

A Model-sensor Framework to Predict Homing Pigeon Flights in Real Time

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Abstract

Advances in sensor technology have triggered the development of model-sensor frameworks that integrate real-time sensor data into simulation models. Successful implementations include sensor streams of physical properties of the environment, and traces of human mobility as captured by mobile devices. Implementation of real-time sensor-data streams from tagged animals is not yet in place. However, these are anticipated in the near future. In this research, we explore a model-sensor framework with a novel agent-based flocking model for homing pigeons and an emulated sensor stream that is derived from a previously recorded GPS track. Results point to conceptual shortcomings but also opportunities in transferring conventional models to an integrated model-sensor framework. From these insights, directions for further research towards automatic model-calibration and adaptive rulesets were identified.

Keywords:

spatial simulation; real-time sensors; agent-based modelling; movement ecology

1 Introduction

Lack of high resolution spatio-temporal information on animal movement has for a long time been highlighted as a key impediment in research to understand animal migratory behaviour (Nagy et al., 2010; Partridge et al., 1980). Only recently have technological advances led to wide availability of real-time sensor data on the environment, which provides a novel means for the understanding of the underlying dynamics and processes of ecosystems. For the research community in ecological modelling in particular, real-time sensor data provide a source of accurate and up-to-date information with which to 'train', calibrate and validate models in real-time.

Sensor networks for ecological applications rely on robust, low-cost, power-efficient, location-aware micro-sensors (Bröring et al., 2011) and an infrastructure of sensor technology and wireless communication networks (Nittel, 2009). The availability of sensors that can capture spatio-temporal characteristics of processes at high resolution has also strengthened the long-held feeling that concepts from agent-based modelling and Geographic Information Science can be integrated to develop robust methods of modelling

dynamic phenomena (Brown et al., 2005; Tischendorf, 1997). Ecological sciences provide an ideal arena in which further collaboration and research in the integration of geospatial concepts, agent-based modelling and sensor-generated data can be explored (O'Sullivan, 2008). This is particularly thanks to the extensive work that has been carried out in the use of agent-based models to understand ecological processes and the behaviour of individual organisms within ecosystems (Grimm & Railsback, 2013).

The successful integration of spatial data, agent-based models and sensor networks for ecological applications requires two major ingredients:

(1) The availability of adequate models with sound theoretical foundations (Grimm, 1999; O'Sullivan, et al., 2015), from which further lessons can be learned by the integration of representative spatial information and sensor data. In the research presented here, we focus particularly on Reynolds's (1987) Boids model. Reynolds reasoned that flocks of birds or schools of fish emerge when the agents in motion obey simple rules of local interaction with their nearest neighbours, including separation, cohesion and alignment. The Boids model has inspired a large number of related flocking models. For example, Codling et al. (2007) demonstrated by an individual-based flocking model that movement in groups improves the navigational abilities of individual birds; and Bode et al. (2011) investigated the influence of social networks on collective movements.

(2) The wide availability of GPS animal tracks (Bridge et al., 2011; Nathan & Giuggioli, 2013; Wikelski, 2013). A recent breakthrough in the availability of data is due to the development of miniature GPS sensors to tag animals as small as wasps. These sensors make it possible to capture flight trajectories of individual insects at high spatial and temporal resolution (Cagnacci et al., 2010). Additionally, new platforms have been established (e.g. www.movebank.org) to manage animal-track data and share it with the research community. This development has triggered research beyond the individual projects for which the data was recorded (Kranstauber et al., 2011). Other developments foresee, in the near future, space-based observation methods using the latest earth-observing sensor systems endowed with the ability to stream real-time data on animal tracks. A case in point is the ICARUS project, which was launched in 2012 and is scheduled to start streaming in 2016 (Gross, 2015). Such systems are particularly advantageous because of their ability to stream animal-movement data over large spatio-temporal extents (Wikelski et al., 2007).

These recent developments offer novel opportunities for testing and enriching conventional ecological simulation models with animal-movement data in real time. In the literature, attempts at model-sensor integration have been carried out mostly in the context of Dynamic Data Driven Application Simulation (DDDAS) (Darema, 2004). The overriding purpose of DDDAS research is to enable a dynamic bi-directional flow of sensor data to validate and to modify models, and to enable simulated data to be used in informing sensing strategies. Demonstrations of this method have integrated real-time data with simulation models, primarily in the social domain and the non-living environment, for example to influence a simulation of the spread of fire (Hu, 2011), to identify airborne contaminants in real time (Akçelik et al., 2005), to model evacuation plans in emergency scenarios (Gaynor et al., 2005), to investigate the potential of a camera system for monitoring of animals (Pereira, 2007), or to monitor pedestrian movement based on data streams from wireless

communications (Schoenharl & Madey, 2008). This new method of integrating real-time data into the modelling environment thus introduces a paradigm shift in the way models are calibrated and validated, from the original method of using historical data to a ‘smart’ mode in which a model interacts with real-time data from subjects as they are moving.

Real-time data streams on animal movements are not yet in place, and thus research into model-sensor frameworks has not received much attention. This research aims to explore potential obstacles, opportunities and implications of using model-sensor frameworks in movement ecology compared to conventional approaches of agent-based simulation modelling.

In this paper we combine an agent-based model of social pigeon flights (‘PigeonModel’) with an emulated data stream from previously recorded GPS tracks in order to develop a model-sensor framework. The model-sensor framework was implemented in three steps. First, the PigeonModel was designed, implemented and calibrated following the conventional development cycle of an agent-based model (Grimm & Railsback, 2013): the simulation ran through the entire homing flight from the release site to the home loft and was then compared with GPS data for calibration and validation. The calibrated PigeonModel was then updated with the emulated GPS data stream at each time step to dynamically predict individual movements, adjust to the predicted location, and compute prediction errors in real-time. Finally, the validation results of the model-sensor framework were compared with those of the conventional modelling workflow. We implemented the model for a flock of eight homing pigeons at a study site close to a home-loft in Seuzach, Switzerland, presented in a study by Santos et al. (2014).

2 Methods

Data

A total of five GPS tracks of homing flights near Seuzach, Switzerland (Santos et al., 2014) were available from the online repository Movebank (www.movebank.org) at high spatial and temporal resolution. Santos et al. released pigeons simultaneously, which then navigated their way home together in flocks. GPS data of homing flights were considered only as long as the birds stayed together in a flock: from when the flock formed after release until it dispersed, when birds entered familiar ‘home’ territory. The average flight speed of the pigeons was 16m/s, which translates to a movement distance of approximately four metres at each time step. The release site was about 15km from the loft. The absolute spatial accuracy of the GPS measurements ranged around one metre; relative positions can be expected to be significantly more accurate.

The agent-based ‘PigeonModel’

The purpose of the PigeonModel was to gain a better understanding of the social and navigational behaviour of pigeons by exploring simulated flight patterns of flocking pigeon agents in comparison to observed flight trajectories. The flocking behaviour in the model is

an extension of the flocking model available in the Model Library of the NetLogo modelling software (Wilensky, 1999), which in turn is an implementation of the Boids model (Reynolds, 1987). The agents were eight homing pigeons; together they formed a flock in which each pigeon had a social rank. A single time step in the model represented 0.25 seconds. The choice of this temporal resolution was motivated by two factors: firstly, this time duration is approximately equal to the delay time of a following pigeon in reacting to a turn initiated by a leading pigeon (Nagy et al., 2010); secondly, this temporal resolution made it possible to compare the results of the model to the validation data which was captured at the same resolution (Santos et al., 2014). The entire homing flight took between 15 and 20 minutes. The rules that guided the flocking and orientation behaviour affected a bird's heading, but not its flight speed; each bird moved forward at a uniform speed of 16m/s. The landscape was represented by a digital elevation model derived from a Shuttle Radar Topography Mission (SRTM) dataset of the study area, with a spatial resolution of 25m by 25m. The spatial extent of the area of study was 17km by 17km. The geometry of the flight path of each individual bird was exported as temporal point vector data at the end of a simulation. Figure 1 shows the model's structure as governed by changes of flight directions at each time step, which are controlled by flocking, navigation and leadership behaviour.

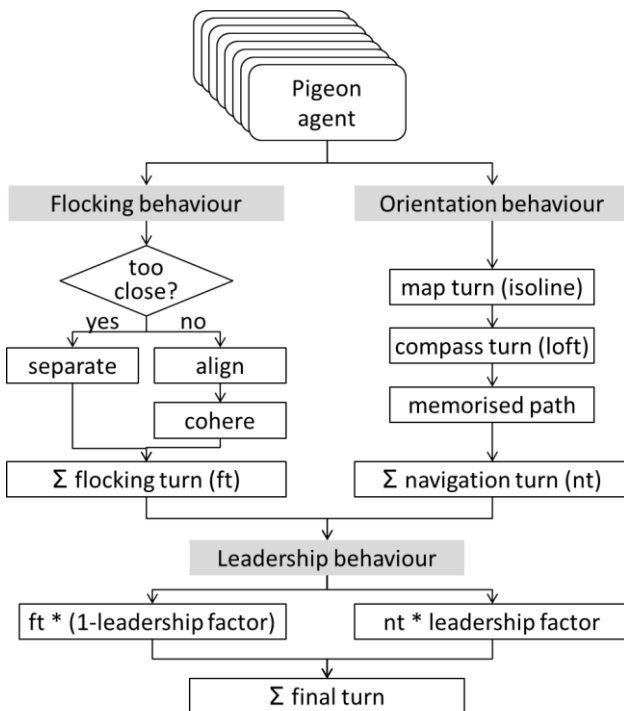


Figure 1: Flow diagram of the PigeonModel.

Flocking behaviour is controlled by three possible rules – of ‘separation’, ‘alignment’ and ‘cohesion’ – depending on a bird’s position relative to its neighbours. If a neighbouring bird is too close, the bird separates by turning away from the neighbouring bird. If the closest

neighbour is farther away than the minimum distance, the bird coheres by turning towards its neighbours and it aligns its heading to the average flight direction of its flock mates. It has been observed that the maximum number of neighbours that are considered by flocking birds is seven (Ballerini et al., 2008). As the flock modelled consisted of eight individuals, all flock mates within a bird's angle of view of 340° (Nagy et al., 2010) were considered neighbours in the PigeonModel. A pigeon agent which is 50m away from the flock ceases to be a flock mate and eventually splits off. Each of the three flocking turns (separate, align and cohere) was parameterized with a maximum turn angle per time step. Compounded together, these turns represent the 'flocking turn' of an individual pigeon at any particular time step.

Complementary to the flocking behaviour, pigeon agents also exhibit navigation behaviour. In the literature, navigation behaviour of pigeons is described in terms of a combination of map and compass strategies (Blaser et al., 2013), as well as a tendency to follow routes memorized from previous flights (Biro et al., 2004). In the map strategy, birds follow landmarks and topographical features. In the PigeonModel, the map strategy was implemented by a rule that guides birds along elevation isolines. To represent memorized routes in the PigeonModel, each of the eight pigeon agents was first 'trained' to memorize its individual homing route. This training was accomplished by simulation of solo flights for which 'landmark points' were recorded at every 100th time step. Each bird was assigned a list of landmarks as its individual attribute. After the simulated training flights, the navigation of the pigeons was based on a movement consisting of three successive turns combined: (1) map turn, to head towards the point with the most similar elevation within a distance of 200m, and within the pigeon's 340° view; (2) compass turn, to head towards the loft; (3) memorized route turn, to head towards the upcoming memorized landmark. Analogously to the flocking behaviour, each of the three navigation turns was parameterized with a maximum turn angle per time step. For each bird, a composite of the three turns represented the 'navigation turn' at any given time step.

Finally, leadership behaviour describes an individual bird's valuation of the importance of orientation and flocking as trade-offs of the two objectives of either flying home or staying in the flock. Birds that are ranked highly in the social hierarchy prioritized orientation turns, whereas low-ranked pigeons weighted flocking turns higher. This represents a hierarchical organization of leadership in bird flocks, as described in the literature (Flack et al., 2013; Nagy, et al., 2010; Nagy et al., 2013; Santos et al., 2014). Leadership is implemented by weighting navigation and flocking turns with a 'leadership factor' that ranges between zero and one. Navigation turns are weighted by the leadership factor, whereas flocking turns are weighed by '1 – leadership'. For example, the navigation turns of a pigeon with a high rank and a leadership factor of 0.8 (80% navigation) are weighted with 0.8, whereas the flocking turns of the same bird are weighted by the remaining factor of 0.2 (20% flocking).

The PigeonModel was implemented in a two-dimensional environment due to computational limitations of true 3D representations in NetLogo modelling software (Wilensky, 1999). Further analysis was carried out in ArcGIS 10.3 and the R statistics software.

State variables

Simulated movement patterns were quantified by a set of state variables to facilitate the comparison of the simulated flight paths with the observed pigeon trajectories. This pattern-oriented modelling approach (Grimm et al., 2005) is a rigorous calibration and validation strategy in which a model is assumed to have captured the essence of the system of interest only if all the patterns are reproduced simultaneously. In the context of this research, movement patterns did not relate to absolute locations and flight geometries, but rather to relative positions and parameters of shape (Ranacher & Tzavella, 2014). A set of state variables was selected based on the following criteria (Wallentin & Car, 2012). First, the state variables describe the movement patterns of interest that relate to the purpose of the model. Second, the state variables describe patterns at all scale levels, including the individual (pigeon) and aggregate (flock) levels, in both spatial and temporal dimensions. Third, in order to avoid validation uncertainty, the state variables are observable equally well in both the simulation and the validation data. As a result, the following set of four state variables was selected to quantify the outcomes of the PigeonModel for calibration and validation purposes:

- *Range of headings (mean)*: a synopsis of individual-level parameters that captures the relation of the agent trajectories in a flock at a certain point in time. It describes the general alignment of birds in a flock and may hint at disagreements in leadership.
- *Turning angle*: the average angular turn of a bird in each time step. The turning angle represents a flock's consistency in heading to a target destination. A beeline flight would have a turn angle of zero. This state variable describes the spatio-temporal dimension of the flight path (Ranacher & Tzavella, 2014). Here, it is aggregated over the entire flock to allow comparison with the validation data.
- *Mean distance between flock mates*: a flock-level parameter that captures the mean distance between birds in the flock. It describes the coherence of a flock.
- *Standard deviation of distance between flock mates*: This variable gives an indication of the bias in the mean distance between flock mates, for instance if the mean is influenced by the considerably greater distance of a single bird from the rest of the flock.

Calibration of parameters

The PigeonModel has eight user-defined parameters (see Table 1): maximum turn angles for the three flocking turns, and for the three navigation turns; a minimum distance to the nearest neighbour; a hierarchy steepness factor, ranging between 0 for egalitarian social structure and 1 for a steep hierarchy. Calibration started with an exploratory variation of parameters in order to gain a general understanding of the influence of individual parameters on the results. By comparing the simulation results with GPS track data ('homing flight 1', Santos, et al., 2014), plausible value ranges were refined. In a subsequent step of rigid calibration, plausible values were changed systematically in model experiments in order to identify a set of parameters that provided a good fit of the simulated data to the observed data.

Model-sensor framework

In the model-sensor framework, the PigeonModel received a data stream from a GPS sensor as input to dynamically update the state of its agents. At each time step, the PigeonModel first predicted the upcoming movements for all pigeon agents. Then, it computed the deviation of the simulated variables from the observed state of the system, in order to quantify the prediction error. The computation of the prediction error was based on state variables of flight patterns; deviations in absolute locations were not considered relevant for describing prediction errors. Finally, at the end of each time step, the locations and headings of the birds were updated to match the observed GPS track. These three steps were repeated until the flock reached the home loft.

3 Results

The calibration of the ‘conventional’ PigeonModel resulted in a set of well-fitting parameters (Table 1). In order to account for stochastic elements in the model, the simulation was repeated ten times with the same set of parameters. The maps of simulated flight movement patterns were compared visually to the observed flight paths (Figure 2). The density charts of all four simulated state variables were also close to those that were calculated from observed data (Figure 3).

Table 1: Calibrated set of parameters of the PigeonModel

Parameter	Value
Maximum compass turn [degree]	0
Maximum map turn [degree]	3.5
Maximum memorized landmark turn [degree]	2
Maximum align turn [degree]	8
Maximum cohere turn [degree]	11
Maximum separate turn [degree]	2.5
Minimum separation [m]	1.25
Hierarchy steepness	0.6

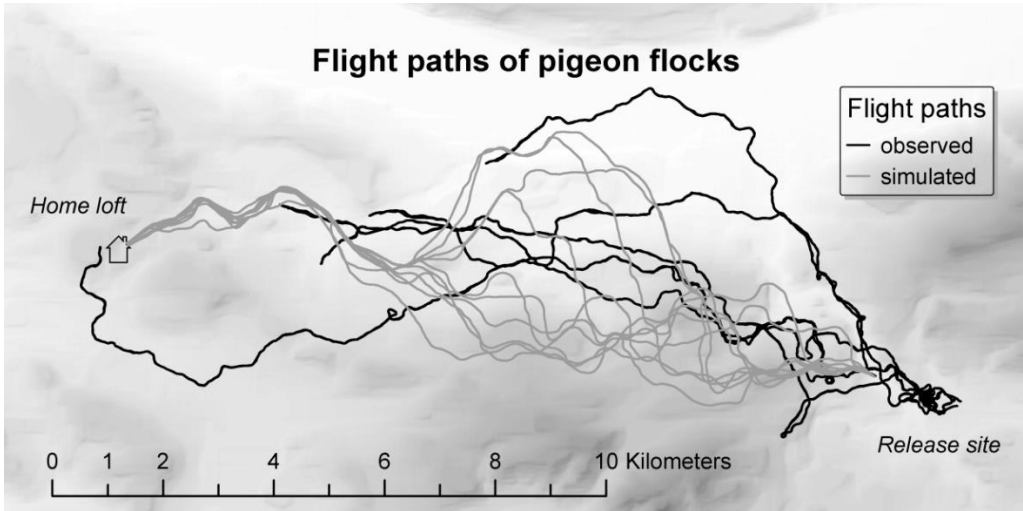


Figure 2: Map of simulated and observed flight paths

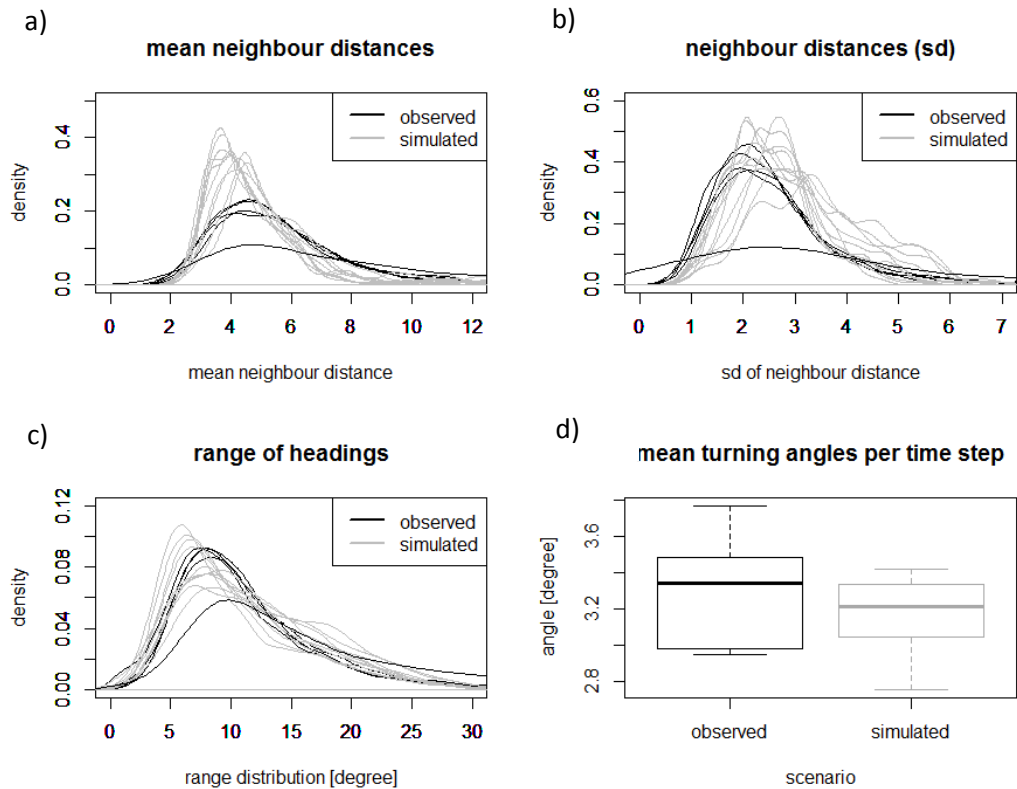


Figure 3: Comparison of various state variables for ten simulated (grey) and five observed (black) pigeon flock flights: (a) mean nearest-neighbour distance between flock mates; (b) standard deviation of nearest-neighbour distances; (c) range of headings in the flock; (d) mean turning angles of all pigeons in the flock per time step.

After calibration, the PigeonModel was connected with the emulated sensor stream to report predictions and prediction errors at each time step, and then to update the predicted location of pigeons with the actual location in real time.

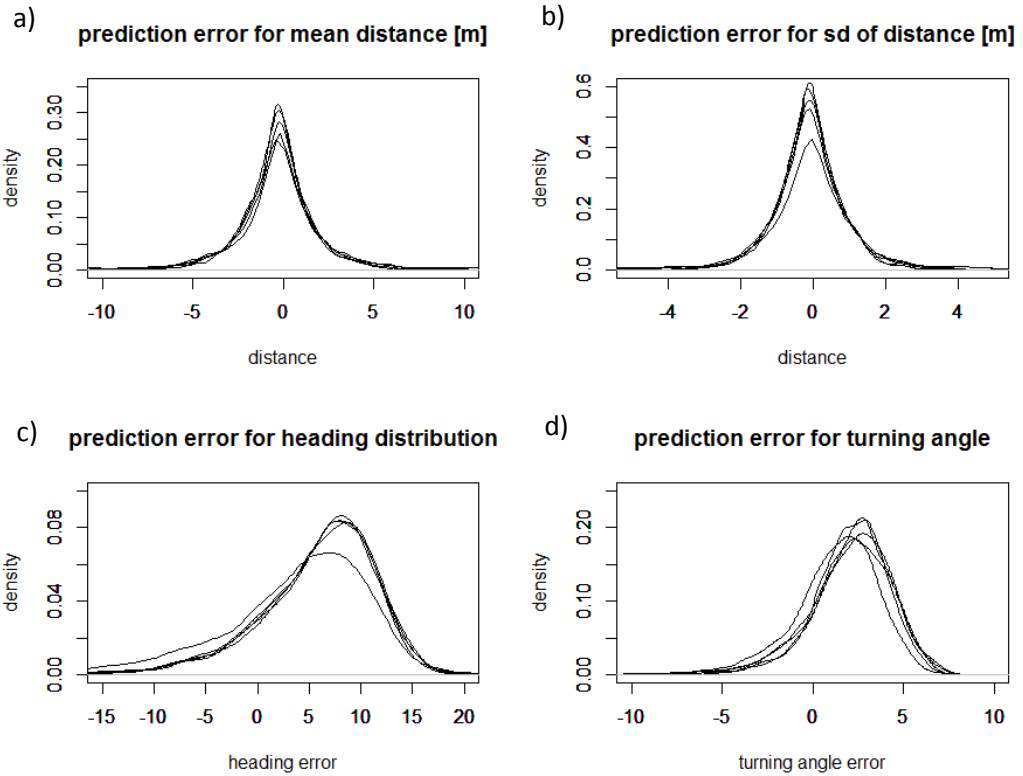


Figure 4: Distribution of prediction errors for the four state variables (a – d) for each of the five flock flights

The error distribution of mean distances between neighbours revolves around zero, which implies that the predictions are not biased. The values are in the range of zero ± 5 metres, which is a reasonable value given that the absolute mean distances in the GPS records range between 2m and 10m (Figure 3a). A similar pattern can be seen for the standard deviation of neighbourdistances: prediction errors range around zero, with reasonable prediction uncertainties. However, the other two state variables show a biased density distribution of prediction errors. The prediction of the range of headings is biased to the right by about 8° , which means that the simulation significantly overestimates the range of headings. Interestingly, this overestimation is not mirrored in the calibration results. The turning angles are also biased to the right, by 3° , which means that the simulation overestimates turnings in the flock. Again, this prediction error does not mirror calibration results, where the means of turning angles deviate by only 0.1° .

4 Discussion

There is a significant difference in the results between conventional pigeon flight simulations and the data-driven simulations of the model-sensor framework. In the conventional model, the simulated flock reproduced observed patterns well. However, when the pigeon agents were repeatedly forced into the observed locations by adapting to the sensor stream, the model resulted in biased predictions. In the search for possible explanations, calibration can be excluded as a source of error, as the same set of parameters resulted in significantly different outcomes. Potential errors in the implementation of code can also be excluded, as the simulations are both based on the same instance of the PigeonModel. The following question thus arises: Is there a conceptual flaw in transferring a conventional model that aims at predicting characteristics of an entire flight path to a data-driven model that aims at stepwise predictions? Further, if such a flaw exists, how can it be overcome?

The question is connected to equifinality, which states that in living systems the same outcome can be reached by different pathways (Bertalanffy, 1968; Beven & Freer, 2001). With regard to the conceptual structure of the model, a pigeon turns at each time step due to its individual flocking and navigation behaviour. A major part of navigation depends on the memorized paths of training flights. In the conventional model, the flight evolves along stochastically simulated training paths. Real training flight trajectories are unknown. However, if locations are dynamically updated with ‘real’ positions, the pigeon agents attempt to head back to their memorized routes, which would explain greater turning angles in data-driven simulations. Also the social rankings of simulated birds are likely to differ from those of their ‘real’ counterparts. Therefore, the pigeon agents may attempt to re-organize themselves according to their randomly-assigned social flock structures, which in turn results in increased flocking turns when forced into observed social structures. However, degrees of freedom in the representation of natural systems are high and a number of further explanations for the deviations between conventional and data-driven simulations could be found, including flaws in the conceptual model. Such uncertainties in the assessment of model results have led to the quest for effective approaches in the evaluation of structural validity as a key challenge in agent-based modelling (Grimm et al., 2005; O’Sullivan et al., 2015).

To this end, model-sensor frameworks may offer an alternative approach to conventional model analysis and calibration. Due to their stepwise iteration, such frameworks offer the opportunity to dynamically confront the model with data and thus integrate calibration procedures more closely into the simulation. A decisive added value can be expected if sensor data streams are connected to self-learning algorithms and adaptive rulesets. Such an approach has the potential to reduce long development cycles of conventional modelling that iterate through model-building, model implementation, calibration, simulation, analysis of outcomes and testing. Further research should thus be directed to integrating feedback from sensor data streams with adaptive rulesets. Such integration may combine advantages derived from the theory-driven development of rulesets and the data-driven adaptation of these rulesets.

Such a data-driven approach could help researchers to decode information in the patterns of natural systems by providing an automatized identification of the underlying processes that shape the patterns under study.

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