Mitigating Bat Mortality with Turbine-Specific Curtailment Algorithms: A Model Based Approach

Oliver Behr, Robert Brinkmann, Klaus Hochradel, Jürgen Mages, Fränzi Korner-Nievergelt, Ivo Niermann, Michael Reich, Ralph Simon, Natalie Weber and Martina Nagy

Abstract Alarmingly high numbers of bats are being killed at wind turbines worldwide, raising concerns about the cumulative effects of bat mortality on bat populations. Mitigation measures to effectively reduce bat mortality at wind turbines while maximising energy production are of paramount importance. Operational mitigation (i.e. feathering wind turbine rotors at times of high collision risk for bats) is currently the only strategy that has been shown to substantially reduce bat mortality. This study presents a model based approach for developing curtailment algorithms that account for differences in bat activity over the year and night-time and are specific to the activity level at a certain wind turbine. The results show that easily measurable variables (wind speed, month, time of night) can predict times of higher bat activity with a high temporal resolution. A recently published collision model that was developed based on an excessive carcass search study is then applied to predict bat collision rate based on the modelled bat activity. Using the ratio of wind energy revenue and collision rate, 10 min intervals were weighted, so that turbines are stopped when collision rate is high and loss in revenue is low. A threshold of two dead bats per year and turbine resulted in a mean loss in annual revenue of 1.4%. The presented approach of acoustic monitoring at the nacelle and turbine specific curtailment has become the standard method to mitigate collision risk of bats at wind turbines in Germany.

O. Behr (✉) · K. Hochradel · J. Mages · R. Simon · N. Weber · M. Nagy
Friedrich-Alexander-University Erlangen-Nürnberg, Erlangen, Germany
e-mail: oli.behr@fau.de

R. Brinkmann
Freiburg Institute of Applied Animal Ecology, Freiburg, Germany

F. Korner-Nievergelt
Oikostat GmbH, Ettiswil, Switzerland

F. Korner-Nievergelt
Swiss Ornithological Institute, Sempach, Switzerland

I. Niermann · M. Reich
Leibniz University Hannover, Institute of Environmental Planning, Hannover, Germany

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Introduction

Bats are killed at wind turbines worldwide and frequently at high numbers (see overview in Arnett et al. 2016). Over a 12 year period (2000–2011) cumulative bat fatalities at wind turbines in the U.S. and Canada were estimated to range from 0.8 to 1.7 million bats (Arnett and Baerwald 2013) and similarly high fatality numbers have been suggested to occur in Germany (Voigt et al. 2015). Due to their long generation times and low reproductive rates, bats rely on high adult survival to maintain populations (Racey and Entwistle 2000; Barclay and Harder 2003). However, data on bat populations is scarce (O'Shea et al. 2003) and the known or suspected decline of some bat populations around the world due to numerous threats (e.g. loss of roosting and foraging habitat, climate change, white nose syndrome; e.g. Pierson 1998; Frick et al. 2010a, b; Winhold et al. 2008; O'Shea et al. 2016) raises warranted concerns about biologically significant additive mortality. Mitigation measures to reduce bat fatalities at wind turbines are thus critically important to maintain viable bat populations and their ecosystem services, and also for the environmental-friendly development and the public acceptance of wind energy.

Pre-construction estimation of bat collision risk at wind facilities is methodologically extremely difficult, involving considerable effort and expense and is associated with high prediction uncertainty. Hein et al. (2013) reviewed results from 12 study sites in the USA and failed to find a significant relationship between pre-construction acoustic activity (measured at ground level or up to 30 m above ground level) and post-construction fatalities of bats, suggesting that acoustic data gathered prior to the construction of wind facilities cannot reliably predict post-construction bat fatalities. A possible explanation for difficulties in predicting bat fatalities from pre-construction data could be that the presence of wind turbines alters the bats' habitat and behaviour. Bats may be attracted to wind turbines (Cryan et al. 2014) and/or change their habits of site use due to changes in habitat. These changes may include the creation of new hunting grounds (e.g. clearings and crane pads) and guidance structures (e.g. aisles, access routes) (Arnett et al. 2008; Cryan 2008; Cryan and Barclay 2009).

The evaluation of habitat characteristics (e.g. proximity to open water sources or known roosts) in the vicinity of planned wind energy facilities is commonly used in pre-construction fatality assessments to avoid building wind turbines close to bats' flight paths, roosts or foraging areas. However, most studies find weak or no correlations between bat fatalities or acoustic activity at the nacelle and habitat characteristics. These studies include land cover and distance to nearest wetland or woodlot/woodlands and forest (Johnson et al. 2004; Niermann et al. 2011) and the proximity of turbines to the coast or vegetation (Hull and Cawthen 2013). Thus, habitat characteristics do not seem to provide robust information on the risk of bat fatalities and their contribution to developing mitigating strategies seems to be limited.

Carcass searches have frequently been used to estimate the number of bats that die at existing wind turbines. However, the actual number of fatalities may be vastly underestimated if detection biases (i.e. scavenger removal, searcher efficiency and searchable area) are not accounted for (Kerns et al. 2005; Huso 2010; Korner-Nievergelt et al. 2011b). At many sites in Central Europe collision rate is difficult and expensive to assess with carcass searches, because in comparison to North America collision rates are often lower, removal rates by scavengers are high and searching conditions are often poor (Bispo et al. 2013; Korner-Nievergelt et al. 2013). Predicting collision rates from variables, like acoustic activity or wind speed, that are more easy to measure, seems more appropriate for many sites in Central Europe, including forest areas and off-shore sites.

Currently, only operational mitigation (i.e. stopping the rotors of wind turbines at times of high collision risk for bats) has been shown to substantially reduce the number of bats killed at wind energy facilities (Arnett et al. 2013, 2009). Peak numbers of bat fatalities have consistently been associated with low wind speeds and specific periods of the year, such as late summer to early fall in the temperate northern Hemisphere (Kerns et al. 2005; reviewed in Arnett et al. 2008; Schuster et al. 2015). Thus, a frequent and successful strategy to mitigate bat mortality consists in raising a turbine's cut-in wind speed (i.e. wind speed at which turbines start generating power to the utility system) above the manufacturer's cut-in wind speed (usually 2.5–4.0 ms^{-1}) and to allow only very slow movements of the rotor below the cut-in wind speed.

Increasing the cut-in speed should prevent the rotor from turning at a speed dangerous for bats, such as low wind speeds when bats are highly active. Usually this is done by feathering rotor blades at 90° until the cut-in speed is reached (Arnett et al. 2013). Most operational mitigation studies from North America and Europe demonstrated a substantial reduction in bat fatalities (frequently exceeding 50%) when raising the cut-in speed to 5.0−6.5 ms^{-1} (North America: e.g. Arnett et al. 2009; Baerwald et al. 2009; see also synthesis in Arnett et al. 2013; Europe: Behr and von Helversen 2006; Beucher et al. 2011). The few studies that estimated the costs of increasing cut-in speed reported that loss in power revenue due to curtailed operation of turbines during short periods (e.g. 75 days) of high collision risk would constitute 3–11% lost power output during this period. This is less than 1% of the total annual output (see synthesis in Arnett et al. 2013).

Substantial reductions in bat mortality at wind turbines can already be achieved with relatively unspecific operational curtailment based solely on wind speed (Arnett et al. 2013). However, further research is needed on more efficient operational mitigation that incorporates additional variables (e.g. time of night, bat activity) to define operation rules that are turbine specific and maximize energy production with the lowest possible collision risk for bats (Arnett et al. 2013; Weller and Baldwin 2011). Korner-Nievergelt et al. (2013) published a model-based approach to predict the collision rate of bats at wind turbines based on fatality search data, wind speed and acoustic activity measured at the nacelle. Once the model has been calibrated based on a sufficiently large data set, its predictors can be used to assess collision rate for new turbines with no need for carcass searches and to develop turbine-specific curtailment algorithms (Korner-Nievergelt et al. 2013).

This chapter outlines the development of turbine specific curtailment algorithms based on the same data set from German wind turbines used by Korner-Nievergelt et al. (2013). First, the data necessary to calculate the algorithms is outlined: acoustic activity data and predictive parameters like wind speed, time of year, and time of night. Then the modelling approach (GLM) is presented to predict bat activity based on parameters like wind speed, month, and time of night with a high time resolution (10 min intervals). Based on the predicted bat activity, collision risk and collision rate of bats will subsequently be estimated with the mixture model presented in Korner-Nievergelt et al. (2013). Finally, by calculating the ratio Q of power revenue (or wind speed to the third power that shows a linear correlation to the power produced) and estimated collision rate for each 10 min interval, the times with low power revenue and high collision rate for bats are identified (i.e. 10 min intervals with low values of Q). These are the times when turbines should preferably be stopped. Using the ratio Q and by setting a threshold for the number of accepted bat fatalities per turbine and year, the cut-in wind speeds that are specific for the bat activity level at a single turbine are calculated and then differentiated for different months and night-times.

Methods

Data-Set

In 2008, 70 wind turbines were sampled at 35 different sites (two turbines each) in four different natural regions in Germany (Fig. 1). All turbines sampled were Enercon turbines (ENERCON GmbH, Aurich, Germany) of the types E66, E70, and E82 with rotor diameters of 66, 70, and 82 m, respectively.

Batcorders (Model 1.0, ecoObs GmbH, Nürnberg, Germany) were installed by Enercon service teams in the nacelle of each turbine to continuously record acoustic bat activity in the rotor swept area. Batcorders were positioned inside and in the bottom of the nacelle between the rotor and the tower with the microphone pointing downwards, through the nacelle floor. Holes were drilled into the nacelle floor for this purpose (Fig. 2). Installation of detectors commenced in April, but by the end of April less than 10 detectors were successfully installed; and hence were excluded in April in this analysis. Data included into the analysis was recorded from 2008-05-01 until 2008-10-31 with a minimum of eight (beginning of May) and a maximum of 68 (in August) detectors sampling valid data during the same night.

Batcorders were operated with the following settings: Quality 20, threshold −36 dB, posttrigger 200 ms, and critical frequency 16 kHz. Batcorders ran continuously but produced valid data only during 71% of the nights sampled. Batcorder downtimes were mostly due to power, microphone or SD-card-failures, full

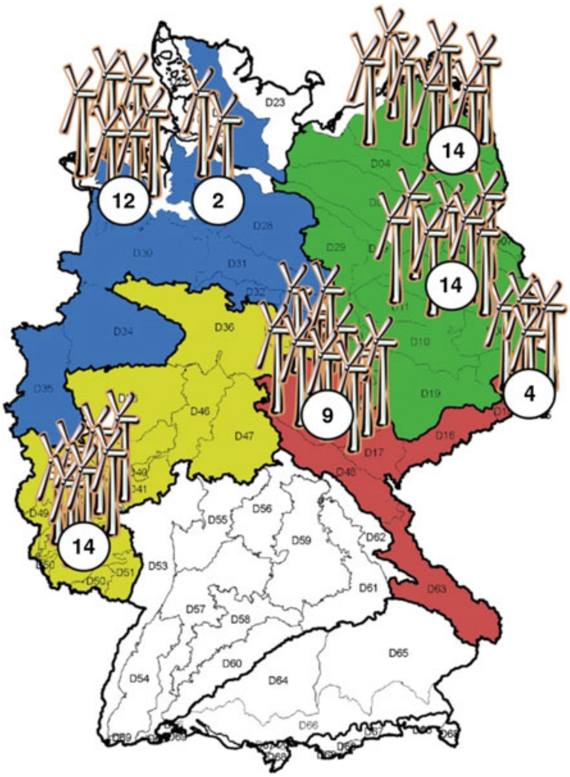


Fig. 1 Location of the wind turbines sampled in different natural regions of Germany. Numbers in *white circles* indicate the number of turbines sampled per area. Turbines were located in the Northwest German Plain (*blue*), the Northeast German Plain (*green*), the Western Central Uplands (*yellow*) and in the Eastern Central Uplands (*red*) (Color figure online)

SD-cards, or other technical problems with the detectors. Data from one turbine were excluded from the data set due to problems with microphone sensitivity. For the remaining 69 turbines, the mean number of nights with valid data was 126 per turbine (minimum 7, maximum 184) of a total of 184 nights sampled with a total sample time of 96,838 h. More than a million files were recorded (more than 400 Gbyte), of which 72,756 contained bat calls.

One temperature sensor was also installed (Sensor KTY81-110, Philips, Amsterdam, Netherlands), as well as one precipitation sensor (Sensor 5.4103.20.041, Adolf Thies GmbH, Göttingen, Germany) at most of the nacelles (68 temperature and 60 precipitation sensors). Temperature sensors were positioned in the nacelle floor at about half a meter distance from the detector microphone. Precipitation sensors were installed on top of the nacelle at the framework supporting turbine lighting and anemometer. The owners of the turbines provided access to the wind speed data measured with an anemometer recorded by the SCADA-System (Supervisory Control and Data Acquisition System) controlling the turbine. Wind speed data was available as mean values for 10 min intervals.

On two occasions at two different turbines, exceptionally high acoustic activity was recorded (1903 and 2071 recordings with bat calls, respectively) within a short

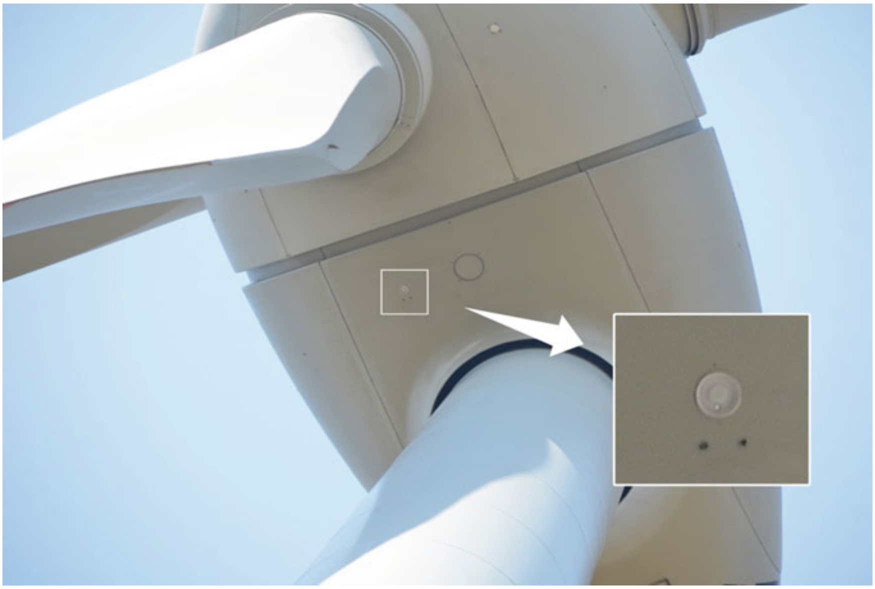


Fig. 2 Microphone mounted in a disc in the *bottom* of a nacelle (highlighted area on the *left*). The inlay on the *right* shows this area at a larger scale. The microphone disc has a *light grey* colour and the two *dark spots below* it are additional sensors (e.g. temperature) (Color figure online)

time period (1.3 and 2.8 h). This activity was mostly caused by calls of the Common Pipistrelle (*Pipistrellus pipistrellus*) and is most likely attributed to swarming behaviour. *P. pipistrellus* is well known for swarming behaviour, which can result in a short-term occurrence of a large number of bats, especially around existing or potential roosts (Simon et al. 2004). On both occasions wind speed was very low (max. 2.4 and 1.9 ms^{-1}) and so was the collision risk because rotors were only moving very slowly. Even a minor increase in wind speed of 0.5 ms^{-1} would have resulted in a large collision risk for the bats. Predictions of the frequency and occurrence of swarming behaviour in *P. pipistrellus* were not possible with such limited data (i.e. a sample size of 2 nights). Thus it was decided to exclude these swarming periods from the dataset, also because they appeared to be clear outliers in our analysis.

Identification of Species and Species Groups

To produce standardised results that can be compared to other studies, the software bcAdmin was used (Ver. 1.13, ecoObs; Call filter: Amplitude threshold 1.585, smoothness 2.00, Samples Hi 200, Min. call distance 15 ms, Min. call length

1.50 ms; Call Extraction: Min call interruption 1.10 ms, Forward MSE 0.060, Samples for regr. 8, Regression size 200 μs) and bcDiscriminator [Ver. 1.13, ecoObs; in combination with R 2.7.2 (R Core Team 2015) and the packages kernlab and RandomForest (Liaw and Wiener 2002)] to automatically identify bat calls in the batcorder recordings and also to identify species and species groups. All recordings that were automatically identified by the software as bat calls were manually checked and misclassified noise recordings were manually removed from this dataset.

Statistical Modelling of Bat Activity

Statistical modelling was used to predict bat activity (number of recordings; total activity of all bat species—Chiroptera) from predictive variables such as wind speed or temperature. Bat activity was modelled for 10 min intervals as wind speed data was available as mean values per 10 min intervals and because intervals of 10 min length were considered appropriate to map the temporal variability in bat activity and wind speed. Temperature and precipitation were also assigned to 10 min intervals as 10 min mean values. To attribute 10 min intervals to relative times of night, the center-time of that interval was used (5 min after its commencement).

All modelling was done in R (R Core Team 2015). Generalised linear models were used (function glm of the R-package stats) with Poisson error distribution and the logarithm link function. Different models were tested, including different combinations of predictive variables, including wind speed and wind speed^2 as continuous variables, temperature, precipitation, month, time of night, and turbine as categorical variables. The correlation of activity with temperature and precipitation did not follow a simple mathematical function but could be fitted when including them as categorical variables into the model (precipitation was categorised in pseudo-logarithmic categories with the margins 0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10,000 lx; temperature was categorised in steps of 5 °C from 0 to 40 °C). The turbine variable would usually be considered a random effect. Due to the high number of sampled nights per turbine the turbine variable could be included as a fixed effect (equal to the rest of the predictive variables). This increased the stability of the model fitting algorithm.

The full model contained wind-speed, the square of wind-speed, temperature, precipitation, month, time of night and turbine as predictor variables. Model selection was done based on AIC (Akaike information criterion, Burnham and Anderson 2002) and economic trade-offs. All models included the wind speed and turbine variables.

Studies quantifying the activity of bats with acoustic detectors make implicit assumptions about data structure (Hayes 2000; Sherwin et al. 2000; Gannon et al. 2003). In this study, it was assumed that recordings at a turbine within one night were correlated. Hence, autocorrelation was corrected by thinning to every 20th sample from the dataset. This selected dataset showed no relevant autocorrelation in the acf-plot. It was also assumed that recordings at different turbines and in different nights were independent.

Predicting the Collision Risk

The GLM model described in the previous chapter was used to differentiate times of low and high bat activity. Since access to wind speed data was obtained for all turbines for the entire year of 2008, the GLM model could be used to predict bat activity at all turbines, not only for times that had been sampled acoustically. As a result the month of April could be included into the dataset, applying the effect of this month measured at a turbine subset to all turbines. Time intervals without wind speed (Table 1) were extrapolated assuming that the effects of wind speed, month, time of night, and turbine did not differ between extrapolated and sample times.

The n-mixture-model published in Korner-Nievergelt et al. (2013) was used to calculate the collision rate from the acoustic activity predicted by the GLM (see also Table 4 on page 338, model type A in Korner-Nievergelt et al. 2011a). The n-mixture-model has been developed to predict the collision rate for entire nights from acoustic activity and from wind speed data. In order to use the model to predict the collision rate during 10 min intervals, subsequent calculations were undertaken and the following assumptions were made: (1) The activity predicted for a 10 min interval was extrapolated to the entire night using the length of the night (number of 10 min intervals) and weighted by the distribution of activity over night times shown in Fig. 4. (2) Then the collision rate for the entire night was calculated using the wind speed measured during the 10 min interval as predictor in the model. When applying the model to entire nights, the median of 10 min wind speed data per night was used as predictor. Therefore it was assumed that the effect of wind speed on fatality rates was the same during different times of night. (3) The predicted fatality rate during the entire night was then split into single 10 min intervals using, again, the length of the night (number of 10 min intervals) and the distribution of activity over night times shown in Fig. 4. Thus, it was assumed that the distribution of fatality risk over the night equals that of the acoustic activity.

Table 1 Sample size of the datasets for acoustic bat activity and meteorological parameters in 2008

Detector/sensor	Turbines	Nights	Hours
Batcorder	70	9.074	99.135
Wind	69	11.495	125.088
Temperature	68	9.878	109.644
Precipitation	60	7.238	84.588

Calculating the Loss in Power Production

The potential loss in revenue caused by curtailment algorithms was calculated from the turbine data provided by the owners. Data was available on the power production during 10 min intervals (the total time with valid data was the same as for wind speed, see Table 1) and for the entire year of 2008. Potential loss in power production was calculated by simply adding the power produced during 10 min intervals that were part of the curtailment periods defined by these algorithms. The loss in power production was calculated as a percentage of annual production, since these relative numbers are easier to compare for different sites and turbine types.

Results

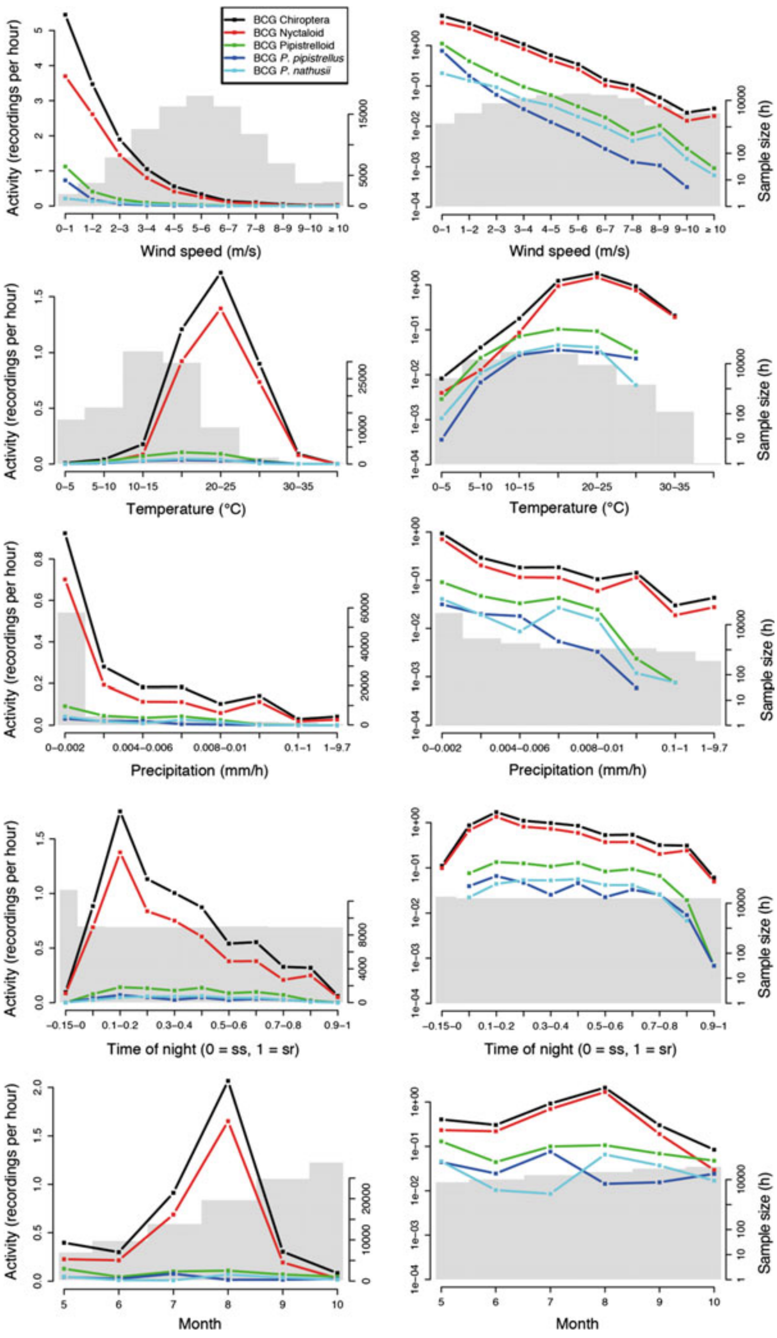
Bat Species Recorded

Two species-groups together accounted for 86% of all recordings. The larger of these two groups (70.4% of all bat recordings) was the "Nyctaloid" group with larger species producing lower frequency echolocation calls. This group contained recordings mostly from the species *Nyctalus noctula* (Common Noctule, 15.0% of all bat recordings) and *Vespertilio murinus* (Parti-coloured Bat, 4.9%), and some *N. leisleri* (Lesser Noctule 0.2%), *Eptesicus nilssonii* (Northern Bat, 0.1%), and *E. serotinus* (Serotine Bat, 0.03%). The second was the "Pipistrelloid" group (16.1% of all recordings) with smaller species producing higher frequency calls. Recordings in this group contained calls mostly from *Pipistrellus pipistrellus* (Common Pipistrelle, 9.4%) und *P. nathusii* (Nathusius' Pipistrelle, 4.4%), and some *P. pygmaeus* (Soprano Pipistrelle, 0.1%) calls. Almost all remaining recordings (13%) were identified as bat calls by the software but could not be assigned to any species or species group.

Factors Affecting Bat Activity

Bat activity varied greatly depending on wind speed, temperature, precipitation, time of night, and month (Fig. 3).

Wind speed had a strong influence on bat activity (number of recordings) in all species and species groups and showed an approximately logarithmic trend. Only 15% of all bat activity (Chiroptera) was recorded at wind speeds ≥5 ms^{-1}, and only 6% at wind speeds ≥6 ms^{-1} (see Fig. 4). It is apparent from the log-plot that the decrease of activity with higher wind speeds was more pronounced in *P. pipistrellus* (6.4% of activity at wind speeds ≥5 ms^{-1}) than in the other species, while *P. nathusii* showed the greatest wind tolerance (18% of activity ≥5 ms^{-1}). The highest wind speed with activity recorded was 11.5 ms^{-1}. Bat activity


BCG Chiroptera
BCG Nyctaloid
BCG Pipistrelloid
BCG P. pipistrellus
BCG P. nathusii
Activity (recordings per hour)
Sample size (h)
Wind speed (m/s)
Temperature (°C)
Precipitation (mm/h)
Time of night (0 = ss, 1 = sr)
Month

◂**Fig. 3** Effect of different parameters (x-axes) on acoustic bat activity (number of recordings per hour) measured at the nacelle of 69 wind turbines at 35 sites in 5 different natural regions in Germany in 2008. The panels on the *left* have a linear y-axis and panels on the *right* show the same data with a logarithmic y-axis (zero values not shown). Lines of different colours show values for different species or species groups. Variables on the x-axis were factorised in intervals for the purpose of this plot: intervals for wind speed and temperature include the lower and exclude the upper margin shown. Precipitation was factorised in a pseudo-logarithmic scale (excluding the lower and including the upper margin). To compare nights of different lengths, relative times of night were used, from 0 (sunset, ss) to 1 (sunrise, sr). Then the night was split into 10 intervals of equal length (0–0.1, 0.1–0.2, etc.—lower margin included and upper margin excluded). In addition, an interval before sunset was included (−0.15 to 0) that had a 50% longer duration than the intervals during the night and included bat activity at dusk (no bat activity was recorded after sunrise). The months cover the time sampled from April to October. *Grey bars* in the background indicate the sample size in hours (right y-axes) for the respective intervals (Color figure online)

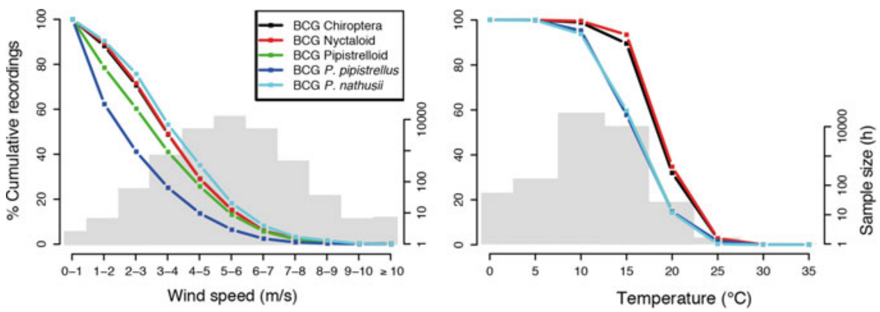


Fig. 4 Effect of wind speed and temperature on acoustic activity (recordings per hour) of bats at the nacelle of turbines. Activity is plotted cumulatively to show the remaining percentage of activity above a certain threshold of wind speed or temperature. The dataset was the same as in Fig. 3

increased markedly for **temperatures** between 10 and 25 °C. Low activity at temperatures above 25 °C is based on a small sample, was mostly recorded during the dusk interval before sunset (time of night −0.15 to 0), and is, hence, almost exclusively due to activity of the Common Noctule, a species frequently active before sunset.

Bat activity decreased with small rates of **precipitation** (fog or clouds with 0.002–0.004 mm min^{-1}). The sample size for higher rates of precipitation is low and rain periods amounted only to a small fraction of the entire time sampled. **Time of night**: bat activity peaked during the first half of the night. Activity of the Nyctaloid group (mostly Common Noctule) started before sunset and earlier than for the Pipistrelloid group. After the first quarter of the night, activity started to decrease continuously until sunrise, with a stronger decrease shortly before sunrise. At a few turbines a second, lower activity peak was recorded at the end of the night that was mostly due to activity of Nyctaloid species. Nathusius' Pipistrelle, again, showed a slightly different pattern than the other species: activity peaked during the middle of the night. Activity patterns during different **months** varied for the species recorded: all species and species groups showed a minor decrease of activity from May to June and a marked peak in late summer or autumn. For the Common Pipistrelle, this peak was recorded in July, while the activity of the Nyctaloid group peaked in August, and still later in August and September for Nathusius'Pipistrelle.

Predicting Bat Activity

Generalised linear modelling (GLM) was used to predict bat activity (number of recordings; total activity of all bat species) and, hence, times of high collision risk for bats at the wind turbines from the predictive variables wind speed, wind speed^2, temperature, precipitation, month, time of night, and turbine. The turbine effect described differences in the activity level between different turbines.

Interactions between variables either made no sense from a biological point of view (and were, therefore, not tested) or showed only small effects on the activity predicted. Interactions in each month were tested with each factor: wind speed, temperature, and time of night and of turbine with each of wind speed, month, and time of night. The final model used to predict times of high bat activity was calculated without interactions, which also increased the stability of the model fitting algorithm. Accordingly, differences were not modelled between different turbines in phenology or bat activity pattern over the night.

All predictive variables highly significantly improved the model fit (likelihood-ratio-test) and reduced AIC. Since the model is being used to calculate curtailment algorithms for wind turbines the decisions on whether to include predictive variables into the final model were also based on an economic trade-off. The cost of collecting the respective data during a site assessment (e.g. installation and maintenance of sensors, or data collection and analysis) was balanced against the higher energy yield when turbines operate with more sophisticated algorithms. This led to an exclusion of temperature and precipitation from the final model, since the increase in energy yield amounted to a mean of 13,970 kWh per turbine during 20 years of operation, which is not enough to justify the sampling of these variables. The coefficients of the final model are shown in Table 2. The final model used for the prediction of bat activity included wind-speed, the square of wind-speed, month, time of night and turbine as predictors.

Model effects reflected the univariate distributions shown in Fig. 3: Predicted activity sharply decreased with higher wind speeds, peaked in late summer and autumn, and in the first quarter of the night.

Predicting Collision Rate

The model presented in the previous section was used to predict the level of bat activity for all 10 min intervals during the entire period of 2008-04-01 to 2008-10-31

Table 2 Generalised linear model parameters for the prediction of bat activity (log of the number of recordings of all bat species per 10 min interval) from continuous variables (wind speed and wind speed^2) and categorical variables (temperature, precipitation, month, time of night, and turbine)

Effect	Total number of 10 min intervals	Number of 10 min intervals with bat activity	Number of recordings	Coefficient	p
(Intercept)	581,028	10,159	65,823	−5.03	<0.001
Wind-speed	581,028	10,159	65,823	−0.71	<0.001
Wind-speed^2	581,028	10,159	65,823	0.01	0.001
Month: May	38,338	475	2612	0.00	NA
Month: June	54,204	542	2800	−0.41	0.213
Month: July	76,380	1552	12,012	1.06	<0.001
Month: August	109,145	5279	38,996	1.74	<0.001
Month: September	139,770	1754	7094	−0.31	0.267
Month: October	163,191	557	2309	−1.36	<0.001
Time: −0.15 to 0	55,354	242	1043	0.00	NA
Time: 0–0.1	52,913	1494	7768	2.07	<0.001
Time: 0.1–0.2	52,670	2142	15,250	2.79	<0.001
Time: 0.2–0.3	52,716	1432	9839	2.40	<0.001
Time: 0.3–0.4	52,598	1176	8722	2.33	<0.001
Time: 0.4–0.5	51,952	1002	7506	2.16	<0.001
Time: 0.5–0.6	52,858	779	4751	1.73	<0.001
Time: 0.6–0.7	52,737	700	4829	1.73	<0.001
Time: 0.7–0.8	52,534	572	2830	1.21	<0.001
Time: 0.8–0.9	52,434	477	2747	1.16	<0.001
Time: 0.9–1	52,262	143	538	−0.48	0.188
Turbine: min	10,619	1	7	−1.44	NA
Turbine: 1st quartile	9636	41	213	1.90	0.989
Turbine: median	5712	106	454	2.78	0.296
Turbine: 3rd quartile	10,805	151	1316	3.36	<0.001
Turbine: max	9635	503	3571	4.69	<0.001

Reference levels of categorical variables have no level of significance assigned. From the effects of 69 turbines sampled, only the min, quartiles, and max are shown

(detailed in the methods section "Statistical Modelling of Bat Activity"). Then the n-mixture-model published in Korner-Nievergelt et al. (2013) was applied to calculate the collision risk from the predicted activity for each 10 min interval (for details and implicit assumptions see methods section "Predicting the Collision Risk").

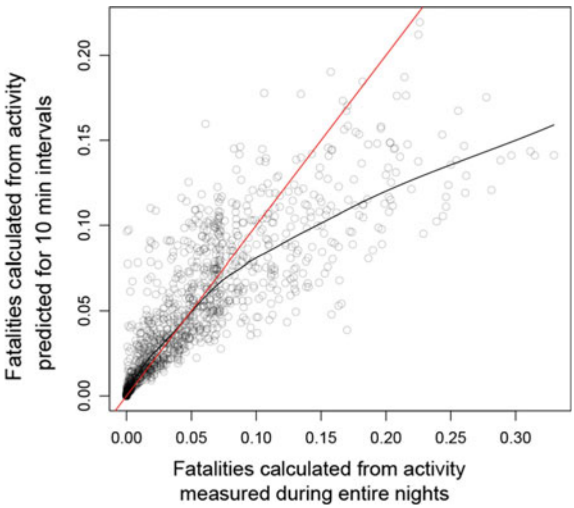


Fig. 5 The number of bat fatalities were calculated: (1) for 10 min intervals from the acoustic activity predicted by the GLM and with the method described here (fatality numbers then pooled for nights and turbines for comparison) on the y-axis, and (2) for entire nights from the acoustic activity measured on the x-axis. Calculations for the values on both axes are based on (Korner-Nievergelt et al. 2013). Transparent *circles* show figures for one night at a single turbine (*black* for three overlapping *circles*). The *red line* shows a perfect 1:1 correspondence, the *black line* a moving average (function loess in r-packet stats, span = 0.5) (Color figure online)

To test this approach and the underlying assumptions the number of fatalities predicted for 10 min intervals were pooled for each night and turbine and compared the result to the fatality numbers predicted when applying the model to entire nights and the activity measured (Fig. 5). The values generally showed a good correspondence, but very high activity during outlier nights was underestimated by the GLM and so was, in consequence, the fatality risk for these nights.

Curtailment Algorithms

To reduce the number of bat fatalities occurring at a wind turbine while minimising the curtailment cost, 10 min intervals were weighted. This was done by calculating the ratio Q of power revenue and estimating the collision rate per 10 min interval. When revenue data is not available, wind speed to the third power can be used that has a linear correlation to the power produced. Through this, times with low power revenue and high collision rates for bats (i.e. 10 min intervals with low values of Q) could then by identified. These are the times when turbines should preferably be stopped if necessary.

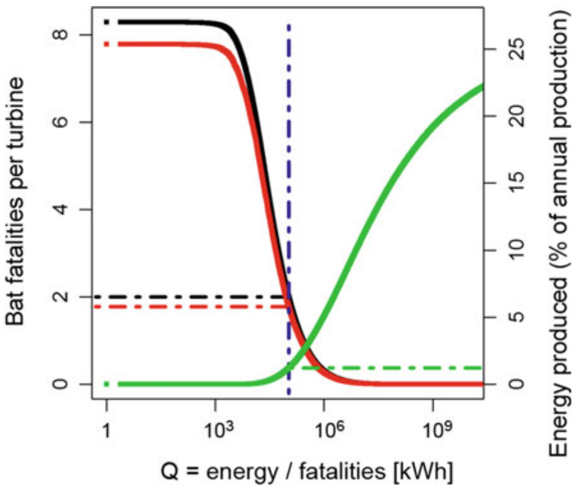


Fig. 6 Weighting of single 10 min intervals when running wind turbines with the curtailment algorithms described in this paper. Calculations are based on data from 2008-04-01 to 2008-10-31 (missing data have been intrapolated) and are mean values for the 69 turbines sampled. The **X-axis** in log-scale is the ratio of energy produced [kWh]/predicted number of bat fatalities (i.e. weighting factor Q for single 10 min intervals; plotting Q + 1 to avoid null-values on the logarithmic x-axis for intervals without energy produced. The upper limit of the x-axis was set to 10^{10} to render it easier to read. The **Y-axis on the left for the *black* and *red lines*** is the cumulative number of predicted fatalities (cumulated from high values of Q on the right to low values on the *left* of the x-axis). The *black line* shows the number of fatalities calculated from the activity numbers predicted by the GLM, the *red line* shows the slightly lower numbers calculated from the actual activity measured. The **Y-axis on the *right* for the *green line*** is the mean cumulative energy produced as a percentage of the annual revenue per turbine (cumulated from low values of Q on the left of the x-axis to high values of Q on the *right*). *Dashed lines* show the implementation of mitigation: a threshold of two dead bats per year and turbine on the left y-axis (*black line*) corresponds to a certain threshold for Q on the x-axis (*blue*) and a loss in revenue by mitigation und the right y-axis (*green*). The area *left* of the vertical *dashed blue line* contains 10 min intervals that have to be included into curtailment in order to keep the number of fatalities below the threshold (Color figure online)

To reduce the number of bat fatalities to a certain threshold (e.g. two dead bats per turbine per year—a threshold commonly used in Germany—dashed black line in Fig. 6), 10 min intervals have to be included into the curtailment periods starting with the intervals with the lowest values for Q (on the left hand side of Fig. 6). This has to be done until the cumulative fatality number predicted for the remaining intervals (Fig. 4, black line: based on activity predicted by the GLM; red line: based on measured activity), which are not included in curtailment periods, falls below the threshold. The value of Q at that point (dashed blue line in Fig. 6), then defines the criterion for single 10 min intervals to either slow the rotor to a speed not dangerous for bats (when Q for that 10 min interval is below the threshold) or to have the turbine run in normal mode (when Q is above the threshold).

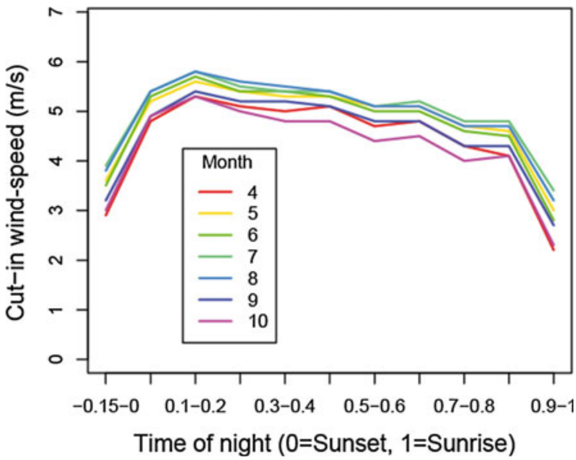


Fig. 7 Cut-in wind speeds defined by a curtailment algorithm for a sample turbine with a high level of bat activity to reduce the number of fatalities to two bats per year. In Germany turbines are frequently curtailed from April (4) to October (10). Cut-in wind speeds depend on the time of night (x-axis) and month (*colours*)

The value of Q for a specific 10 min interval depends on wind speed, on the fatality threshold, on the effects of month, time of night, and on the turbine effect on acoustic activity. Since the latter four are fixed and known, once the activity level of the turbine has been acoustically sampled, the models can be simplified to a cut-in wind speed for each combination of month and time of night (Fig. 7). These cut-in wind speeds are specific for the level of bat activity at a single turbine.

Curtailment Costs

The expected loss in power revenue can easily be calculated by adding up the power produced during all 10 min intervals included in curtailment periods (green line in Fig. 6). Losses in power production were calculated as a percentage of annual production (mean annual production was 2761 MWh for all turbines sampled) for different thresholds of bats killed per year and turbine (Fig. 8). With a threshold of two dead bats per year and turbine, the mean loss in power production was 1.4% (95% confidence interval: 1.0–1.8%, min 0.1%, max 4.2%) of annual revenue. Operational mitigation based solely on wind speed was more expensive (Fig. 8): for two dead bats per year and turbine the mean loss in power production was 1.8% (95% confidence interval: 1.7–2.3%, min 0.2%, max 5.8%) of annual revenue.

Discussion

The only method currently available to consistently reduce the number of bat fatalities at wind turbines is operational mitigation (Arnett et al. 2013), i.e. stopping the rotors of wind turbines at times of high collision risk for bats. Operational

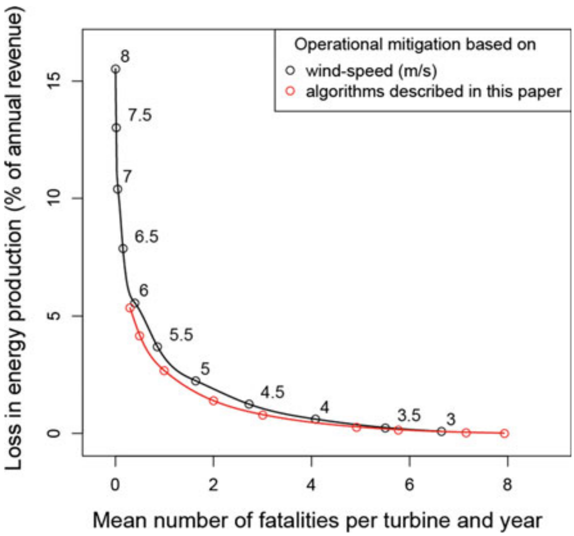


Fig. 8 Efficiency of operational mitigation based on wind speed only (*black line* and *black circles*—the numbers indicate the cut-in wind speed for each circle in ms^{-1}), or based on wind speed, time of night, and month (*red line* and *red circles*). *Circles* show the mean predicted loss in revenue (percentage of annual production) caused by curtailment algorithms for different thresholds of bats being killed per turbine and year with curtailment from April 1st to October 31st. Lines were drawn with R-function spline (Color figure online)

mitigation is usually achieved by feathering the rotor blades at low wind speeds. The exact effect on fatality numbers of curtailing up to a certain wind speed (e.g. 5.0–6.5 ms^{-1}) is, however, difficult to predict and, depending on the site specific fatality risk, may lead to very different results at different turbines.

Here, this study proposes a refinement of the operational mitigation that is hitherto based solely on wind speed, in two ways. First, times of bat activity are more precisely predicted and, hence, collision risk is more precisely predicted with a model that includes more predictive variables (time of night and month in addition to wind speed). Second, a turbine specific method is presented to reduce the fatality risk for bats at wind turbines in central Europe to a threshold set by the relevant authorities.

Applying Curtailment Algorithms to New Turbines

To apply this method to a new turbine, the level of acoustic activity at the new turbine has to be measured, which, in Germany, is done at the nacelle. These measurements usually last for at least two years, from April through October (although mandatory sample times differ in federal states). Acoustic data has to be comparable to the dataset presented here. Therefore, one of the three detector systems for which reference datasets were gathered (Anabat SD1 and SD2, Titley and Avisoft/BATmode system, Avisoft Bioacoustics/bat bioacoustictechnology GmbH in addition to the Batcorder described here) has to be used with a specific configuration of microphone sensitivity and settings (Behr et al. 2015). Also, the wind speed data measured at the nacelle of the turbine has to be provided by the turbine operator. The software-tool ProBat (available in German and English from http://windbat.techfak.fau.de) that is free of cost, estimates fatality rates, and calculates cut-in wind speeds based on acoustic activity data and wind speed and the methods described here.

During the first year of operation of a turbine (i.e. when no acoustic data is available yet), the turbine is often operated with a general curtailment algorithm (e.g. raising cut-in wind speed to 6.0 ms^{-1} at night). For the second year of operation turbine specific curtailment algorithms can be calculated (e.g. with ProBat) based on the activity measured in the first year. Subsequently, starting with the third year of turbine operation, the final set of cut-in wind speeds can be calculated based on two years of data on acoustic activity and wind speed.

Monitoring Acoustic Bat Activity at the Nacelle of Wind Turbines

Recording acoustic bat activity at the nacelle of wind turbines has become a standard method, at least in central Europe. Different acoustic detector systems have been used at a large number of different turbine types from all major manufacturers. The most common problems are microphone or detector failures and large numbers of noise files recorded due to the harsh conditions at the turbine nacelle. A daily status text containing information on microphone sensitivity, remaining memory, and a confirmation that the system is running properly is, therefore, best practice.

Generally, acoustic recording is suitable to detect the species most affected by collisions with wind turbines due to the properties of their echolocation calls – mostly a high level of sound pressure, allowing their detection over a large enough distance. There are, however, marked differences between species and species groups in peak frequency; for example, species of the Nyctaloid group have lower calls (mostly between 18 and 35 kHz) than those of the Pipistrelloid group (mostly 37–57 kHz; Skiba 2003). Since lower frequency calls are less attenuated in air, species of the Nyctaloid group can be detected over larger distances. At present differences in detectability cannot be accounted for, because in these models all species are pooled. This may cause bias in estimations of fatality numbers when these models are applied to sites with a different species composition (and, hence different call characteristics). Therefore, regional models are currently being developed that take into account the specific species composition in different areas in Central Europe.

Species Recorded

The most common species in the acoustic dataset (Common Noctule, *N. noctula*, Nathusius' Pipistrelle, *P. nathusii*, and Common Pipistrelle, *P. pipistrellus*) were also the species most commonly found in the fatality searches for this study. This is in parallel to the acoustic survey (Korner-Nievergelt et al. 2013) and to fatality searches in Germany in general (Dürr 2015). The Common and the Nathusius' Pipistrelle accounted for a lower percentage of the acoustic dataset as compared to their proportion in fatality numbers, which is probably due to their lower detectability caused by high call frequency. The number of recordings per fatality was still lower in the Nathusius' Pipistrelle than in the Common Pipistrelle.

Activity and Predictive Variables

A peak in bat activity was recorded from late July to mid-September, which corresponds to several reports of a peak in bat fatalities at wind turbines in late summer and autumn in Europe and also North America (see reviews in Arnett et al. 2008; Schuster et al. 2015). Time of night also had a strong influence on bat activity with a peak during the first quarter of the night and a continuous decrease until sunrise that is in accordance with findings from North America for bat recordings on towers (Arnett et al. 2006, 2007). Some turbines in the dataset showed a smaller second peak of activity during the morning hours that might reflect the morning activity at a nearby roost. Nathusius' Pipistrelle showed a different pattern with the main activity in the middle of the night and a decrease towards both, sunset and sunrise (a possible reason for this is discussed below). The Common Noctule was the only species to show substantial activity before sunset.

Bat activity steeply declined with higher wind speeds (only 15% of activity recorded at wind speeds ≥5 ms^{-1}). This was also the case in two acoustic studies in North America, where activity was measured at meteorological towers and declined by 4–13% (Redell et al. 2006) and 11–39% (Arnett et al. 2006) per 1 ms^{-1} increase in wind speed and in a thermal imaging study (Horn et al. 2008). For a review of the effect of wind and other metherological parameters, see Schuster et al. 2015. In California, Weller and Baldwin (2011) also reported higher activity at lower wind speeds for a dataset recorded at meteorological and portable towers. The authors also highlighted the improved fit of models that are based on several predictive variables, not just wind speed.

In this study's dataset, *P. pipistrellus* showed the steepest decline in activity with higher wind speeds. This small species has a relatively slow transfer-flight speed of 6 ms^{-1} (Kalko 1991; Simon et al. 2004) and might have difficulties in coping with wind. However, *P. nathusii*, a similarly small species, was the most wind-resistant species recorded. In contrary to the Common Pipistrelle, the Nathusius' Pipistrelle is a long-distance migrant and its activity at high wind speeds and deviating activity pattern during the night (see above) might indicate a high percentage of migration activity in the dataset (as opposed to foraging).

Bat activity increased with temperature up to approximately 25 °C but decreased with higher temperatures. Activity below 10 °C was very low. Similarly, Arnett et al. (2006) showed a peak of acoustic bat activity at around 20 °C measured at a tower 22 m above ground level and Reynolds (2006) also recorded very little activity below 10.5 °C in New York State. In this study, precipitation also had a strong influence on activity with almost no bat calls recorded at more than 0.002–0.004 mm/min (fog or clouds). This may, however, be partly due to a higher attenuation of sound in more humid air.

GLM

Generalised linear modelling (GLM) was used to predict bat activity and, hence, times of high collision risk from wind speed, month, time of night, and turbine (the latter described differences in the activity level among different turbines).

The results show that the tested predictive variables had a highly significant effect on the activity of bats at the turbines and that the model can be used to predict times of higher bat activity with a high temporal resolution of 10 min intervals. However, very high peaks of activity were underestimated. Concerning the calculations for mitigation algorithms presented here this is only a minor problem because the collision risk calculated for the few 10 min intervals in question is still very high resulting in an inclusion of those intervals in curtailment times. Generally, the GLM supplied a prediction of collision risk, not an exact prediction of the number of recordings for each 10 min interval.

Temperature and precipitation were excluded as predictive variables from the final model since the resulting increase in energy yield was not enough to justify the sampling of these variables. This may, however, be different for larger turbine types or for time periods with low temperatures very early or late in the year.

10 Minute Intervals as Temporal Units

Intervals of 10 min were used as temporal units to assess the collision risk and, if necessary, to stop the turbine rotor from moving at a speed that is dangerous for bats. Intervals of 10 min are commonly used by the SCADA systems running the turbines, which makes the implementation of the algorithms easier. Intervals of 10 min were considered short enough to react to changes in wind speed, the most variable of the factors influencing bat activity in this model. If shorter intervals were used, this would increase the number of cut-in and cut-out events and, hence, the wear on turbine components. The rotor will only be stopped after the value of Q (energy produced/collision risk) has fallen below the threshold during a 10 min interval. From the experience with this dataset it was considered that a delay of 10 min was short enough to react even to quick changes in bat activity and collision risk.

Implementation of Acoustic Surveys and Operational Mitigation in Germany

In Germany, acoustic monitoring at the nacelle and operational mitigation has become the standard method to assess and mitigate collision risk of bats at wind turbines. By the summer of 2015, seven of the sixteen German federal states (Bavaria, Brandenburg, Hesse, North Rhine-Westphalia, Rhineland-Palatinate, Saarland, Schleswig-Holstein) employed post-construction acoustic monitoring at the nacelle and gave very specific recommendations for conducting the acoustic survey or directly referred to the methods of the research project (final report in German): Brinkmann et al. (2011). The German federal states aforementioned also mandate operational mitigation (mostly the curtailment algorithms presented here) and often set thresholds for the number of accepted bat fatalities per year and turbine (e.g. one dead bat in Schleswig-Holstein, two dead bats in Bavaria, Rhineland-Palatinate and Saarland; Mayer et al. 2015).

Transferring These Methods to New Turbines

The GLM model presented here is based on a large dataset of 69 Enercon turbines with rotor diameters between 66 and 82 m. Datasets from site assessment studies are often small (one to two turbines sampled during one to two years) and, hence, strongly influenced by random effects (e.g. a rainy August, warm spring, etc.). For these cases it is recommended that the effects for the parameters influencing bat activity (wind speed, time of night, and month) should be taken from the GLM based on this large dataset. Only the level of activity at the respective turbine should be extracted from the dataset recorded at the turbine in question. For example this can be done by calculating an “offset” Model where all effects, except for “turbine”, are pre-set. This is implemented in the software tool, ProBat.

If this method of acoustic sampling is adopted, the analyses and calculations shown here can usually be applied. There are, however some important restrictions: (1) Species at the new site should not differ to a great extend from the species recorded at this study’s sites, (2) Rotor diameters should be similar to the mean in this dataset. A correction has been developed for differing rotor diameters that is implemented in ProBat (differences in tower height are less important since the activity is sampled at the nacelle), (3) Implementation at turbines of different manufacturers will depend on technical details of the respective turbine type.

The n-mixture model from Korner-Nievergelt et al. (2013) is based on simultaneous acoustic sampling and carcass searches at 30 turbines from July to September. In this data set, wind-speed had a higher predictive value for collision rate than acoustic activity. As a consequence, the current algorithm implemented in ProBat tends to overestimate collision rates during times with low bat activity, e.g. very early or late in the year. We are currently working on a new, hierarchical version of the collision rate model with a larger effect of bat activity on collision rate that is able to more precisely predict collision rates during times with low bat activity.

Effectiveness of Operational Mitigation

Although, due to differences in the conservation status of bats, operational mitigation is much more common in Europe (all bat species protected by European laws) than in North America (protection status is species specific), almost all publications (but see: Beucher et al. 2011; Behr and von Helversen 2006) on operational mitigation experiments are from the US and Canada (see review in Arnett et al. 2013). In all publications mentioned, curtailment was based on wind speed alone and the cut-in wind speed was chosen more or less arbitrarily between 5.0 and 6.5 ms^{-1} (the normal cut-in wind speed of the turbines was between 3.0 and 4.0 ms^{-1}).

At a site in southern France, Beucher et al. (2011) found 73 dead bats in 2008 and 98 bats in 2009 (all numbers at this site not corrected for biases). In the following year, a cut-in wind speed of 6.5 ms^{-1} was implemented and the lighting at the foot of the turbine towers was deactivated. This reduced the number of fatalities found to two in 2010 and three in 2011 (cut-in wind speed in 2011 was 5.5 ms^{-1}).

Most studies in North America (reviewed in Arnett et al. 2013) reported a reduction in fatality numbers of at least 50% when raising the cut-in wind speed at least 1.5 ms^{-1} above that of the manufacturer. Some studies did not show a comparable effect (this might, however, be explained by the wind speed conditions or the species present at this sites). Most studies that reported on the costs of mitigation estimated a loss of less than 1% of the yearly revenue for curtailment during the main times of collision risk.

The operational algorithms presented here also include the time of night and the month and have proven more efficient than the ones based on wind speed alone. A threshold of two dead bats per year results in a mean loss in power production of 1.4% of the annual revenue as opposed to 1.8% based on wind speed alone. Further costs arise from site assessment and implementation of the mitigation. Moreover, the collision risk for bats at a turbine was estimated from the acoustic activity recorded. Therefore, cut-in wind speeds are not set arbitrarily but tailored to the turbine specific collision risk. This is important because turbines differ vastly in collision risk. As a result unnecessary losses in energy production are avoided while meeting the reduction in collision risk required by the authorities.

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