# Behaviour related flight speeds of Sandwich Terns and their implications for wind farm collision rate modelling and impact assessment

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ABSTRACT

Accurate quantification of flight speeds is a prerequisite to accurately predict the numbers of collision victims of proposed wind farms using collision rate models that are a vital part of Environmental Impact Assessments. We used GPS-loggers on Sandwich Terns to collect novel data on instantaneous flight speeds during foraging trips, separated for different behavioural stages, and applied these estimates in a widely used collision rate model. Average flight speed during a foraging trip corrected for individual variation and flight type was $36.9 \pm 12.3\,\mathrm{SD\,km\,h^{-1}}$ and flight speed was highest during inbound commuting ($44.4 \pm 12.0\,\mathrm{km\,h^{-1}}$) and lowest during foraging ($29.9 \pm 10.7\,\mathrm{km\,h^{-1}}$). Our results show significant differences in flight speeds of Sandwich Terns between behaviour stages during foraging trips, which resulted in divergent estimates of collision victims due to wind turbines depending on the function of the area in which wind farms are proposed. Since these conclusions are likely to hold for many other bird species, we conclude that behaviour of birds in a proposed wind farm is a factor to take into account when modelling collision rates as part of the Environmental Impact Assessment.

## 1. Introduction

The recent use of electronic tracking devices such as GPS-loggers has dramatically increased our abilities to study avian flight characteristics such as flight speed in more quantitative detail compared to earlier estimates using methods like observational data, or tracking with boats and radars (e.g. Gudmundsson et al., 1992; Wakeling and Hodgson, 1992; Perrow et al., 2011). Flight speed is one of the main input parameters of the more commonly used models to estimate collision rates as part of Environmental Impact Assessments, e.g. the Band model (Band, 2012). Higher flight speeds can lead to higher estimates of collision victims in the Band model, as flight speed is positively used to convert measured densities of birds into fluxes that cross the rotor-swept zones of wind turbines: i.e. locally observed densities have a higher turnover rate in an area if the birds have a higher flight speed (Band, 2012). Although on the other hand there is a negative correlation between flight speed and collision probability (i.e. faster flying birds pass the rotor-swept zone faster), this effect is generally smaller than the positive correlation between flight speed and flux. All in all, accurate quantification of flight speeds is therefore, among other parameters, a prerequisite to accurately predict the numbers of collision victims of proposed wind farms (Masden, 2015). Species-specific estimates of flight speeds are generally extracted from literature on flight behaviour of birds (e.g. Hamer et al., 2000; Kotzerka et al., 2010; Kogure et al., 2016), however, the flight data used is usually of insufficient quantity and quality (Green et al., 2016). For instance, in many cases "averaged" (or smoothed) flight speeds are used. These speeds are generally referred to as "travel speed" and are calculated based on the elapsed time and the distance between two subsequent GPS positions. These measurements often lack information on bird behaviour, consequently the calculated speeds could comprise several different behaviours, not necessarily only flight. Since only flying birds are prone to collide with wind turbines, non-mobile or slow-moving behaviours (e.g. walking or floating on water) are irrelevant in collision risk models. In contrast, instantaneous ('momentary') speed measurements are explicit samples of the current velocity at that moment. As birds need to keep a minimum flight speed to stay airborne (Pennycuick, 2008), instantaneous speed measurements provide indirectly also information on the behaviour of the bird at that moment. In order to feed Environmental Impact Assessments with the most accurate collision rate assessments, more robust empirical data is needed and can nowadays be obtained by constantly improving GPS logger techniques. However, for several, mostly smaller species, flight speed data measured with GPS-loggers has still to be published. Terns are among these smaller species that have been found as collision victims of wind turbines (Everaert and Stienen, 2006), and the Sandwich Terns

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*Thalasseus sandvicensis* (Latham, 1787), a species of conservation concern that breeds in a few colonies along European coasts, is currently one of the smallest tern species (~240 g) that can be tracked with GPS-loggers. In this paper, besides reporting accurately measured figures on flight speed for different behavioural flight types, we discuss the implications of variable flight speeds on the outcome of collision rate models, and the consequences for Environmental Impact Assessments in which these results are used.

## 2. Material and methods

During four consecutive breeding seasons (2012–2015) we tracked 39 Sandwich Terns with GPS-loggers to study habitat use and foraging trip statistics in a colony in the southwestern part of the Netherlands. Birds were captured during different stages of the breeding season, either on the nest during the last week of incubation with walk-in traps, or during later stages of chick rearing with spring traps. Five birds were equipped with solar-powered GPS-loggers (Ecotone (Gdynia, Poland) PICA-55 GPS-UHF, ~4.5 g, L: 35 × W: 15 × H: 15 mm), while all others were equipped with regular battery-powered GPS-loggers (Ecotone (Gdynia, Poland) ALLE-55 GPS-UHF, ~4 g, L: 35 × W: 15 × H: 10 mm). Generally, a limit of 3% of the body mass (Phillips et al., 2003; Vandenabeele et al., 2012) is applied to deployments of external data loggers. The weight of our loggers including rings and attachment material was 5.8–6.3 g, which is well within this range (~2.4–2.6%), as Sandwich Terns in our study weighed an average of 241 ± 13.4 g. The battery-powered loggers can take up to ~400 GPS-fixes on one battery load depending on environmental conditions and sampling interval, whereas the solar-powered logger can top up its battery load and can record ~30,000 GPS-positions over a much longer period. All regular loggers stored GPS fixes with 5-minute intervals to the device memory, the solar panel loggers were able to store fixes every 15 min. These GPS-fixes included date, time, and a calculation of the actual latitude, longitude and an instantaneous speed measurement at the time of taking the fix. These calculations are based on the time interval between sending and receiving the location information from the GPS-satellites. The flight speeds used in this article are thus actual instantaneous flight speed measurements at individual positions, rather than calculated average ('smoothed') flight speeds between subsequent points. Accordingly, we refer to the instantaneous flight speed as recorded by GPS devices at each fix as 'flight speed'. In general, the mean speed error of similar GPS-loggers on birds lies between 0.01 and 0.82 m/s (Bouten et al., 2013), and increasing the sampling intervals increases the error (Thaxter et al., 2011). Data were automatically transferred from a distance up to ~100 m to base stations placed in the colony and on a loafing site. More detailed information on the actual tracking study is described in Fijn et al. (2016).

A total of 27 out of 39 loggers successfully transferred positional data to the base station and in total 7238 GPS-fixes (and thus also samples of instantaneous speed) were collected during 221 trips, where a trip is defined as the period between the moment a bird leaves the colony and its subsequent return to the colony. Based on the relative turning angle in flight direction between subsequent points, flight speed and habitat characteristics at the position of the fix, these fixes were manually classified into behavioural states by visual inspection of each GPS fix. These states were 1. resting (speed of $0 \, \mathrm{km \, h^{-1}}$ and in suitable resting habitat), 2. commuting to the foraging area (straighter movements away from colony, speed above $0 \, \mathrm{km \, h^{-1}}$), 3. foraging (reduced speed in combination with sinuous turning angles, above water), 4. commuting to the colony (straighter movements towards colony, speed above $0 \, \mathrm{km \, h^{-1}}$), and 5. transit (straighter movements not coming from or going to the colony, speed above $0 \, \mathrm{km \, h^{-1}}$) (Fijn et al., 2016). Subsequently, based on visual inspection of the speed histograms (Fig. 1), fixes with low speeds ($< 5 \, \mathrm{km \, h^{-1}}$) were excluded from the analysis, as being likely recorded during stationary, non-flight behaviour. In this analysis we exclusively used the categories foraging,

commute in, commute out and transit, totalling 3587 location fixes.

Individual birds varied substantially in the amount of samples of instantaneous flight speeds. In order to avoid the influence of individuals with substantially more data, but also ensure that each individual has a representative sample size per behavioural category, we only used individuals that recorded at least four different foraging trips ($N = 19$ individuals with altogether 3514 location fixes). Subsequently, we calculated mean flight speeds per behavioural state (i.e. foraging, inbound- and outbound flights and transits) during each trip. In order to estimate the mean speed of foraging, inbound- and outbound flights, we calculated mean flight speeds per behavioural state within 70 randomly selected trips. Transit flights form a separate type of flight behaviour, not necessarily being part of a foraging trip, and also occurred at a lower number of individuals ($N = 7$), resulting in a lower number of trips ($N = 21$) for this behavioural state in the final database. By calculating mean flight speeds based on the mean of randomly selected trips instead of randomly selected point measurements, we limited the effect of eventual outliers among the point measurements to come to a more reliable estimate of flight speed. By doing so we were also able to avoid the influence of autocorrelation on subsequent behavioural states within a trip.

Based on the final dataset, variation in average speeds of the different behavioural flight types was statistically tested. As speed measurements were not normally distributed, even after transformations, a non-parametric Kruskal-Wallis test was conducted. Post-hoc comparison of significant results was conducted with pairwise *t*-tests using Bonferroni correction.

The Extended Band model (Band, 2012) was run to calculate hypothesized collision victims with the newly obtained speeds of the different flight types. In order to simulate collision rates for realistic a wind farm scenario, we used characteristics of the Dutch OWEZ wind farm filled with 36 Vestas V90 turbines of 3 MW. To calculate the number of collisions occurring in a single breeding season, bird density was set for two months at 1 bird/km² in the wind farm area and at 0 in the rest of the year. Bird length (0.385 m) and wingspan (1 m) were taken from mean values presented by Cramp and Simmons (1978). Birds were assumed to conduct flapping flights, with 50% of the flights occurring upwind. The Extended Band model uses a flight height distribution per 1 m altitude classes, which was taken from Johnston et al. (2014). This study reports modelled flight heights, based on data collected at 32 different offshore wind farms, including OWEZ. In OWEZ, Krijgsveld et al. (2011) carried out visual observations and reported mean flight heights and flight height distributions relative to the rotor height of turbines, but not providing enough detail to can be applied in the Extended Band model.

Finally, results on collision victims based on the 'overall mean flight speed' recorded in this study (the parameter that is standardly used in collision rate modelling) and also per flight type are presented as a relative change compared to the mean flight speed reported by Wakeling and Hodgson (1992), the current standard value that is widely used in collision rate models.

## 3. Results

Average instantaneous flight speed ± standard deviation during a foraging trip was $36.9 ± 12.3 \, \mathrm{km \, h^{-1}}$ after correction for individual differences and flight type (Fig. 1). Flight speed of Sandwich Terns varied significantly among different behavioural stages (Kruskal-Wallis $\chi^2 = 53.2$; $P < 0.0001$; Fig. 2). The highest flight speeds were obtained during inbound commutes ($44.4 ± 12.0 \, \mathrm{km \, h^{-1}}$; median = 41.9), in fact significantly higher than during any other flight types (post-hoc tests all $P < 0.05$). Outward flights ($37.3 ± 9.8 \, \mathrm{km \, h^{-1}}$; median = 37.0) were significantly slower than inbound commutes ($P < 0.0001$), but faster ($P < 0.0001$) than during foraging ($29.9 ± 10.7 \, \mathrm{km \, h^{-1}}$; median = 29.6). The flight speed of transiting terns ($35.6 ± 7.40 \, \mathrm{km \, h^{-1}}$; median = 34.1) differed