

PREDICTING BIRD MIGRATION: DATA-DRIVEN VERSUS CONCEPT- DRIVEN MODELS**Willem Bouten¹, Jelmer van Belle^{1,2}, Hans van Gasteren^{1,2}, Jasper A. Vrugt³, Judy Shamoun¹
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Abstract

Bird migration causes a serious threat to flight safety. As part of the total set of Bird Avoidance Models, the Dutch BAMBAS team models the migration intensity as a function of weather conditions. Data-driven log-linear multivariate regression models and Artificial Neural Networks were developed by statistical analyses of three years of data of bird density, measured with a long-range medium-power radar in the Netherlands. Although migration density shows a highly dynamic and complex behaviour, with distinct peaks, the dynamics could be largely explained and predicted from the weather conditions, especially wind speed and wind direction. The root mean squared error of the predictions was below 0.9 for all models on a logarithmic intensity scale ranging from 0 to 6. However, the measurements underlying the predictions are local and therefore the applicability of the models is limited to (part of) the Netherlands. A concept-driven model was also developed as it is generally assumed that concept driven models can be better extrapolated to other areas. This model performed equally well in the studied area.

Although the models perform differently for the various periods, none of the models clearly performs better than the others. Therefore the Royal Netherlands Airforce will use an ensemble forecast which includes all relevant results and which is capable of issuing migration intensity forecasts four days in advance.

As these models only describe the migration dynamics in the North of the Netherlands, another concept driven model was developed for nocturnal passerines that migrate from Scandinavia to Africa. This model describes energetic dynamics as a result of flight mechanics in a spatially explicit framework, to simulate the migration route and timing of an individual bird under dynamic weather conditions. Until now the model has largely contributed to the understanding of the spatial distribution of migration routes and the temporal dynamics of migration intensity in general, but not with the accuracy and at the temporal resolution that is needed for warnings. Further research is needed to develop methodologies for merging modelled and measured migration intensities into a predictive Bird Avoidance System.

1. Introduction

Bird migration causes a serious threat to flight safety. To avoid bird strikes during training flights of the Royal Netherlands Air Force (RNLAf), bird intensity warnings (BirdTAMs) are issued by the Nature Bureau of the Directorate of Operations. Since the early eighties, these BirdTAMs are based on radar measurements in the North of the Netherlands. The interpretation of the radar image and the spatial extrapolation over the rest of the Netherlands and adjacent countries is done by expert judgement. Forecasts of migration intensity for the coming days are not available. The spatial uncertainties and abrupt temporal changes of the migration warnings, in combination with the great impact of the warnings on flight operations, prompted the RNLAf to improve the reliability of the warnings by modelling the dynamics of bird migration.

The strong relationships between migration intensity and weather have long been recognised. The use of multiple regression models to quantify these relationships facilitated predictions of mass bird migration and in several countries weather based- regression models were used to prevent collisions of aircraft with birds (Blokpoel 1969; Geil et al., 1974; Alerstam & Ulfstrand 1976). Most of these studies at least partly explain the variance in bird migration intensity with multiple regression models based on local weather variables, although bird migration may be more related to large-scale synoptic weather phenomena than to local weather variables (Richardson 1978). Wind, rain, sea level pressure, temperature, cloud cover and derivatives of all these are the common predictors of migration (Richardson 1990; Zehnder et al., 2001; Erni et al., 2002; Schaub et al., 2004). However, the relative contributions of these variables to migration intensity differ strongly between studies and the predictive values of these models under different conditions in time and space have never been tested.

This paper describes the migration models that we developed for the Netherlands in the context of the BAMBAS-project (Bouten et al., 2003). We didn't limit ourselves to multiple linear regression models but also used Artificial Neural Networks (ANN) that can easily cope with non-linear relations. In addition to these data-driven types of models we also developed a concept driven model in which we incorporated our knowledge of migratory behaviour. The parameters of this model were tuned to fit the observed migration patterns. Generally concept based models can be better extrapolated to other areas.

2. Methods

2.1 Migration intensity data

We analysed migration intensities of 215 nights measured with a 10 cm medium-power radar, in a period from the 1st of August until the 15th of November of 2001, 2002 and 2003. The radar, which detects birds between 100-1500 m altitude up to 150 km distance, is situated in the Northeast of the Netherlands. The measurement window is located 50-60 km from the radar, 20-60 km from the northern coast of the Netherlands, with its centre at 52° 54' N and 6° 11' E and has a surface of 850 km².

Each hour during 10 rotations of 10 seconds, an automated bird detection program extracted the aerial bird echoes from the radar image. The underlying algorithm is based on the reoccurrence of bird echoes in consecutive radar images and yields flight directions and speeds for all detected bird echoes. Migration intensity is defined as the number of bird echoes per km², corrected for the clutter area within the window. Migration intensity was set to 0 for hours with missing bird data due to intense rain (Erni et al., 2002). When bird echo densities exceeded 10 echoes per km², migration intensity was estimated manually from the total measured reflection.

All analyses were based on hourly nocturnal migration intensities integrated over the period between sunset and sunrise. Intensities for missing hours were interpolated using the measured intensities for that night and a normalized nocturnal pattern. Nights with more than 50% missing data were omitted from the analysis. This resulted in 214 measurements of total nocturnal migration intensity. The predominant reasons for missing data were radar downtime (especially in September 2001) and intense rain clutter. Although the mean migration intensities differed between years, those differences were not significant (ANOVA, P<0.05). Therefore we used data sets of pooled and separated years for our analyses.

Mean nocturnal migration intensities, measured with the same radar during 1989-1995, were used to establish a general seasonal trend of migration intensities. This trend served as a baseline for our models and was used as an independent input variable in addition to meteorological variables. The model is expected to explain the daily deviations from this baseline as caused by varying meteorological conditions.

2.2 Input variables

Meteorological variables were taken from the weather station data in Eelde (53° 10' N and 6° 35' E), 25 km north-east of the centre of the radar window (source: Netherlands Meteorological Institute KNMI), and sounding data of wind directions and speeds at 1000, 925 and 850 hPa pressure levels (approximately 0, 750 and 1500m altitude) measured at Emden (53° 21' N and 7° 13' E), 65 km north-east of the centre of the radar window (source: NOAA radiosonde database, <http://raob.fsl.noaa.gov/>, WMO station identifier 10200).

All sounding and surface data were collected at 23:00 UTC. Additionally, hourly precipitation data were integrated over the period between sunset and sunrise. The 28 tested meteorological variables were derived from surface and altitudinal wind speeds and directions, surface barometric pressure, surface temperatures, precipitation rate at 23:00 UTC and precipitation integrated over night time. As described above, the baseline migration intensity (I_b) was used as an additional input variable.

2.3 Regression analyses

We developed multivariate regression models using meteorological variables as input and the log-transformed migration intensity as output variable. To test the models we split the dataset into two: one set for calibrating the model and one set for independent testing. Multiple input variables were selected by stepwise procedures. Only significant variables ($p < 0.05$) were included. To enable direct comparison of the contribution of individual input variables to each model, we normalised the input variables by taking the normal deviates or Z-scores ($Z = (x - \mu) / \sigma$, Zar 1982) of each variable, prior to model development.

To investigate the importance of calibration sample size on robustness of the input variables, we carried out repeated automated stepwise regressions on randomly selected calibration sets of different sizes: 30, 60, 90 and 120 data points. For each calibration set size, the data set was randomly split 2000 times into a calibration set and a test set. Test sets always contained 80 data points. Performances of all models were compared by the root mean squared error (RMSE) in the test period.

We analysed 28 weather variables but here we only present the variables that were included in our final models. For rain, we used the total nocturnal rainfall R_t (mm) and the proportion of hours with rain intensity > 0.01 mm hr⁻¹ between sunset and sunrise (R_p): i.e. nights with rain during 6 out of 8 nocturnal hours would result in $R_p = 0.75$. For barometric pressure P (hPa) and temperature T (°C), we also used the 24-hours increase (ΔP resp. ΔT) by subtracting the values of the previous nights. Wind profits were calculated from the wind vector (consisting of wind speed S_w and wind direction α_w) and the mean bird vector (bird speed S_b and bird direction α_b): wind profit is defined as the length of the bird vector minus the length of the displacement vector (Liechti, 1995):

$$W_p = S_b - \sqrt{S_b^2 + S_w^2 - 2 \cdot S_b \cdot S_w \cdot \cos(\alpha_w - \alpha_b)} \quad \text{eq.1}$$

The preferred flight direction α_b was set to 223°, bird flight speed S_b was set to 12 m s⁻¹. The input variable for wind profit W_p (m s⁻¹) was based on the mean of all wind profits up to the 850 hPa pressure level. Note that W_p can attain negative values in headwind conditions, with strong lateral wind or with very strong tailwinds. Based on W_p the categorical variable for negative wind profits W_a was set to 1 for wind profits lower than a (negative) threshold; this threshold was optimised manually in steps of 0.1 m s⁻¹.

Furthermore, a factor for increasing migration pressure from previous nights with adverse weather was adopted from Erni et al. (2002):

$$Acc_t = \frac{1}{3} \cdot Acc_{t-1} + \frac{2}{3} \cdot W_{t-1} \quad \text{eq. 2}$$

where Acc is the accumulation effect, W is the adverse weather parameter, t relates to the current night and $t-1$ relates to the previous night. Independent accumulation variables were set up for the

effect of rain (Acc_r) and the effect of negative wind profit (Acc_w), based on $R_p > 0$ or $W_a > 0$ respectively.

2.4 Artificial Neural Networks

An Artificial Neural Network (ANN) is a mathematical structure that can represent any complex non-linear input-output relation. The inspiration for the technique originates from attempts to model bioelectrical networks in the human brain. In a neural network, simple nodes –the neurons – are connected together to form a network. A typical simple ANN consists of three layers with nodes. The first layer connects with the input variables – in our case the meteorological variables and the seasonal trend. The last layer connects with the output variables, which in our case is the migration intensity. In between, we use a so called hidden layer that connects all variables. Each of the nodes is connected to all nodes of the adjacent layers. The weight of each connection, times its input, is summed for all incoming connections. If the sum is greater than a certain threshold, then a value is propagated through the connections to the next layer. During “training” the weights of the ANN are tuned to obtain the best fit of the ANN to the calibration data set. The art of modelling is to design a network with an optimal number of nodes in the various layers. The number of nodes is a trade off between a best fit to the calibration data (many nodes) and the robustness of the ANN (few nodes), which is based on its performance when applied to an independent test data set. The meteorological data and the multi-year trend were used as the input layer. The migration intensity (not log-transformed) was used as output layer.

2.5 Concept-driven model

A concept driven dynamic model consists of concepts that are translated into mathematical equations and model parameters that are representations of the system properties. The idea of a generic concept driven model is that if we want to apply the model to a different area, that we need not change the concept but only the parameters to simulate the dynamics of that system. Unfortunately, the estimation of the correct values of these parameters is not simple as the parameters represent properties that are not easily observable or measurable. Instead, the typical way to estimate the model parameters is to adjust them in such a way that the input-output behaviour of the model approximates, as closely and consistently as possible, the data of the underlying system over some chosen period of time. This process is known as “model calibration”, also called “parameter optimisation”. For our study we used the SCEM algorithm which is a general-purpose global optimisation algorithm. SCEM is a very efficient optimisation algorithm that can be linked to any model to identify its parameters on the basis of some predefined objective function (Vrugt et al. 2003b). In this case the objective is to minimize the discrepancy between model results and measurements.

The concept driven model was built iteratively. After each model evaluation, by comparing the model results with the measurements, the model structure was adapted until no further improvement could be achieved. In the final model, the nocturnal migration intensity (M) is calculated from:

$$M = e^{c_w \cdot W_p} \cdot I_b^{c_b \cdot \varphi_{bw}} \cdot A^{c_a} \quad \text{eq. 3}$$

with:

W_p	Input windprofit as explained before (Liechti, 1995)
I_b	Input baseline migration intensity determined from the years 1989-1995
A	Calculated accumulation due to adverse weather conditions defined as $A_t = \beta \cdot A_{t-1} + (1 - \beta) \cdot \text{Unfavwind}_{t-1}$
c_w, c_b, c_a	Calibrated model parameters
φ	Calibrated reduction parameter (equals 0 if Unfavwind does not reach its threshold value)
β	Calibrated model parameter $0 < \beta < 1$
Unfavwind	Calibrated threshold for opposing wind that determines bad (=0) and good (=1) migration nights.

3. Results and discussion

3.1 Regression models

Regression models were based on the data of one or two years. Depending on the period they contained two to four significant input variables: wind profit W_p (m s^{-1}), baseline daily migration intensity I_b (echoes/ km^2/night), 24-hour trend in barometric pressure ΔP (hPa day^{-1}) and nocturnal proportion of hours with rain R_p (relative number, 0-1). W_p and I_b were the most important explanatory variables in all models. ΔP was a significant variable for all subsets of years except for the year 2001. R_p was significant in all models based on two and more years. Comparison of the normalised coefficients shows that W_p has the largest effect on migration intensity.

Model structure and validation performances of the regression models were more robust for larger calibration sets (table 1). Calibrations on smaller data sets yielded fewer significant variables and a larger variation of selected variables. Sub-samples of 30 nights occasionally even yielded models without baseline or wind profit, something that never occurred with larger sample sizes. RMSE's of the test sets were smaller and more consistent with increasing calibration sample size: mean RMSE's decreased from 1.05 ± 0.19 to 0.89 ± 0.07 for models calibrated with 30 and 120 nights respectively.

Table 1. Effect of calibration sample size on model structure and performance. Relative occurrence of input variables and some statistics of regression models calibrated by 2000 random samples of 30, 60 90 and 120 data points.

	Calibration sample size			
	n=30	n=60	n=90	n=120
W_p	0.88	1	1	1
I_b	0.59	0.94	1	1
ΔP	0.18	0.44	0.63	0.80
R_d	0.11	0.19	0.30	0.47
R_t	0.13	0.25	0.25	0.21
P	0.14	0.19	0.24	0.19
ΔT	0.10	0.18	0.19	0.17
Acc_w	0.9	0.13	0.12	0.13
Nr of variables	2	3	4	4
RMSE	1.05 ± 0.19	0.93 ± 0.083	0.90 ± 0.072	0.89 ± 0.069

Considering the importance of calibration sample size and the problem of over-specified models, we decided to use the data of all three years for calibrating our operational model that predicts the migration intensity:

$$\log(M_{123}) = 1.24 + 0.84I_b + 0.154W_p + 0.043\Delta P - 0.79R_p \quad \text{eq. 4}$$

As we do not have any independent measurements, the RMSE was calculated for the calibration data set and appeared to be as low as 0.81.

3.2 Artificial Neural Networks

In this study we used 2/3 of the dataset for training and 1/3 for testing. After extensive testing it was found that the models performed best with input nodes for windprofit, the multi-year baseline of migration intensity, and the 24-hours increase in air pressure. Two nodes were used in the hidden layer. Adding more nodes for input or more hidden nodes increased the flexibility of the ANN and indeed improved the fit of the calibration data sets but reduced the performance on the independent test sets. The mean RMSE of the ANN's, when applied to independent test sets, was 0.89 which is equal to the RMSE of the regression models when using an equal size of data set for calibration. The main difference is that the ANN's perform slightly better at high migration intensities, whereas regressions perform better at low migration intensities.

3.3 Concept-driven model

Upon optimisation, SCEM produces a full posterior distribution of parameter values including the correlation structure of the parameters. It is beyond the scope of this paper to fully discuss this issue. In summary, all parameters could very well be identified although the threshold for rain had a rather wide range. The final model, trained on the full dataset, can be represented by:

$$M = e^{0.20W_p} \cdot I_b^{1.21\phi_{bw}} \cdot A^{4.57} \quad \text{eq. 5}$$

with the following values: $\phi=0.62$, $\beta=0.67$, and thresholds Rain=7.57 and Unfavwind=-7.69.

In a concept driven model, the model structure is defined by the modeller which makes the structure less flexible than an ANN. In general this leads to a poorer performance of the model. However, the RMSE of the present model was 0.90 which is almost as good as the regression models and the ANN's.

As an illustration all modelled migration intensities are plotted against the measured intensities in figure 1.

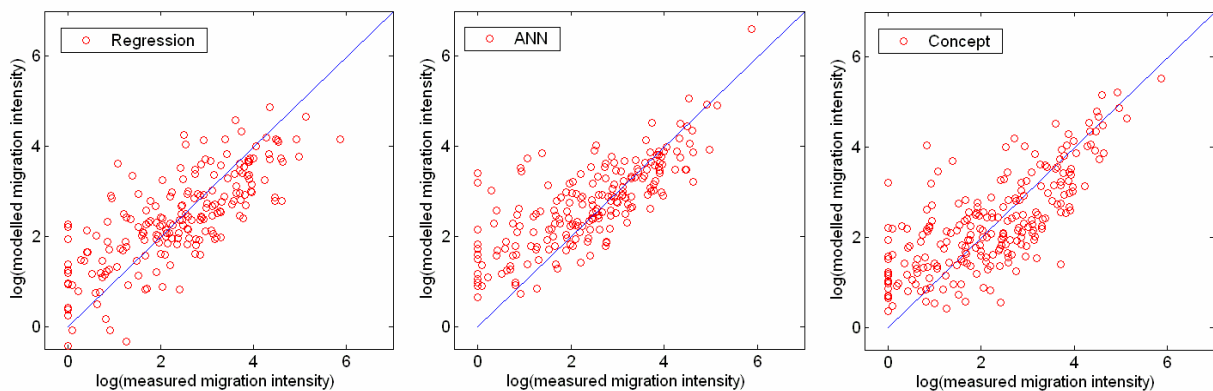


Figure 1. Scatter plots of the results of the various types of models

4. Conclusions

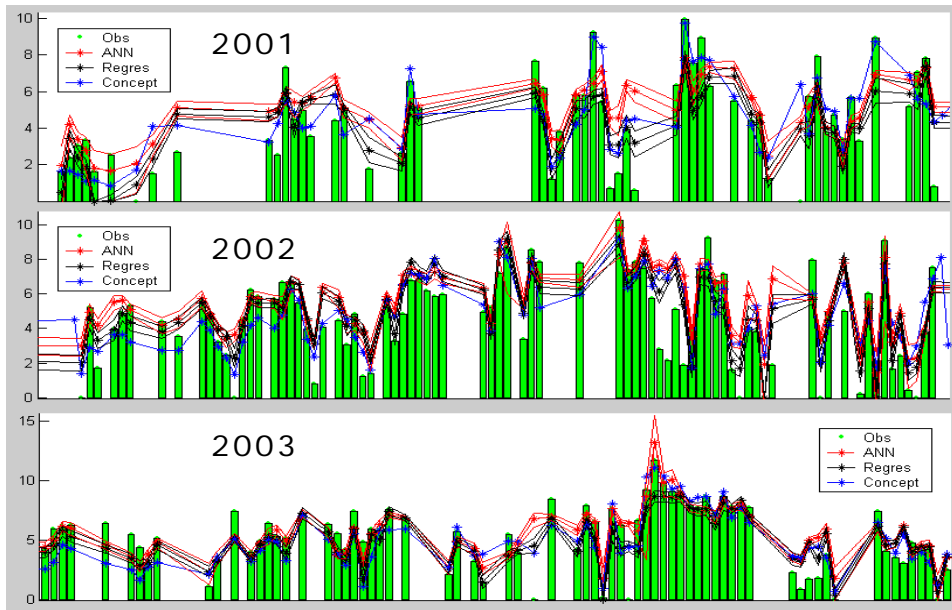


Figure 2. Measured (bars) and modelled (symbols) migration intensities in the autumns of 2001, 2002 and 2003.

Although the used modelling techniques are rather different, they all perform almost equally well (figure 2). Given these results, there is no reason to reject any of the models. This means that the forecast can best be based on the ensemble of models, thus including both the uncertainties of model structures as well as parametrizations. In the operational situation of the RNLAf, meteorological data, available from NOAA's Air Resource Laboratory, are now downloaded from the Internet (http://www.westwind.ch/w_soua.php where one can select a certain region). With these data the models can be run to calculate the expected migration intensity for the coming days. The model results will not be used to automatically generate BIRDTAMs but will be used as a decision support by the staff that issues the BIRDTAMs (figure 3).

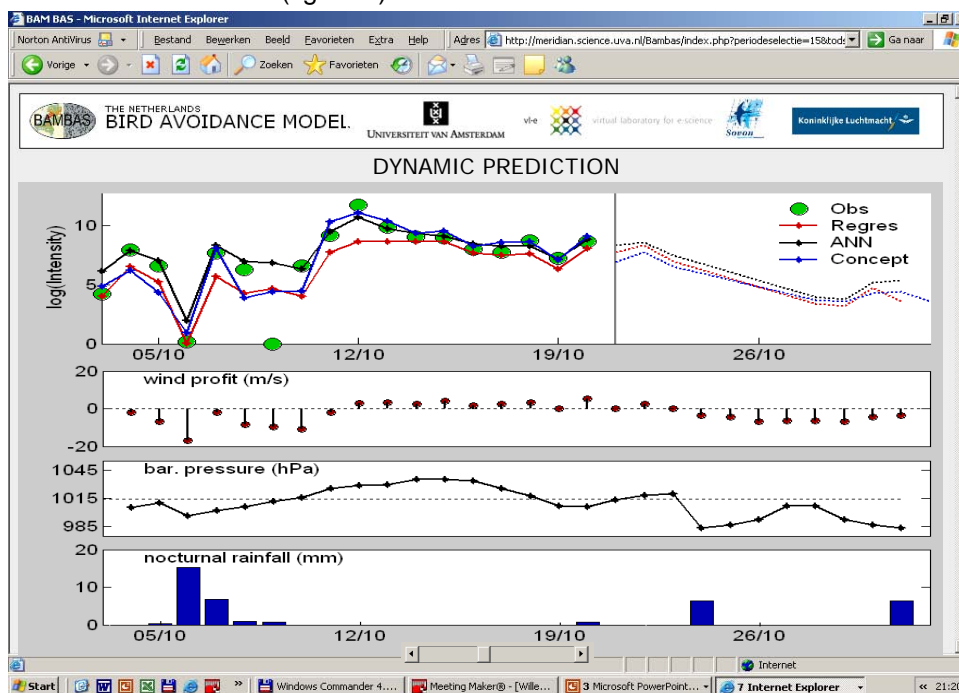


Figure 3. Dynamic migration predictions as presented in the decision support system

5. Future research on bird migration

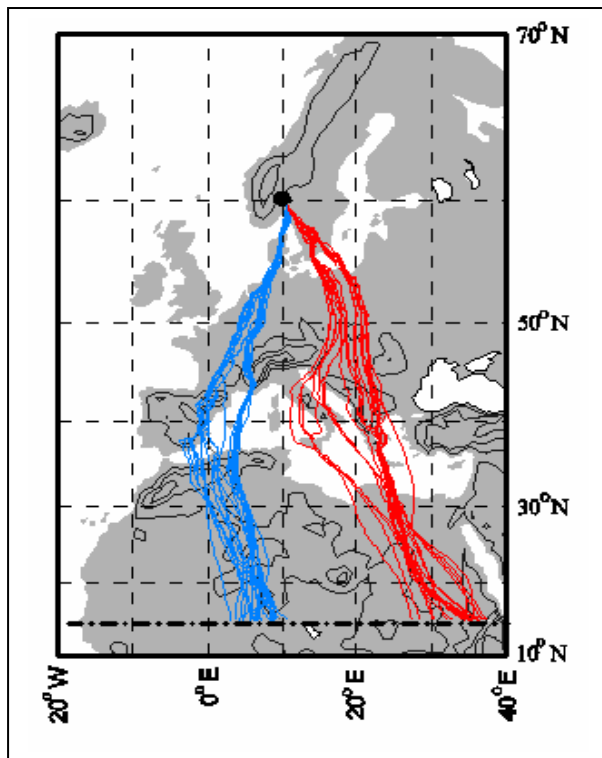
The main limitation of the presented models is the local nature of this study. Although migration in this region often occurs as broad front migration, the radar window that is used for this study may not be representative for the whole of the Netherlands, not to mention the rest of western Europe. Therefore we are extending our research in two directions a) the use of the weather radar network to identify bird migration at a larger spatial scale and to study the altitude of migration, and b) the development of a spatially explicit dynamic simulation model. Finally the aim is to combine both research directions and to develop a Bird Avoidance System that merges the information flows of measurements and models.

5.1 Radar comparison

This study compares measurements of two types of radar. Contaminated wind profiles of a C-band Doppler weather radar of the Royal Netherlands Meteorological Institute are compared with bird data obtained with the Flycatcher tracking radar of the RNLAf. Preliminary results show that the standard deviation of the radial velocity of the Doppler can be used to separate the profile data from the weather radar into “true” wind vectors and bird movement vectors. This implies that not only high quality wind vector data can be obtained, but that the Doppler weather profiles also contain information on the temporal and vertical distribution of migrating birds while they are in “weather-mode”. This creates an opportunity for developing a warning system based on the existing European Doppler radar network.

5.2 Spatially explicit migration model

We developed a two-dimensional spatially explicit dynamic model that simulates the time evolution of the spatial location and airframe, muscle, and fat amounts of an individual bird under a given set of behavioural rules. These rules, being characterized by a set of parameter values, define the decisions and actions of the bird that experiences dynamic environmental conditions. The model combines the strengths of the flight mechanical theory presented in Pennycuik (1998; 2003) and the two-dimensional spatially explicit modelling framework of Erni et al. (2002; 2003), but includes several



additional features to increase flexibility and applicability. The multi-objective optimisation algorithm MOSCEM (Vrugt et al., 2003a) was applied to the model to study the long-distance migration patterns of nocturnal passerines. By minimizing flight-time and energy-use (Alerstam and Lindström, 1990) in the optimisation procedure, we found the optimal parameter sets and thus the bird's behaviour and migration patterns that lead to maximum fitness. The results of our models clearly show that birds that optimise their flight-time choose a more westerly route than birds that optimise their energy-use (figure 4). This type of theoretical results is not yet applicable in Bird Avoidance Models. However, more detailed studies and a comparison between model results and high resolution measurements will further enhance our understanding of complex migratory behaviour. It is to be expected that this will finally also contribute to improving the reliability of Bird Avoidance Models.

Figure 4. Migration routes of birds minimizing their flight-time (towards the west) and energy-use (more east).

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