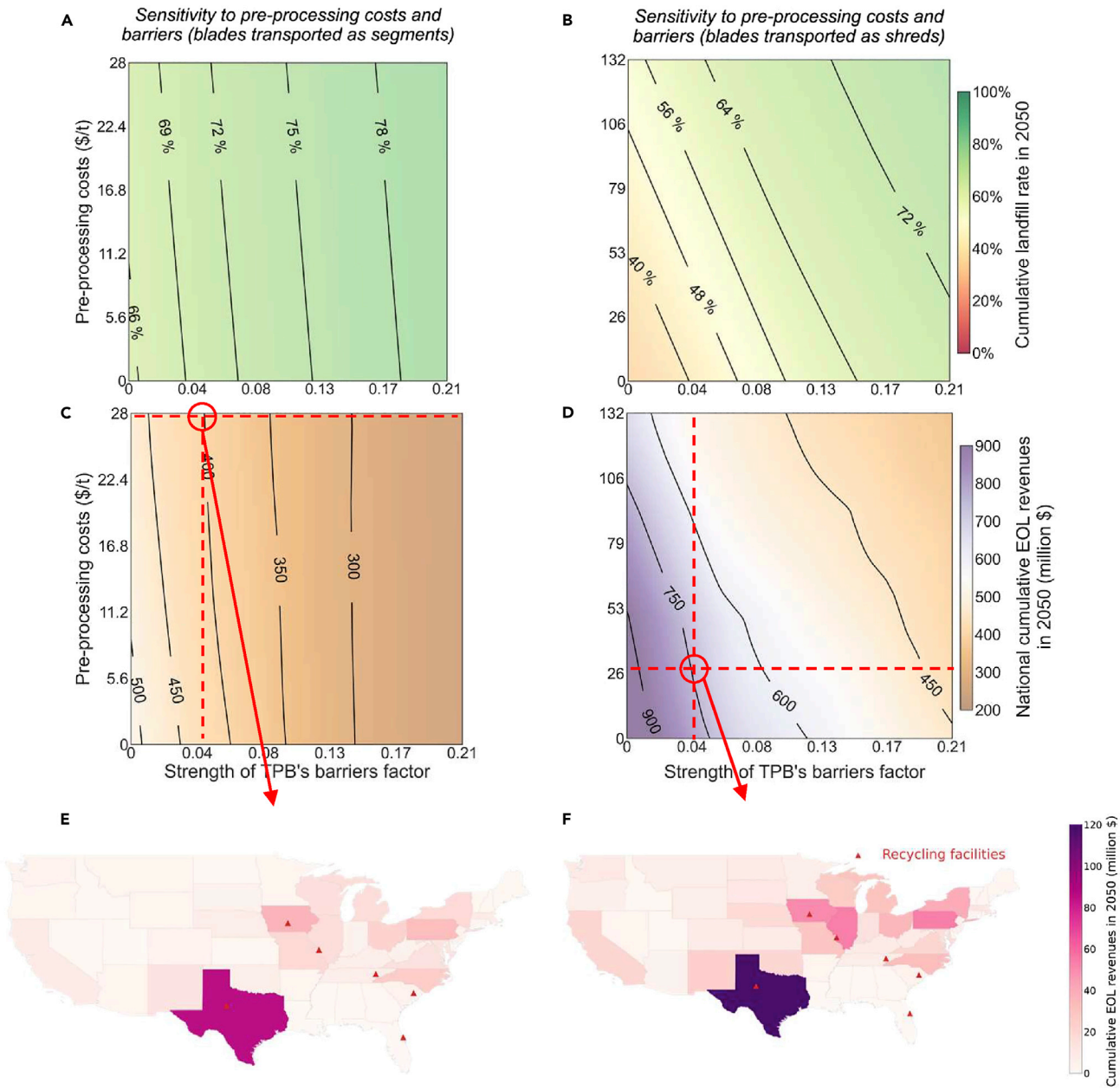


Figure 2. Sensitivity analysis of the 2050 cumulative mean landfill rate and mean recycling revenues to the preprocessing costs required to shred or cut EOL wind blades and the weight of the barriers factors in the wind plant owners' EOL decisions

Panels A and C present the 2050 cumulative rate and national recycling revenues depending on preprocessing costs (i.e., costs required to cut blades into segments) and logistical barriers, respectively.

Panels B and D present the 2050 cumulative rate and national recycling revenues depending on preprocessing costs (i.e., costs required to shred blades) and logistical barriers, respectively.

Panels E and F present the states' recycling revenues when EOL wind blades are transported as segments and shreds (for the parameter combinations indicated by the red dotted lines in panels C and D), respectively. Data for panels A, B, C, and D are generated with a ML metamodel trained on 2,407 parameter combinations (Sobol sequences) replicated 6 times.

could lower the landfill rate. However, from our analysis, it seems that when logistical barriers are high (e.g., in states with constraining transportation regulations), decreasing the preprocessing costs would have little effect. On the other hand, decreasing preprocessing costs when logistical barriers are low seems to affect the landfill rate significantly. For instance, for a logistical barriers weight of 0.04, halving the preprocessing

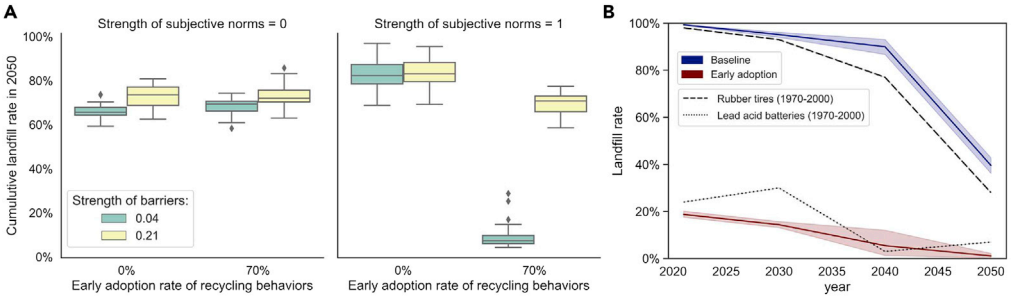


Figure 3. Landfilling behaviors under different assumptions about logistical barriers, subjective norms, and early adoption

Panel A presents the cumulative landfill rate in 2050, assuming fully subsidized take-back recycling programs, with various assumptions regarding the strength of subjective norms, logistical barriers, and the early adoption rate of recycling behaviors (error bars are 95% confidence intervals).

Panel B shows the yearly landfill rate of four cases: historical landfilling of rubber tires, historical landfilling of lead-acid batteries, the model's results in the baseline, and a scenario with a 70% early adoption rate, a high influence of subjective norms on EOL decisions, and low logistical barriers (far-right green box in panel A).

costs from $132/metric ton to $66/metric ton reduces the landfill rate by almost 20%. Moreover, Figure 2 identifies how results may quickly fluctuate with a change in either factor. For instance, logistical barriers weights below 0.1 seem to rapidly decrease the landfill rate (Figure 2B), whereas preprocessing costs below $79/metric ton (i.e., about two-thirds of current costs) seem to rapidly increase recycling revenues (Figure 2D). Thus, policymakers could increase wind blade recycling by easing logistical hurdles—for instance, by developing a simplified process to obtain all necessary states' transportation permits – and lowering preprocessing costs. Further policy implications from those results are discussed below.

Next, Figures 2E and 2F present the regional distribution of the provenance of the recycling revenues for a barriers factor strength of 0.04 and preprocessing costs of $28/metric ton (the same preprocessing costs as for segmented blades in the baseline). Because Texas is projected to represent 14% of 2050 cumulative installed wind power capacity and 19% of 2050 cumulative EOL wind blades, most recycling revenues originate from this state, even if Texas does not have the highest recycling rate. Transporting blades as shreds rather than segments almost doubles recycling revenues. The transportation of shredded blades also lowers (although to a lesser extent) the EOL costs borne by the wind plant owners (Figure S6).

Recycling behaviors in an early adoption scenario

Recently announced industry-led recycling programs and engagement for US EOL wind blades (Ørsted, 2021; Siemens Gamesa, 2021; Veolia, 2021; Vestas, 2021) hint that early recycling behavior adoption in the US could occur in the next few years. This early adoption could set a new norm regarding EOL management of wind blades, significantly reducing the cumulative amount of landfilled wind blades. Figure 3B presents the yearly landfill rate under such a hypothetical scenario and compares it with historical trends for two products—rubber tires and lead-acid batteries—and the model's baseline.

To further explore the conditions under which such early adoption would occur, Figure 3A presents a sensitivity analysis involving two of the TPB's factors—the subjective norms and logistical barriers. Assigning specific values to those factors yields early adoption of recycling behaviors, as depicted in Figure 3B (solid red curve). When no peer influence is assumed (i.e., the weight of subjective norms set to 0), even an 80% decrease of logistical barriers' strength from the baseline still hinders recycling (far-left panel of Figure 3A). On the other hand, strong subjective norms could help significantly reduce the 2050 cumulative landfill rate: the far-right panel of Figure 3A shows that under strong subjective norms and low logistical barriers, encouraging early adoption of recycling behaviors becomes an effective strategy (green box on the far-right).

These results further highlight the relevance of solving logistical issues related to wind blade transportation (e.g., by shredding EOL wind blades). Moreover, given that peer influence can lead to lock-ins where "bad habits" persist, it seems crucial to encourage early adoption of recycling behaviors. Ceschi et al. (2021) suggest that establishing strong injunctive norms (i.e., what people think they ought to do) regarding recycling,

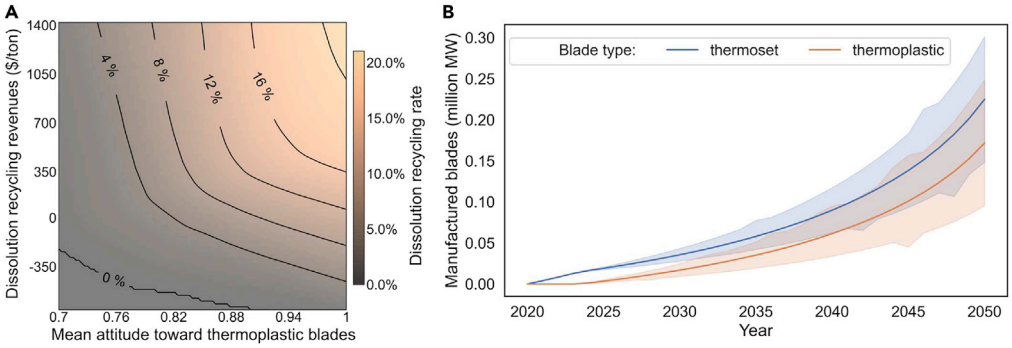


Figure 4. Adoption of thermoplastic blade designs and the dissolution recycling pathway

Panel A presents the dissolution-based recycling rate as a function of OEM and wind plant developers' attitudes toward thermoplastic blades and revenues of the dissolution recycling process.

Panel B shows the quantity (in MW) of wind blades produced for two resin options. The adoption of thermoplastic blades is simulated by setting attitude and dissolution net cost values of 0.8 and $600/metric ton, respectively, yielding a similar recycling rate as in the baseline. In panel B, shaded areas represent the 95% confidence interval. Data for panel A were generated with a ML metamodel trained on 1,609 parameter combinations (Sobol sequences) replicated 6 times.

such as through public information campaigns, is a prerequisite for implementing other policies based on peer influence. Figure 3A illustrates that argument, as a certain number of early adopters are necessary for peer influence to have a positive effect.

Behavioral factors affecting adoption of thermoplastic blade designs

Besides EOL strategies, wind blade circularity could be increased through a new blade design, such as using a thermoplastic rather than a thermoset resin. Thermoplastic resins could increase composites' recyclability because they are currently more easily recycled than thermoset resins (Cousins et al., 2019; Murray et al., 2019; Sakellariou, 2018). Thermoplastic blades could also present other advantages, such as cheaper manufacturing costs (Murray et al., 2019). However, OEM attitudes toward adopting thermoplastic blade designs could be negative if manufacturing such blades was believed to lower profits (Luo et al., 2017). Although unlikely, wind plant developers' attitudes toward thermoplastic blades could also be low, for instance, because of a lack of empirical feedback. The lack of trust in new technology and perceived risks could also affect OEM and developer attitudes (Bae and Chang, 2021; Canova et al., 2020).

However, adopting more easily recycled blade designs is just one side of the coin. Those blades still need to be effectively recycled at EOL. A high gate fee associated with the recycling process of such blades (e.g., through dissolution (Cousins et al., 2019)) could hinder their overall circularity. Indeed, there are still high uncertainties associated with the recycling costs of such blades (Cousins et al., 2019). Therefore, improving wind blade circularity through a new thermoplastic blade design requires the adoption of both the new design and recycling behaviors. Figure 4A shows the influence of OEM and developers' attitudes toward thermoplastic blades and the revenues of a hypothetical dissolution process. Figure 4B shows the adoption of the two types of blades for given values of those variables. In this scenario, the dissolution recycling facility locations are assumed to be the same as for the other recycling processes.

In Figure 4A, the dissolution-based recycling rate remains below 2% for attitude values below 0.7, no matter revenues. This result indicates that OEMs would need to have strong beliefs regarding the advantages of thermoplastic blades to adopt such a design. In line with the TPB, the slight difference in production costs and the low number of OEMs in the US (which hinders early adoption) means that a positive attitude is necessary to tip the OEMs' preferences in favor of this new design. Figure 4A also shows that wind plant owners' adoption of dissolution recycling mainly occurs for positive revenues. Because of the influence of the other TPB factors (such as regulatory pressures), some wind plant owners could still choose this EOL pathway even if a gate fee is required.

Finally, Figure 4A presents the dissolution-based recycling rate rather than the landfill rate because the latter does not vary much with the variables of interest. This result is explained by the fact that dissolution

replaces (or competes with) other recycling pathways, rather than landfilling. The assumption that dissolution recycling facilities are located at the same locations as the other recycling pathways is responsible for this outcome.

DISCUSSION

As recently argued by Peng et al. (2021) regarding integrated assessment models, misrepresenting how people behave can lead to unforeseen policy missteps. An example is the 2018 "gilets jaunes" (yellow vests) protests triggered by a fuel tax increase in France (Laurent, 2019; Peng et al., 2021). As suggested by Peng et al. (2021), our study uses insights from psychology and organizational behavior to shed light on factors that could potentially hinder or boost EOL wind blade recycling. For instance, although thermoplastic blades seem to be advantageous for OEMs (Murray et al., 2019), our study shows that perceived risks or other antecedents of attitude could cause OEMs to "stick with old, familiar technologies even when new ones are much superior" (Peng et al., 2021) (Figure 4).

Besides attitude, subjective norms also play a role in recycling behavior adoption (Abrahamse and Steg, 2013; Ceschi et al., 2021; Geiger et al., 2019). These norms are a key determinant of the lack of recycling behaviors; people are discouraged from recycling if they observe others not recycling or a dirty environment (Ceschi et al., 2021). This observation is also valid for organizational behaviors, where the knowledge of other organizations' participation in recycling may influence an organization's own recycling behaviors (Khan et al., 2020). Interestingly, subjective norms can either hinder or boost recycling (Ceschi et al., 2021). In our study, Figure 1 presents a case where subjective norms hinder recycling, whereas Figure 3 shows that subjective norms further boost recycling when there are enough early adopters. (Figure 3 shows that if subjective norms were not influencing wind plant owners' decisions, early adoption would not have any effects on results).

In line with the literature, positive attitudes and regulatory pressures positively influence circular organizational behaviors in our study (Khan et al., 2020). Because a single wind plant owner may operate in several states, observing regulations adopted in a particular state may push the organization to change its practices for all its plants, even outside the state with regulations. Moreover, logistical barriers strongly hinder the adoption of circular behaviors in our simulations, as observed in other works (Khan et al., 2020; Liu and Bai, 2014; Ormazabal et al., 2018; Ritzén and Sandström, 2017).

Also in line with the literature, perceived behavioral control plays a crucial role in recycling adoption in our study, particularly in combination with barriers (Geiger et al., 2019). As Yuriev et al. (2020) argue, and as demonstrated in our study, barriers must first be mitigated for perceived behavioral control to have a significant influence. In Figure 2B, transporting blades as shreds rather than segments decreases transport costs and thus enhances perceived behavioral control. However, only when logistical barriers are low are recycling behaviors adopted, lowering the landfill rate.

Transportation plays a crucial role in our study. By using an ABM approach, we were able to use spatially resolved data to account for wind industry actors' heterogeneity (e.g., regarding locations, power capacities of wind plant projects, and landfill remaining capacities)—a feature not necessarily easily achieved with top-down approaches such as material flow analysis or system dynamics. Using wind plant owners', landfills', and recycling facilities' geographical coordinates, we used a detailed transportation model. Using accurate distances between wind plant owners and EOL sites is particularly relevant in our ABM because they affect both perceived behavioral control and logistical barriers (supplemental methods). In line with our work, another study found that the two most prevalent barriers to recycling were lack of easy access to a recycling facility and difficulty in transporting waste (Khan et al., 2020).

Crucially, three main policy implications stand out from our analysis. First, reducing costs linked to transportation could significantly increase wind blade recycling (i.e., reduce landfilling), especially if this cost reduction also decreases logistical barriers (e.g., because of a more easily transported physical form such as shreds). A preprocessing cost target of $79/ton (i.e., about two-thirds of current costs), for instance, could lower the landfill rate below 50% if shredding effectively removes logistical barriers (Figure 2B). Second, wind industry recycling programs could leverage enough early adopters to set a new social norm: recycling blades rather than landfilling them (Figure 3). Third, Figure 4 shows that developing a new blade

design may not affect the landfill rate significantly on its own (as it does not necessarily solve transportation issues).

Limitations of the study

Besides results presented in Figure S5, our analysis has not extensively investigated the effect of having additional recycling facilities in the US (e.g., on the West Coast) because existing US mechanical and pyrolysis recycling facilities are believed to have enough capacity to handle near-to-medium term EOL wind blade volumes (Ginder, 2020; Global Fiberglass Solutions, 2020). Future work could study how increasing the number of recycling facilities affects results and optimize their geographical distribution. Indeed, given the relative youth of the installed fleet and the rate at which wind power will need to be deployed for decarbonization, the deployment of wind blade recycling facilities across the US seems to present a great opportunity for EOL wind blade recycling.

Another limit of our study is that the weights in the TPB model have come from secondary sources. Although the strengths of various behavioral factors have been evaluated in many studies on recycling behavior adoption (Ceschi et al., 2021; Geiger et al., 2019; Jain et al., 2020; Khan et al., 2020), there is no study specific to the wind industry. Thus, another research avenue could be to conduct a behavioral survey of wind stakeholders. Results from the CE wind ABM demonstrate that assessing the strengths of barriers and social norms would be particularly relevant.

Moreover, our study was limited to five EOL pathways, but other options could prove to be more advantageous and be more widely adopted, especially in the long-term. For instance, in a study using multiple criteria decision analysis, blade repurposing (such as building bridges or making furniture) systematically performed better than landfilling, cement co-processing, and energy recovery (Deeney et al., 2021). Other recycling processes such as high-voltage fragmentation and microwave pyrolysis also present some advantages compared to the mechanical recycling and pyrolysis processes analyzed in this study (higher fiber quality and lower energy requirements resp.) (Cooperman et al., 2021).

Finally, by accounting for the behavioral factors affecting wind blades EOL management, and exploring possible interventions outside of technology development, this study bridges disciplines to provide guidance to policymakers regarding wind power circularity. The method developed in this work could further be used to investigate the application of CE strategies to other technologies.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
  - Lead contact
  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - Overview
  - Design concepts
  - Details
  - Initialization
  - Wind plant owner agents
  - Wind plant developer agents
  - Recycler agents
  - Original equipment manufacturer agents
  - Landfill agents
  - Regulator agents
  - Machine-learning metamodel
- QUANTIFICATION AND STATISTICAL ANALYSIS

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.104734.

ACKNOWLEDGMENTS

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the US Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the Advanced Manufacturing Office and the Office of Strategic Programs. The views expressed in the article do not necessarily represent the views of the DOE or the US Government. The US Government retains and the publisher, by accepting the article for publication, acknowledges that the US Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for US Government purposes. We would also like to thank Michael Deneen for his insightful edits, Robynne Murray for her insights on thermoplastic blades, Karl Englund and Ryan Ginder for useful discussions regarding recycling processes, Taylor Curtis and Jesse Carey for their review of transportation requirements and EOL regulations, and Patrick Gilman, Kara Podkaminer, Daniel Desantis, Joe Cresko, Richard Tusing, and Tyler Christoffel for their helpful guidance.

AUTHOR CONTRIBUTIONS

J.W., A.Co, A.L.E., A.Ca., and G.A.H. developed the study concept. J.W. designed the methodology. J.W. and L.W. built the model. J.W. performed the analysis. J.W., A.Co, L.W., A.L.E., A.Ca., and G.A.H wrote the paper.

DECLARATIONS OF INTEREST

None.

Received: November 24, 2021
Revised: June 22, 2022
Accepted: July 2, 2022
Published: August 19, 2022

REFERENCES

Abrahamse, W., and Steg, L. (2013). Social influence approaches to encourage resource conservation: a meta-analysis. Global Environ. Change *23*, 1773–1785. https://doi.org/10.1016/j.gloenvcha.2013.07.029.

Ajzen, I. (1991). The theory of planned behavior. Organ. Behav. Hum. Decis. Process. *50*, 179–211.

Arkema (2022). Elium® Thermoplastic Resins for Composites. https://www.arkema.com/global/en/products/product-finder/product-range/incubator/elium_resins/.

ATRI (2019). An Analysis of the Operational Costs of Trucking: 2019 Update (ATRI).

AWEA (2020). Wind Powers America Annual Report 2019 (AWEA).

Bae, S.Y., and Chang, P.-J. (2021). The effect of coronavirus disease-19 (COVID-19) risk perception on behavioural intention towards 'untact' tourism in South Korea during the first wave of the pandemic (March 2020). Curr. Issues Tourism *24*, 1017–1035. https://doi.org/10.1080/13683500.2020.1798895.

Bedeschi, B. (2020). GE Goes beyond Carbon Neutral to Cut Blade Waste. https://www.reutersevents.com/renewables/wind-energy-update/ge-goes-beyond-carbon-neutral-cut-blade-waste.

Bergesen, J.D., and Suh, S. (2016). A framework for technological learning in the supply chain: a case study on CdTe photovoltaics. Appl. Energy *169*, 721–728. https://doi.org/10.1016/j.apenergy.2016.02.013.

Bortolotti, P., Berry, D.S., Murray, R., Gaertner, E., Jenne, D.S., Damiani, R.R., Barter, G.E., and Dykes, K.L. (2019). A Detailed Wind Turbine Blade Cost Model (National Renewable Energy Lab. (NREL)). NREL/TP-5000-73585. https://doi.org/10.2172/1529217. https://www.osti.gov/servlets/purl/1529217.

Byrka, K., Jędrzejewski, A., Sznajd-Weron, K., and Weron, R. (2016). Difficulty is critical: the importance of social factors in modeling diffusion of green products and practices. Renew. Sustain. Energy Rev. *62*, 723–735. https://doi.org/10.1016/j.rser.2016.04.063.

Caduff, M., Huijbregts, M.A.J., Althaus, H.-J., Koehler, A., and Hellweg, S. (2012). Wind power electricity: the bigger the turbine, the greener the electricity? Environ. Sci. Technol. *46*, 4725–4733. https://doi.org/10.1021/es204108n.

Canova, L., Bobbio, A., and Manganelli, A.M. (2020). Buying organic food products: the role of trust in the theory of planned behavior. Front. Psychol. *11*, 575820. https://doi.org/10.3389/fpsyg.2020.575820.

Cantzler, J., Creutzig, F., Ayargarnchanakul, E., Javaid, A., Wong, L., and Haas, W. (2020). Saving resources and the climate? A systematic review of the circular economy and its mitigation potential. Environ. Res. Lett. *15*, 123001.

Ceschi, A., Sartori, R., Dickert, S., Scalco, A., Tur, E.M., Tommasi, F., and Delfini, K. (2021). Testing a norm-based policy for waste management: an agent-based modeling simulation on nudging recycling behavior. J. Environ. Manage. *294*, 112938. https://doi.org/10.1016/j.jenvman.2021.112938.

Chang, N.-B. (2008). Economic and policy instrument analyses in support of the scrap tire recycling program in Taiwan. J. Environ. Manage. *86*, 435–450. https://doi.org/10.1016/j.jenvman.2006.12.026.

CompositeWorld (2020). Composites Recycling is Gaining Traction. https://www.compositesworld.com/articles/composites-recycling-is-gaining-traction.

Cooperman, A., Eberle, A., and Lantz, E. (2021). Wind turbine blade material in the United States: quantities, costs, and end-of-life options. Resour. Conserv. Recycl. *168*, 105439. https://doi.org/10.1016/j.resconrec.2021.105439.

Cousins, D.S., Suzuki, Y., Murray, R.E., Samaniuk, J.R., and Stebner, A.P. (2019). Recycling glass fiber thermoplastic composites from wind turbine blades. J. Clean. Prod. *209*, 1252–1263. https://doi.org/10.1016/j.jclepro.2018.10.286.

Dahlke, J., Bogner, K., Mueller, M., Berger, T., Pyka, A., and Ebersberger, B. (2020). Is the juice worth the squeeze? Machine learning (ML) in and for agent-based modelling (ABM). Preprint at arXiv. https://doi.org/10.48550/arXiv.2003.11985.

Deeney, P., Nagle, A.J., Gough, F., Lemmertz, H., Delaney, E.L., McKinley, J.M., Graham, C., Leahy, P.G., Dunphy, N.P., and Mullally, G. (2021). End-of-Life alternatives for wind turbine blades: sustainability Indices based on the UN sustainable development goals. Resour. Conserv.

Recycl. *171*, 105642. https://doi.org/10.1016/j.resconrec.2021.105642.

EIA (2016). Three Turbine Manufacturers Provide More than 75% of U.S. Wind Capacity. https://www.eia.gov/todayinenergy/detail.php?id=28912.

EIA (2022). Electricity Generation, Capacity, and Sales in the United States (EIA).

energyacuity (2018). Top 10 Wind Plant Developers to Brush Shoulders with at AWEA 2018. https://energyacuity.com/blog/top-10-wind-developers-to-brush-shoulders-with-at-awea-2018/.

EPA (1999). State Scrap Tire Programs: A Quick Reference Guide: 1999 Update (EPA). EPA-530-B-99-002.

EPA (2019). Landfill Technical Data [Overviews and Factsheets]. https://www.epa.gov/lmop/landfill-technical-data.

EPA (2021). Vehicle Tires Waste Management: 1960-2018. https://www.epa.gov/.

EPRI (2020). Wind Turbine Blade Recycling: Preliminary Assessment (EPRI). 3002017711.

EREF (2019). Analysis of MSW Landfill Tipping Fees. https://erefdn.org/.

Faulstich, S., Berkhout, V., Mayer, J., and Siebenlist, D. (2016). Modelling the failure behaviour of wind turbines. J. Phys, Conf. Ser. *749*, 012019. https://doi.org/10.1088/1742-6596/749/1/012019.

Fonte, R., and Xydis, G. (2021). Wind turbine blade recycling: an evaluation of the European market potential for recycled composite materials. J. Environ. Manage. *287*, 112269. https://doi.org/10.1016/j.jenvman.2021.112269.

FutureBridge (2020). The Future of Wind Blade Recycling: Driving Circularity to Composites Industry. https://www.futurebridge.com/industry/perspectives-energy/the-future-of-wind-blade-recycling-driving-circularity-to-composites-industry/.

Gainforth, H.L., West, R., and Michie, S. (2015). Assessing connections between behavior change theories using network analysis. Ann. Behav. Med. *49*, 754–761. https://doi.org/10.1007/s12160-015-9710-7.

GE (2020). GE Renewable Energy Announces US Blade Recycling Contract with Veolia. https://www.ge.com/news/press-releases/ge-renewable-energy-announces-us-blade-recycling-contract-with-veolia.

Geiger, J.L., Steg, L., van der Werff, E., and Ünal, A.B. (2019). A meta-analysis of factors related to recycling. J. Environ. Psychol. *64*, 78–97. https://doi.org/10.1016/j.jenvp.2019.05.004.

Ginder, R.S. (2020). In Personal communication, A. Eberle, J. Walzberg, and R. Hanes, eds..

Ginder, R.S., and Ozcan, S. (2019). Recycling of commercial E-glass reinforced thermoset composites via two temperature step pyrolysis to improve recovered fiber tensile strength and failure strain. Recycling *4*, 24.

Global Fiberglass Solutions (2020). In Personal communication, A. Eberle, A. Cooperman, and R. Hanes, eds..

globalcementmagazine (2012). Cement in the USA (globalcementmagazine).

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., et al. (2006). A standard protocol for describing individual-based and agent-based models. Ecol. Model. *198*, 115–126. https://doi.org/10.1016/j.ecolmodel.2006.04.023.

Hagberg, A., Swart, P., and S Chult, D. (2008). Exploring Network Structure, Dynamics, and Function Using NetworkX (Los Alamos National Lab. (LANL)).

Hanes, R., Ghosh, T., Key, A., and Eberle, A. (2021). The circular economy lifecycle assessment and visualization framework: a case study of wind blade circularity in Texas. Front. Sustain. *2*. https://doi.org/10.3389/frsus.2021.671979.

Herman, J., and Usher, W. (2017). SALib: an open-source Python library for sensitivity analysis. J. Open Source Softw. *2*, 97.

Hinkelmann, F., Murrugarra, D., Jarrah, A.S., and Laubenbacher, R. (2011). A mathematical framework for agent based models of complex biological networks. Bull. Math. Biol. *73*, 1583–1602. https://doi.org/10.1007/s11538-010-9582-8. https://www.osti.gov/servlets/purl/1818277.

Hutton, K., and Soulier, C. (2020). Practical Cases of Repowering & Life Extension in France, UK and Ireland. held in Virtual.

Jäger, G. (2019). Replacing rules by neural networks A framework for agent-based modelling. Big Data Cogn. Comput. *3*, 51.

Jain, S., Singhal, S., Jain, N.K., and Bhaskar, K. (2020). Construction and demolition waste recycling: investigating the role of theory of planned behavior, institutional pressures and environmental consciousness. J. Clean. Prod. *263*, 121405. https://doi.org/10.1016/j.jclepro.2020.121405.

Jalili, M. (2013). Social power and opinion formation in complex networks. Phys. Stat. Mech. Appl. *392*, 959–966. https://doi.org/10.1016/j.physa.2012.10.013.

James, T., and Goodrich, A. (2013). Supply Chain and Blade Manufacturing Considerations in the Global Wind Industry (Presentation) (National Renewable Energy Lab. (NREL)). NREL/PR-6A20-60063 United States 10.2172/1115775 NREL English. https://www.osti.gov/servlets/purl/1115775.

Jensen, J.P. (2019). Evaluating the environmental impacts of recycling wind turbines. Wind Energy *22*, 316–326. https://doi.org/10.1002/we.2287.

Jensen, J.P., and Skelton, K. (2018). Wind turbine blade recycling: experiences, challenges and possibilities in a circular economy. Renew. Sustain. Energy Rev. *97*, 165–176. https://doi.org/10.1016/j.rser.2018.08.041.

Khan, O., Daddi, T., Slabbinck, H., Kleinhans, K., Vazquez-Brust, D., and De Meester, S. (2020). Assessing the determinants of intentions and behaviors of organizations towards a circular economy for plastics. Resour. Conserv. Recycl. *163*, 105069. https://doi.org/10.1016/j.resconrec.2020.105069.

Korhonen, J., Honkasalo, A., and Seppälä, J. (2018). Circular economy: the concept and its limitations. Ecol. Econ. *143*, 37–46. https://doi.org/10.1016/j.ecolecon.2017.06.041.

Largeau, C., Martens, J., and Koelers, M. (2020). Zebra Project: Developing 100% Recyclable Wind Blades by 2025. held in Virtual.

Laurent, É. (2019). La transition écologique française: de L'enlisement À L'encastrement. OFCE Policy Brief *52*, 1–8.

Li, J., Zuo, J., Cai, H., and Zillante, G. (2018). Construction waste reduction behavior of contractor employees: an extended theory of planned behavior model approach. J. Clean. Prod. *172*, 1399–1408. https://doi.org/10.1016/j.jclepro.2017.10.138.

Linder, M., Sarasini, S., and van Loon, P. (2017). A metric for quantifying product-level circularity. J. Ind. Ecol. *21*, 545–558. https://doi.org/10.1111/jiec.12552.

Liu, P., and Barlow, C.Y. (2017). Wind turbine blade waste in 2050. Waste Manag. *62*, 229–240. https://doi.org/10.1016/j.wasman.2017.02.007.

Liu, P., Meng, F., and Barlow, C.Y. (2019). Wind turbine blade end-of-life options: an eco-audit comparison. J. Clean. Prod. *212*, 1268–1281. https://doi.org/10.1016/j.jclepro.2018.12.043.

Liu, Y., and Bai, Y. (2014). An exploration of firms' awareness and behavior of developing circular economy: an empirical research in China. Resour. Conserv. Recycl. *87*, 145–152. https://doi.org/10.1016/j.resconrec.2014.04.002.

Luo, Z., Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Hazen, B., and Roubaud, D. (2017). Sustainable production framework for cement manufacturing firms: a behavioural perspective. Renew. Sustain. Energy Rev. *78*, 495–502. https://doi.org/10.1016/j.rser.2017.04.069.

Masad, D., and Kazil, J. (2015). MESA: An Agent-Based Modeling Framework, pp. 53–60. https://doi.org/10.25080/Majora-7b98e3ed-009.

Montalvo Corral, C. (2003). Sustainable production and consumption systems—cooperation for change: assessing and simulating the willingness of the firm to adopt/develop cleaner technologies. The case of the In-Bond industry in northern Mexico. J. Clean. Prod. *11*, 411–426. https://doi.org/10.1016/S0959-6526(02)00063-X.

Moraga, G., Huysveld, S., Mathieux, F., Blengini, G.A., Alaerts, L., Van Acker, K., de Meester, S., and Dewulf, J. (2019). Circular economy indicators: what do they measure? Resour. Conserv. Recycl. *146*, 452–461. https://doi.org/10.1016/j.resconrec.2019.03.045.

Murray, R.E., Jenne, S., Snowberg, D., Berry, D., and Cousins, D. (2019). Techno-economic analysis of a megawatt-scale thermoplastic resin wind turbine blade. Renew. Energy *131*,

111–119. https://doi.org/10.1016/j.renene.2018.07.032.

Nagle, A.J., Delaney, E.L., Bank, L.C., and Leahy, P.G. (2020). A Comparative Life Cycle Assessment between landfilling and Co-Processing of waste from decommissioned Irish wind turbine blades. J. Clean. Prod. *277*, 123321. https://doi.org/10.1016/j.jclepro.2020.123321.

Naqvi, S.R., Prabhakara, H.M., Bramer, E.A., Dierkes, W., Akkerman, R., and Brem, G. (2018). A critical review on recycling of end-of-life carbon fibre/glass fibre reinforced composites waste using pyrolysis towards a circular economy. Resour. Conserv. Recycl. *136*, 118–129. https://doi.org/10.1016/j.resconrec.2018.04.013.

NREL (2020). Standard Scenarios. https://www.nrel.gov/analysis/standard-scenarios.html.

NREL (2021). Annual Technology Baseline. https://atb.nrel.gov/.

Oliveux, G., Dandy, L.O., and Leeke, G.A. (2015). Current status of recycling of fibre reinforced polymers: review of technologies, reuse and resulting properties. Prog. Mater. Sci. *72*, 61–99. https://doi.org/10.1016/j.pmatsci.2015.01.004.

Openrouteservice (2021). Openrouteservice API Services. https://openrouteservice.org/.

OpenStreetMap (2021). OpenStreetMap. https://www.openstreetmap.org.

Ormazabal, M., Prieto-Sandoval, V., Puga-Leal, R., and Jaca, C. (2018). Circular economy in Spanish SMEs: challenges and opportunities. J. Clean. Prod. *185*, 157–167. https://doi.org/10.1016/j.jclepro.2018.03.031.

Ørsted (2021). Ørsted Commits to Sustainable Recycling of Wind Turbine Blades. https://orsted.com/.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., and Dubourg, V. (2011). Scikit-learn: machine learning in Python. J. Mach. Learn. Res. *12*, 2825–2830.

Peng, W., Iyer, G., Bosetti, V., Chaturvedi, V., Edmonds, J., Fawcett, A.A., Hallegatte, S., Victor, D.G., van Vuuren, D., and Weyant, J. (2021). Climate Policy Models Need to Get Real about People—Here's How (Nature Publishing Group).

Piel, J.H., Stetter, C., Heumann, M., Westbomke, M., and Breitner, M.H. (2019). Lifetime extension, repowering or decommissioning? Decision support for operators of ageing wind turbines. J. Phys, Conf. Ser. *1222*, 012033. https://doi.org/10.1088/1742-6596/1222/1/012033.

Pietzsch, B., Fiedler, S., Mertens, K.G., Richter, M., Scherer, C., Widyastuti, K., Wimmler, M.C., Zakharova, L., Berger, U., and Berger, U. (2020). Metamodels for evaluating, calibrating and applying agent-based models: a review. J. Artif. Soc. Soc. Simul. *23*, 9. https://doi.org/10.18564/jasss.4274.

Purcell, A.H. (1978). Tire recyling: research trends and needs. Conserv. Recycl. *2*, 137–143. https://doi.org/10.1016/0361-3658(78)90053-X.

Ramôa Correia, J. (2013). 9 - pultrusion of advanced fibre-reinforced polymer (FRP) composites. In Advanced Fibre-Reinforced Polymer (FRP) Composites for Structural Applications, J. Bai, ed. (Woodhead Publishing), pp. 207–251. https://doi.org/10.1533/9780857098641.2.207.

Rand, J.T., Kramer, L.A., Garrity, C.P., Hoen, B.D., Diffendorfer, J.E., Hunt, H.E., and Spears, M. (2020). A continuously updated, geospatially rectified database of utility-scale wind turbines in the United States. Sci. Data *7*, 15. https://doi.org/10.1038/s41597-020-0353-6.

Rand, W. (2019). Theory-interpretable, data-driven agent-based modeling. In Social-Behavioral Modeling for Complex Systems, pp. 337–357. https://doi.org/10.1002/9781119485001.ch15.

Ritzén, S., and Sandström, G.Ö. (2017). Barriers to the circular economy – integration of perspectives and domains. Procedia CIRP *64*, 7–12. https://doi.org/10.1016/j.procir.2017.03.005.

Rybicka, J., Tiwari, A., and Leeke, G.A. (2016). Technology readiness level assessment of composites recycling technologies. J. Clean. Prod. *112*, 1001–1012. https://doi.org/10.1016/j.jclepro.2015.08.104.

Sakellariou, N. (2018). Current and potential decommissioning scenarios for end-of-life composite wind blades. Energy Syst. *9*, 981–1023. https://doi.org/10.1007/s12667-017-0245-9.

Salim, H.K., Stewart, R.A., Sahin, O., and Dudley, M. (2019). Drivers, barriers and enablers to end-of-life management of solar photovoltaic and battery energy storage systems: a systematic literature review. J. Clean. Prod. *211*, 537–554. https://doi.org/10.1016/j.jclepro.2018.11.229.

Shuaib, N.A., Mativenga, P.T., Kazie, J., and Job, S. (2015). Resource efficiency and composite waste in UK supply chain. Procedia CIRP *29*, 662–667. https://doi.org/10.1016/j.procir.2015.02.042.

Siemens Gamesa (2021). Siemens Gamesa Puts Decarbonization, Recyclability and Technological Education at Heart of Ambitious New Sustainability Strategy. https://www.siemensgamesa.com/.

Sovacool, B.K., and Griffiths, S. (2020). Culture and low-carbon energy transitions. Nat. Sustain. *3*, 685–693. https://doi.org/10.1038/s41893-020-0519-4.

Stahel, W.R. (2016). The circular economy. Nature *531*, 435–438. https://doi.org/10.1038/531435a.

Tangler, J. (2000). The Evolution of Rotor and Blade Design (National Renewable Energy Lab. (NREL)).

Tazi, N., Kim, J., Bouzidi, Y., Chatelet, E., and Liu, G. (2019). Waste and material flow analysis in the end-of-life wind energy system. Resour. Conserv. Recycl. *145*, 199–207. https://doi.org/10.1016/j.resconrec.2019.02.039.

Telesford, Q.K., Joyce, K.E., Hayasaka, S., Burdette, J.H., and Laurienti, P.J. (2011). The ubiquity of small-world networks. Brain Connect. *1*, 367–375. https://doi.org/10.1089/brain.2011.0038.

U.S. Census Bureau (2012). United States Summary: 2010 Population and Housing Unit Counts 2010 Census of Population and Housing.

Vahdati, A.R., Weissmann, J.D., Timmermann, A., Ponce de León, M.S., Zollikofer, C.P., and Zollikofer, C.P.E. (2019). Drivers of Late Pleistocene human survival and dispersal: an agent-based modeling and machine learning approach. Quat. Sci. Rev. *221*, 105867. https://doi.org/10.1016/j.quascirev.2019.105867.

Veolia (2021). GE Renewable Energy Announces US Blade Recycling Contract with Veolia. https://www.veolianorthamerica.com/.

Vestas (2021). The Recyclability of Our Turbines. https://www.vestas.com/.

Walzberg, J., Lonca, G., Hanes, R.J., Eberle, A.L., Carpenter, A., and Heath, G.A. (2021a). Do we need a new sustainability assessment method for the circular economy? A critical literature review. Front. Sustain. *1*. https://doi.org/10.3389/frsus.2020.620047.

Walzberg, J., Carpenter, A., and Heath, G.A. (2021b). Role of the social factors in success of solar photovoltaic reuse and recycle programmes. Nat. Energy *6*, 913–924. https://doi.org/10.1038/s41560-021-00888-5.

Walzberg, J.; USDOE Office of Energy Efficiency and Renewable Energy (EERE); Energy Efficiency Office. Advanced Manufacturing Office; USDOE Office of Energy Efficiency and Renewable Energy (EERE), Renewable Power Office. Wind Energy Technologies Office (2021c). CEWAM (Circular Economy Wind Agent-based Model). https://doi.org/10.11578/dc.20211101.2.

Walzberg, J., Burton, R., Zhao, F., Frost, K., Muller, S., Carpenter, A., and Heath, G. (2022). An investigation of hard-disk drive circularity accounting for socio-technical dynamics and data uncertainty. Resour. Conserv. Recycl. *178*, 106102. https://doi.org/10.1016/j.resconrec.2021.106102.

Waste Business Journal (2020) (WBJ Landfills).

Watts, D.J., and Strogatz, S.H. (1998). Collective dynamics of 'small-world'networks. Nature *393*, 440–442.

Wiser, R.H., and Bolinger, M. (2019). 2018 Wind Technologies Market Report (Lawrence Berkeley National Lab. (LBNL)). DOE/GO-102019-5191; Other: ark:/13030/qt2tc1819q United States 10.2172/1559241 Other: ark:/13030/qt2tc1819q LBNLSCH. https://www.osti.gov/servlets/purl/1559241.

Wiser, R.H., Bolinger, M., Hoen, B., Millstein, D., Rand, J., Barbose, G.L., Darghouth, N.R., Gorman, W., Jeong, S., Mills, A.D., and Paulos, B. (2021). Land-Based Wind Market Report: 2021 Edition. https://www.osti.gov/biblio/1818277.

Woodhouse, M.A., Smith, B., Ramdas, A., and Margolis, R.M. (2019). Crystalline Silicon Photovoltaic Module Manufacturing Costs and Sustainable Pricing: 1H 2018 Benchmark and Cost Reduction Road Map (National Renewable

Energy Lab. (NREL)). NREL/TP-6A20-72134 United States 10.2172/1495719 NREL English. https://www.osti.gov/servlets/purl/1495719.

Yang, S., Su, Y., Wang, W., and Hua, K. (2019). Research on developers' green procurement behavior based on the theory of planned behavior. Sustainability *11*, 2949.

Yuriev, A., Dahmen, M., Paillé, P., Boiral, O., and Guillaumie, L. (2020). Pro-environmental behaviors through the lens of the theory of planned behavior: a scoping review. Resour. Conserv. Recycl. *155*, 104660. https://doi.org/10.1016/j.resconrec.2019.104660.

Zhang, B., Yang, S., and Bi, J. (2013). Enterprises' willingness to adopt/develop cleaner production technologies: an empirical study in Changshu, China. J. Clean. Prod. *40*, 62–70. https://doi.org/10.1016/j.jclepro.2010.12.009.

Zhang, G., Zhang, Y., Tian, W., Li, H., Guo, P., and Ye, F. (2021). Bridging the intention–behavior gap: effect of altruistic motives on developers' action towards green redevelopment of industrial brownfields. Sustainability *13*, 977.

Zhang, H., Vorobeychik, Y., Letchford, J., and Lakkaraju, K. (2016). Data-driven agent-based modeling, with application to rooftop solar adoption. Auton. Agent. Multi Agent. Syst. *30*, 1023–1049. https://doi.org/10.1007/s10458-016-9326-8.

Ziegler, L., Gonzalez, E., Rubert, T., Smolka, U., and Melero, J.J. (2018). Lifetime extension of onshore wind turbines: a review covering Germany, Spain, Denmark, and the UK. Renew. Sustain. Energy Rev. *82*, 1261–1271. https://doi.org/10.1016/j.rser.2017.09.100.

CellPress
OPEN ACCESS

STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Software and algorithms		
CE wind ABM GitHub repository	This paper	https://doi.org/10.11578/dc.20211101.2

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Julien Walzberg (julien.walzberg@nrel.gov).

Materials availability

This study did not generate new unique reagents.

Data and code availability

The data supporting the findings of this study are available within the paper, its supplemental information, and the following GitHub repository: https://doi.org/10.11578/dc.20211101.2, except for the *Waste Business Journal* database, which is proprietary. The code used for this study is available on the GitHub repository above.

METHOD DETAILS

The CE wind ABM builds on previous work (Cooperman et al., 2021; Walzberg et al., 2021b, 2022). The model is designed to study the implementation of CE strategies for wind blades and identify the factors that maximize wind blade circularity. The ABM meets those functionalities by representing the heterogeneous actors of the CE transition and their decisions. The ABM's primary output data are the wind blade masses that undergo different CE pathways (i.e., wind blade mass amounts subjected to redesign, lifetime extension, or recycling). The "overview, design concepts, and details" protocol describes the proposed ABM (Walzberg et al., 2021b). This protocol provides a standard framework for describing ABMs, facilitating the communication and reproducibility of such models (Hinkelmann et al., 2011). According to the protocol, the following main elements need to be specified: purpose of the model, main variables and inputs, initialization and simulation steps, overall design, and submodels used (Grimm et al., 2006).

Overview

The CE wind ABM aims to study the implementation of CE strategies within the wind power industry and identify the conditions that maximize circularity. To that end, the model employs six types of agents (Figure S1):

1. OEMs (manufacture wind blades)
2. Wind plant developers (develop new wind plant projects)
3. Wind plant owners (operate wind plants)
4. Recyclers (recover materials from recycling of wind blades)
5. Landfill operators (track remaining capacity for disposal)
6. Regulators (enact local regulations such as landfill bans).

Agents of a specific type behave similarly but have heterogeneous characteristics represented with probability distributions or with assigned values depending on external sources (e.g., each wind plant owner agent is assigned a project capacity and rotor diameter (Rand et al., 2020)). Networks connect the agents to represent social relationships among them. We simplify stakeholders as constituting the six broad

categories listed above as their decisions are likely to have the most impact on circularity. However, we acknowledge that, in the real world, decisions of intermediary actors (for example, insurers and decommissioners) may also affect wind blade circularity to some extent.

The CE wind ABM models the cumulative amount of wind blades in use and the EOL wind blade volumes at each simulation time step. First, the OEM agents decide whether to manufacture thermoplastic blades, and wind plant developers choose which type of blades to purchase when developing new wind plant projects. These steps enable the study of thermoplastic blade design adoption. Next, wind plant owners make decisions regarding the adoption of a particular EOL option. Two CE strategies are modeled: (1) lifetime extension and (2) recycling, either through pyrolysis, grinding (i.e., mechanical recycling), or cement co-processing. If neither of the two aforementioned CE strategies is adopted, blades are landfilled.

The agents' decisions to adopt a particular wind blade design or EOL option are based on the TPB and other rules, which include techno-economic factors (e.g., lifetime extension cannot be chosen if the wind turbine did not pass the required reliability tests) and social factors (e.g., the subjective norms of wind plant owners). Therefore, both techno-economic and social factors are accounted for in the CE wind ABM. The wind blade volumes targeted by each CE strategy are computed at each time step of the simulation and for each agent.

The developed ABM assesses the mass of EOL wind blades that avoids being landfilled and the costs and revenues associated with the different design and EOL options. In addition to the behavioral dynamics captured with the TPB, the ABM accounts for technological development dynamics, such as the increase in wind turbines' rated capacity (NREL, 2021) and the learning effect (i.e., the decrease in recycling costs with increasing recycled volumes due to factors such as economies of scale) that are likely to occur in future wind blade recycling (Hanes et al., 2021). The ABM is also spatially resolved whenever possible (e.g., using the wind turbine coordinates contained in the US Wind Turbine Database [USWTDB]).

Design concepts

In the CE wind ABM, each agent type is defined as a Python class and is contained in a Python module using the Mesa Python package (Masad and Kazil, 2015). The model itself (which contains the model's input and the functions accessed by several agents, and collects simulation outputs) is another Python class. Finally, two Python modules contain functions to run individual and batches of simulations.

Different interactions between agents are modeled: between agents of the same type (e.g., subjective norms may influence wind plant owners' EOL blade decisions (Khan et al., 2020; Yuriev et al., 2020)) and between agents of different types (e.g., wind plant owner agents have information about recycler agents' gate fees and landfill agents' tipping fees).

Like several other ABMs, the CE wind ABM is stochastic. Some of the agents' characteristics are drawn from probability distributions to model their variability (e.g., decommissioning costs). Moreover, a random scheduler is used to activate agents (avoiding the situation that the same agents always make decisions before others in the simulations). Finally, the Watts–Strogatz algorithm, which builds small-world networks (used to represent the agents' social relationships), requires rewiring each edge of a regular graph with a certain probability (Byrka et al., 2016; Hagberg et al., 2008; Watts and Strogatz, 1998).

The overall model behavior emerges from agents changing their states during the simulation. The agents' state changes follow their behavioral rules: their interactions with one another (either direct or indirect) and with their environment. These behavioral rules are detailed in the supplemental methods. In this study, the decision to adopt a thermoplastic blade design is assumed to follow the basic TPB model, whereas the EOL decision is assumed to follow an extended version of the TPB accounting for barriers and regulatory pressures.

Although data can be collected at the agent's level, aggregated results are provided in this study for simplicity. The masses of blades (in metric tons) ending up in each EOL pathway are the primary output metrics collected by the CE wind ABM. Although results presented in this study mainly focus on the landfill rate, the model has the capability to report the costs and revenues associated with each blade or EOL

option, the number of active wind plant projects, the quantity of materials recovered, the average lifetime of all wind plant project turbines, landfill remaining capacities, and other metrics.

Details

This section describes the details of the behavioral rules used in the CE wind ABM. More information on the equations and data supporting the behavioral rules can be found in the supplemental methods.

Initialization

An ABM simulation advances each step from the initial state by repeating the agents' behavioral rules and updating the agents' states accordingly (Hinkelmann et al., 2011). In the CE wind ABM, the initialization includes creating agents' networks (Table S3), defining their instance variables (drawn from probability distributions or assigned constant values), and setting up the agents' environment. The default parameter values used to initiate the model (e.g., parameters of the probability distributions) are defined according to the best data available in the literature (supplemental methods). Thus, data for the ABM were collected from different sources, such as the USWTDB (Rand et al., 2020), research reports, academic publications, and wind power industry websites. The modeler may modify these inputs at the beginning of the simulation (e.g., to conduct sensitivity analysis).

The overall environment of the CE wind ABM is the contiguous US. It is represented by coordinate nodes of all wind turbine project sites, landfill sites, and turbine recycling sites. As a simplifying assumption to reduce the number of nodes, all wind turbines within a plant are represented by the centroid of the individual turbine locations. The total number of nodes was 1,320 turbine project sites, 1,294 landfill sites, and 6 recycling sites.

Because transportation costs (which depend on transportation distances) influence wind plant owners' EOL decisions, a transportation model in the CE wind ABM calculates the distances between wind turbine sites and landfills/recycling sites. These distances are calculated using the open-source Python plugin Openrouteservice (Openrouteservice, 2021). Within this plugin, the distance matrix application of the programming interface service is utilized to generate a 1,320 × 1,300 matrix containing all distances between wind turbine sites and EOL destinations. The plugin uses OpenStreetMap (OpenStreetMap, 2021), an open-license world map containing roads, among other details (Table S3). Therefore, each distance between a turbine site and a landfill/recycler comprises the route distance along roads between the two points, which is more accurate than calculating the straight-line distance between both points, especially over longer distances. The case of future wind plant projects (for which coordinates are not known) is described in the supplemental methods.

According to the TPB, organizations influence each other's decisions (Khan et al., 2020). In an ABM, those interactions are represented by social networks between agents. In the CE ABM, small-world networks are built with the Watts–Strogatz algorithm, as they are considered representative of the real-world social networks found in socio-technical systems (Byrka et al., 2016; Jalili, 2013; Telesford et al., 2011).

Wind plant owner agents

The number of wind plant owner agents and some of their characteristics (such as wind plant capacity, location, and rotor diameter) are determined from the USWTDB (Rand et al., 2020). Other characteristics (e.g., wind turbines' average lifetimes, transportation costs) are determined from other sources (supplemental methods, Figure S7 and Table S4). New agents are added to the ABM depending on the projected growth of wind power in the US. The characteristics of the added agents are derived from the initial agents and the growth rates in each state (e.g., the number of added agents in each state is proportional to the growth of wind power in each). Agents are also removed from the ABM if all wind turbines in their respective wind plants have been decommissioned.

A Weibull function is used to generate the volume of wind blades reaching EOL at each time step (Figure S8). The Weibull function is appropriate to model wind blade waste generation because it accounts for both early failures of blades and projects with a lifespan longer than 20 years (Cooperman et al., 2021). Following the generation of EOL wind blades (and as already mentioned previously), the wind plant owners' EOL management decisions are modeled with the TPB (supplemental methods). Other key data sources are (ATRI, 2019; Bedeschi, 2020; Caduff et al., 2012; EREF, 2019; Faulstich et al., 2016; Fonte and

Xydis, 2021; FutureBridge, 2020; Li et al., 2018; Tangler, 2000; U.S. Census Bureau, 2012; Wiser and Bolinger, 2019; Woodhouse et al., 2019; Ziegler et al., 2018).

Wind plant developer agents

The wind plant developer agents oversee the development of new wind plants (supplemental methods, Figure S9 and Table S5). To that end, wind power yearly growth in each state is determined according to wind power's projected cumulative installed capacity. For this projection, historical cumulative installed capacities in each state from 2000 to 2020 are taken from the USWTDB (Rand et al., 2020). Wind turbine installed capacities between 1981 and 2000 are neglected, as they represent less than 2% of the cumulative installed capacity. Future capacities are projected using the National Renewable Energy Laboratory's standard "mid-case" scenario (NREL, 2020) (Figure S10).

Wind plant developers decide what types of blades are used in the development of the plant (i.e., thermoplastic or conventional blades). They are also responsible for performing a feasibility assessment when wind plant owners adopt the lifetime extension CE strategy (Hutton and Soulier, 2020). The TPB is used once again to model the decision of adopting thermoplastic blades, as some studies have demonstrated that the theory could explain green procurement (Yang et al., 2019; Zhang et al., 2021). If wind turbines are not suitable for lifetime extension, after the wind plant developer's feasibility assessment, the lifetime extension EOL option is made unavailable to the wind plant owner. Other key data sources are (Bortolotti et al., 2019; energyacuity, 2018; Murray et al., 2019).

Recycler agents

Four recycling processes are represented in the CE wind ABM: A dissolution process (only available to wind plant projects with thermoplastic blades), pyrolysis, mechanical recycling, and cement co-processing (supplemental methods, Figure S11 and Table S6). Moreover, recycler agents improve their recycling processes through the learning effect (i.e., decrease recycling costs) and recover materials (Figure S12). The quantities of EOL blades expressed in power units (MW) are converted into a mass unit using data reported in Liu and Barlow (2017) and the USWTDB (Rand et al., 2020). Other key data sources are (Bergesen and Suh, 2016; CompositeWorld, 2020; Ginder and Ozcan, 2019; globalcementmagazine, 2012; Liu et al., 2019; Naqvi et al., 2018; Oliveux et al., 2015).

Original equipment manufacturer agents

As for the wind plant owner and wind plant developer agents, the TPB is used to model the decisions made by OEMs to develop thermoplastic blades (supplemental methods, Figure S13 and Table S7). The TPB has been shown to (at least partially) explain the adoption of sustainable production behaviors (Luo et al., 2017; Montalvo Corral, 2003; Zhang et al., 2013). Once an OEM has decided to develop thermoplastic blades, it is assumed that those new blades are made of a thermoplastic composite. Moreover, it is assumed that the production of thermoplastic blades starts 5 years after the decision is made, a lag time that has been reported by the wind power industry (Largeau et al., 2020). Other key data sources are (AWEA, 2020; EIA, 2016; Shuaib et al., 2015).

Landfill agents

The number of landfill agents and some of their characteristics (such as their capacity, location, and annual waste input) is determined from the *Waste Business Journal* database (Waste Business Journal, 2020). Landfills update their remaining capacity according to the mass of landfilled blades and their annual waste input (supplemental methods, Figure S14 and Table S8). In the baseline, it is assumed that wind plant owners send blades to landfills as large segments (Cooperman et al., 2021). Moreover, only landfills accepting industrial waste and construction and demolition waste are assumed to accept blades; a short review of applicable laws in six states—California, Texas, Wyoming, Iowa, Missouri, and New York—found that EOL wind blades are either considered construction and demolition or industrial waste (Table S2).

Regulator agents

Although local regulators such as cities and counties may enact regulations and incentive programs (supplemental methods, Figure S14 and Table S9), the CE wind ABM only considers 48 regulator agents (one for each state in the contiguous US). Regulators are assumed to act similarly as they historically did regarding EOL rubber tires (EPA, 1999, 2021). Although other incentives and regulations (e.g., increasing landfill taxes

or providing tax cuts to recyclers) could be modeled with the CE wind ABM, those options have not been investigated further in this study. Other key data sources are (EPA, 2019).

Machine-learning metamodel

The use of ML combined with ABM has been gaining traction because of their complementarities (Dahlke et al., 2020; Pietzsch et al., 2020; Rand, 2019). ML techniques can be used to define agent behavioral rules from data (Jäger, 2019; Zhang et al., 2016) or to create a metamodel to explore the ABM behavior in greater depth (i.e., study the effect of varying the ABM parameters) (Pietzsch et al., 2020; Vahdati et al., 2019).

Following prior work (Walzberg et al., 2021b), we generate the ML training data set by applying a quasi Monte Carlo approach. Sobol sequences of parameter value combinations are defined using the SALib Python library (Herman and Usher, 2017). Sobol sequences aim to cover as much of the parameter space as possible as quickly as possible (i.e., with the fewest samples), which enables capturing the CE wind ABM behavior without running too many computationally expensive simulations. The ABM parameters to vary in the quasi Monte Carlo were chosen after a preliminary analysis regarding the influence of the transportation costs and TPB's factors on the ABM results (Figure 1). The upper and lower bounds of the ranges chosen for those parameters were set to their baseline values and 0% of the baseline values, respectively. Other parts of the ABM behavior space could be explored by building a ML metamodel based on quasi Monte Carlo involving other parameters.

Next, we test different ML algorithms, varying their hyperparameters using the Scikit-learn Python library (Pedregosa et al., 2011). A tenfold cross-validation is chosen to evaluate and compare the performance of the ML algorithms, analyzing R^2 and mean square errors (supplemental methods and Table S10). The multilayer perceptron regressor algorithm yielded the highest performance and was therefore the ML metamodel used for our analysis. The ML metamodel is then used to generate results from Figures 2 and 4, and S6.

QUANTIFICATION AND STATISTICAL ANALYSIS

Sensitivity analysis for the data and procedure included in the paper.