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Abstract. Animal societies exhibit complex dynamics that require multi-level descriptions. They are difficult to model, as they encompass information at different levels of description, such as individual physiology, individual behaviour, group behaviour and features of the environment. The collective behaviour of a group of animals can be modelled as a dynamical system. Typically, models of behaviour are either macroscopic (differential equations of population dynamics) or microscopic (such as Markov chains, explicitly specifying the spatio-temporal state of each individual). These two kind of models offer distinct and complementary descriptions of the observed behaviour. Macroscopic models offer mean field description of the collective dynamics, where collective choices are considered as the stable steady states of a nonlinear system governed by control parameters leading to bifurcation diagrams. Microscopic models can be used to perform computer simulations or as building blocks for robot controllers, at the individual level, of the observed spatial behaviour of animals. Here, we present a methodology to translate a macroscopic model into different microscopic models. We automatically calibrate the microscopic models so that the resulting simulated collective dynamics fit the solutions of the reference macroscopic model for a set of parameter values corresponding to a bifurcation diagram leading to multiple steady states. We apply evolutionary algorithms to simultaneously optimize the parameters of the models at different levels of description. This methodology is applied, in simulation, to an experimentally validated shelter-selection problem solved by gregarious insects and robots. Our framework can be used for multi-level modelling of collective behaviour in animals and robots.

1. Introduction

A "mixed society" is defined as a group of robots and animals that are able to integrate and cooperate: each robot is influenced by the animals, but can, in turn, influence the behaviour of the animals and of the other robots. Individuals, natural or artificial, are perceived as equivalent, and the collective decision process results from the interactions

between natural and artificial agents [1, 2, 3, 4]. Robots are useful for a number of reasons [5, 6]: validating models *in silico* [7], inducing stimuli to observe animal feedback [8, 3, 9, 10], modulating animal collective behaviour [2], etc. Earlier research works have used robots in mixed societies to study individual and collective animal behaviours: robots have been mixed with a large and growing number of animal species; including cockroaches in [8, 2], chicks in [3, 11], honeybees in [9], fruit flies in [12], fish in [13, 14, 10, 15, 16, 17, 18, 19, 20] and multi-species societies in [21]. See also [22] for a recent review on mixed societies.

Groups of animals are able to reach collective consensus when presented with mutually exclusive alternatives. Over the years, scientists have compiled a large collection of dynamics observed in collective decision-making systems based on experimental observations. These systems can be complex and it can be challenging to build models that appropriately describe the observed behaviours.

Animal societies are systems with a very large parameter space. They can be modelled in numerous ways, using information about individual physiology, individual behaviour, group behaviour and features of the environment [23, 24, 25]. The collective behaviour of a group of animals can be viewed as a dynamical system, that exhibits dynamics at several levels of organization (hierarchical organization). One of the difficulties in the modelling process is to find the appropriate levels of description.

In such systems, complementary approaches to modelling (macroscopic vs. microscopic; analytical vs. simulation) can be used: different models deliver the data necessary for the robot design process, provide explicit and analytic descriptions of observed collective behaviour, yield predictions that may be used for the modulation of the collective behaviour of the society, and ease the development of robot controllers.

Models describing dynamical systems can typically be categorized into two groups, describing two different levels of abstraction: macroscopic and microscopic (Fig. 1). There are many studies, mainly in physics, examining methods and applications for both groups of models and the relations between them. Macroscopic models describe the system at the population level [26]. They formalize the dynamics of the system mathematically, but they generally cannot describe the state of individual agents. They cannot be used directly to drive the behaviour of agents in simulation, or to drive the behaviour of robots in experiments. Microscopic models explicitly describe the state of each individual agent (*e.g.* agent-based models of flocking, like the Vicsek model [27]). They can capture the individual behaviours and their relations with the environment and, moreover are easier to implement into robotic controllers.

These two kind of models offer complementary descriptions of the system. In this context, collective choices can be described by the stable steady states of a nonlinear system and are governed by control parameters leading to bifurcation diagrams. These diagrams give the mean field asymptotic solutions of the system. Microscopic models can be used to simulate the observed spatial behaviour of animals [28, 2, 29].

However, working with several models at different levels of abstraction can be difficult and requires appropriate modelling frameworks and methodologies [24, 25].

In particular, these models must be designed and calibrated to all exhibit the same individual and collective dynamics. This poses the problem of navigating between models of different levels of abstraction [24, 23].

1.1. Objectives

In this article, we present a methodology that automates the calibration of microscopic target models on the basis of a reference macroscopic model, so that the dynamics of the microscopic model can be described with the same bifurcation diagram as the dynamics of the macroscopic model. The scientific question that we address in this paper is thus the following: **how to automatically calibrate models at different level of description to exhibit the same collective dynamics, at all levels of description, for specific sets of parameter values corresponding to a bifurcation diagram leading to multiple steady states**.

These tasks are usually performed empirically or manually by different authors, sometimes for the same experimental system. Here, our methodology aims to formalise and automate these tasks and at the same time to optimise the parameters of the models according to the experimental data and the different collective behaviours observed.

The proposed method is general and does not depend on the specific details of the models presented here. The selected models serve as a case study because for this experimental system all three types of models exist in the literature.

We propose to automate the calibration of microscopic models, using information both at the macroscopic level (a pre-existing macroscopic model) and the microscopic level (pre-established knowledge of the animal individual behaviour). The objective of this approach is to automatically calibrate this new microscopic model (*i.e.* optimize the parameters) to exhibit collective dynamics that fit the predictions of the macroscopic model, with the added ability of accurately simulating the microscopic interaction between individuals.

Methodologies to calibrate microscopic models directly from experimental data, by using optimization algorithms, were already presented in [23, 30]. Our presented methodology improves upon these works by optimizing a microscopic model to correspond to the dynamics exhibited by an entire bifurcation diagram.

This means that in this type of system, several states can coexist for the same parameter values. Moreover, the calibration takes into account the variation of one or more bifurcation parameters which make the system's states appear or disappear, i.e. different types of coexisting collective behaviour.

Our methodology calibrates models with generalization capabilities, enabling them to exhibit different dynamics for different experimental parameters.

In the following, we apply our methodology to the collective decision-making problem described in [28, 2], where a group of cockroaches must reach a consensus on a preferred resting site (a *shelter*). These papers introduced an experimentally validated ordinary differential equations (ODE) model of cockroach shelter-selection dynamics.

Here, starting from a mean-field ODE model (macroscopic), we use experimental data on individual cockroach behaviour from [31, 7] as *a-priori* microscopic information. We show how our method can be used to calibrate a target model using these two sources of information. We consider two target models: a Markov-Chain (MC) agent-based microscopic model [29] and an agent-based Hybrid model, combining macroscopic and microscopic information, that was already used with manually defined parameters in [2]. These models drive the behaviour of virtual agents in simulation. We use evolutionary algorithms to automatically calibrate the parameters of the MC and Hybrid models. They are validated by comparing their shelter-selection dynamics to those exhibited by the MF model.

In [2], Halloy *et al* integrate robots into a group of cockroaches to modulate their collective behaviour. Here, we consider this problem in simulation, with cockroaches agents and a small number of robotic agents. The cockroach agents are driven by the MC and Hybrid models optimized previously in animal-only simulations. The robotic agents are driven by MC and Hybrid models with human-calibrated parameters. We show that it is possible to program the robots to modulate the collective behaviour of the whole society. As such, we show that our methodology could help the design of robotic controllers to modulate the collective behaviour of societies in biohybrid systems (societies of animals and robots).

Macroscopic models can convincingly describe collective dynamics, but cannot be implemented directly in robotic controllers. Robot controllers are intricately microscopic, as they describe the behaviour of individual agents. **One major challenge must be overcome to design appropriate robotic behaviour in mixed-societies of animals and robots: how to go from the collective decision dynamics observed in animals to an algorithmic implementation in robots.** In previous studies on mixed societies, this process has been carried out empirically. For example, in [2] collective decision-making in cockroaches is modulated using robots. The authors used observation both to build a macroscopic model and to program the robot behaviour by tinkering. Although the results are promising, designing the robot behaviour proved very challenging, suggesting that automation would be highly beneficial.

The relevance of our approach is not limited to the field of animal collective behaviour and biohybrid systems, as it tackles the problem of automatically moving between models at different levels of description (from macroscopic to microscopic), a key problem in the modelling of nonlinear dynamical systems. **It is especially relevant to the design of mixed-societies robotic controllers.** Moreover, in a large portion of the literature, the calibration of model parameters is only done for specific solutions – typically only one state of the system. Here, with our methodology we can automatically calibrate all models for a set of states of the system corresponding to a bifurcation diagram.
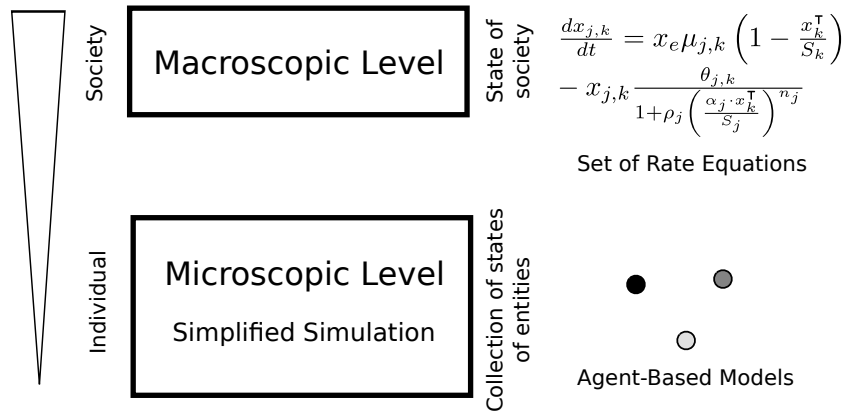
Figure 1: Differences between macroscopic and microscopic models Models of dynamical systems can be separated into two categories: macroscopic and microscopic. Macroscopic models describe the global state of the system (*i.e.* the state of a population). They usually take the form of sets of equations (*e.g.* ODE) encapsulating a mean-field hypothesis. Microscopic models (usually agent-based) describe the state of each individual agent. The agent motion strategy is often represented as a Markov chain. Macroscopic and microscopic models complement each other, describing dynamics at different levels. Microscopic models can include spatial information about the agents, which enables them to be used to simulate the modelled behaviour.

2. Methods

We simulate the experimental set-up from [28, 2] (Fig. 2): this set-up is composed of a circular arena with two identical shelters (resting sites). Each shelter is sufficiently large to host the entire insect group. Two species of cockroaches are considered: *P. americana* and *B. germanica*. The cockroaches choose collectively to rest under one of these shelters [32, 28]. Individuals have no *a priori* information about the shelters occupation and spatial position, and decide only between staying under a shelter and leaving it to search for another. The cockroaches tend to aggregate under the shelters.

This set-up is well adapted to the study of collective decision-making because it allows to quantitatively analyse the interplay of social and environmental mechanisms leading to collective choices. Group-living animals have to choose between alternative resource sites. In this context, a central question includes determining which individuals induce the decision, when and how [28, 2].

We consider three models of cockroach collective behaviour in a shelter selection problem (Table 1): a macroscopic mean-field model (MF model), a microscopic markov chain model (MC model), and a hybrid model combining macroscopic and microscopic levels of abstraction. All three models can handle time-discrete data. The MF model does not include extended spatial information on individuals, while the MC and Hybrid models include explicit spatial information. Because the latter also include a microscopic component, they can be implemented as robotic controllers. A classification of models according to their level of abstraction can be found in [23].
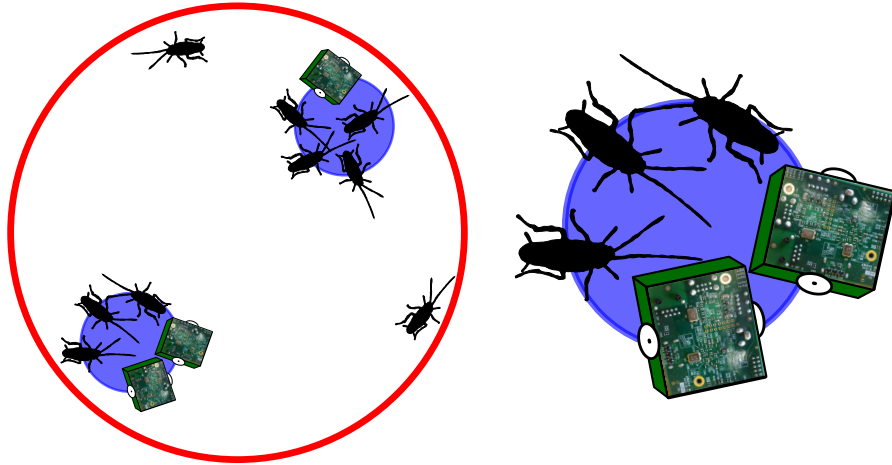
Figure 2: Experimental set-up used in [2]. It includes two identical shelters and both cockroaches (*P. americana*, approximate size: $\sim 4cm$, surface: $600mm^2$, or *B. germanica*, size: $\sim 0.25cm$, surface: $3mm^2$) and robots (surface: $1230mm^2$ in *P. americana* set-ups, $6.15mm^2$ in *B. germanica* set-ups) in a circular arena (diameter: $1m$ for *P. americana*, $14cm$ for *B. germanica*).

Name	Experimentally Validated	Wall-Following Behaviour	Constant Speed
Mean Field (MF)	yes [28, 2]	no	yes
Markov Chain (MC)	yes [31, 7]	yes	no
Hybrid	partially [2]	no	yes

Table 1: Comparison of the models studied. The MF model is a global description of the problem. The MC model is an agent-based model using a Markov chain representation. The Hybrid model combines macroscopic information (nonlinear propensities drawn from the MF model) and spatial information (with an approach similar to that of the MC model).

2.1. Mean field description: Ordinary differential equation model

Halloy *et al.* [2] describe a mathematical model of the collective dynamics of mixed groups of cockroaches and robots in a shelter-selection problem (from [28]). This model was designed to take in account the following experimental facts: (i) individuals explore their environment by moving randomly, and randomly reach the shelters; (ii) they rest in shelters according to their quality (in this set-up, it is mainly determined by darkness); (iii) the presence of conspecifics influences their behaviour, through social amplification of their resting time; and (iv) no long-range (across shelters) interactions occur among individuals. This model describes mixed groups of animals and robots, in set-ups with two shelters; animals and robots exercise an equivalent influence on the collective decision-making process, and exhibit similar and homogeneous behaviour. The model is used as a quantitative explanation as well as an overall (macroscopic)

guidance for the design of the robot and its controller. The model takes in account the fact that robots and insects do not occupy the same surface.

The following set of ODEs represents the evolution of the number of individuals in each shelter (and outside), in a set-up with two shelters:

$$\frac{dx_i}{dt} = x_e \underbrace{\mu_i \left(1 - \frac{x_i + \omega r_i}{S_i}\right)}_{\text{Probability of animals to join site } i} - x_i \underbrace{\frac{\theta_i}{1 + \rho \frac{x_i + \beta r_i}{S_i}^n}}_{\text{Probability of animals to leave site } i} \tag{1}$$

$$\frac{dr_i}{dt} = r_e \underbrace{\mu_{ri} \left(1 - \frac{x_i + \omega r_i}{S_i}\right)}_{\text{Probability of robots to join site } i} - r_i \underbrace{\frac{\theta_{ri}}{1 + \rho_r \frac{\gamma x_i + \delta r_i}{S_i}^{n_r}}}_{\text{Probability of robots to leave site } i} \tag{2}$$

$$C = x_e + x_1 + x_2, \quad R = r_e + r_1 + r_2, \quad M = R + C \tag{3}$$

We use a mean field description of the system, instead of a exact representation, to take the fluctuations of the system into account. Table 2 describes the parameters of this ODE model.

Variables x_i and r_i represent respectively the numbers of cockroaches and robots present in shelter i; and x_e and r_e the numbers outside the shelters. Parameters C and R are respectively the total numbers of cockroaches and robots (state variables). Parameter M is the total number of agents (cockroaches and robots). Parameter S_i is the carrying capacity of shelter i. The parameter ω corresponds to the surface of one robot expressed as a multiple of the surface of one cockroach. Equations 1 and 2 take into account the probabilities of animals and robots to join or leave (corresponding to 1/mean resting time) a site. The parameter μ_i is the maximal kinetic constant of entering the shelters for insects; μ_{ri} is the equivalent parameter for robots. The parameter θ_i is the maximal probability of leaving a shelter for insects (θ_{ri} for robots). The parameters ρ and n characterise the influence of the insect conspecifics (ρ_r and n_r for robots). When both shelters are identical (as it is the case in this study), the parameters describing them are equal: $S_1 = S_2$; $\mu_1 = \mu_2$; $\mu_{r1} = \mu_{r2}$; $\theta_1 = \theta_2$; $\theta_{r1} = \theta_{r2}$. Parameters γ, β and δ are respectively the influence of cockroaches on robots, of robots on cockroaches, and of robots on robots. The greater they are, the greater the mutual influences. The influence of animals on animals is equal to 1.0, and is not considered in [2]: the assumption is made that this parameter is imposed by biology, and cannot be changed in experiments. However, parameters γ, β and δ can be modulated by changing the design of the robots, either in term of hardware or control (behaviour). In [2], the robots are coated with a pheromone, as the interaction dynamics of cockroaches societies is mainly chemotactile. A higher concentration of pheromone corresponds to a higher value of β.

Because of crowding effects, the probability of an individual joining a shelter decreases with its level of occupancy. We define a measure $\sigma = S/C$, corresponding to the sites' carrying capacity as a multiple of the total population.

When no robots are present ($R = 0$) and only animals are considered, two different dynamics are observed. The bifurcation point is close to $\sigma = 0.8$ for *P. americana*, and $\sigma = 1.0$ for *B. germanica*. Before the bifurcation point ($0.4 \leq \sigma < 0.8$ for *P. americana*, $0.4 \leq \sigma < 1.0$ for *B. germanica*), only one configuration exists, corresponding of an equipartition of the individuals ($x_1/C = x_2/C = 1/2, x_e = 0$). After the bifurcation point ($\sigma > 0.8$ for *P. americana*, $\sigma > 1.0$ for *P. americana*), two stable configurations exist, corresponding to all individuals in one of the shelters (either $x_1 \approx 0, x_2 \approx 1, x_e \approx 0$ or $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$) [28]. Only results with a population of 50 cockroaches are represented in Fig. 3, but similar dynamics are observed with different population sizes.

	Parameter	Value for *P. americana*	Value for *B. germanica*	Optimized	Description
	P	2			Number of sites
	S_i				Carrying capacity of shelter i
	C	50			Number of agents
	x_i				Number of agents in shelter i
	x_e				Number of agents outside the shelters
MF	μ_i	$0.0027 s^{-1}$	$0.001 s^{-1}$		Maximal kinetic constant of entering a shelter
	θ_i	$0.44 s^{-1}$	$0.01 s^{-1}$		Maximal rate of leaving a shelter
	ρ, n	4193, 2.0	1667, 2.0		Influence of conspecifics
MC	l_c	$[1.0, 500.0]\,cm$		yes	Mean length of path
	a_c	$[-\pi, \pi]$		yes	Geometric mean, angle of departure
	$\tau_{c,exit}$	$]0.0, 10.0[\,s$		yes	Mean time an agent follows a wall
	$v_{c,c}$	$]0.0, 3.0[\,cm.s^1$		yes	Mean speed in central zone
	$v_{c,p}$	$]0.0, 3.0[\,cm.s^1$		yes	Mean speed in peripheral zone
	$s_{c,i,n}$	$[0.0, 1.0]$		yes	Probability of stopping in shelter i with n neighbours
	$\tau_{c,i,n}$	$]0.0, 1000.0[\,s$		yes	Mean stop duration in shelter i with n neighbours
	d	$]0.8, 1.0[\,m$		yes	Diameter of the central zone
Hybrid	θ_i	$]0.0, 0.50]\,s^{-1}$		yes	Maximum rate of leaving a shelter
	ρ, n	$[500, 5000], 2.0$		yes	Influence of conspecifics
	l	$[1.0, 500.0]\,cm$		yes	Mean length of path
	a	$[-\pi, \pi]$		yes	Geometric mean, angle of departure
	v	$]0.0, 3.0[\,cm.s^{-1}$		yes	Constant speed of agents

Table 2: Parameters in the MF, MC, and Hybrid models. The parameter values for the MF model are from [2] and [28]. We only consider the case where $M = 50$. In set-ups with two shelters, the MF, MC, and Hybrid models have 18, 46 and 20 parameters respectively. The parameter values used for the MC and Hybrid models were obtained through the calibration process described in Sec. 3 and Supplementary S1. The animal influence on animals is equal to 1.0, and is kept constant in [2]: we assume that this parameter is imposed by biology and cannot be changed in experiments. All parameters of the MC and Hybrid models are optimized, using the method described in Supplementary S1, to exhibit the collective dynamics described in the reference MF model.
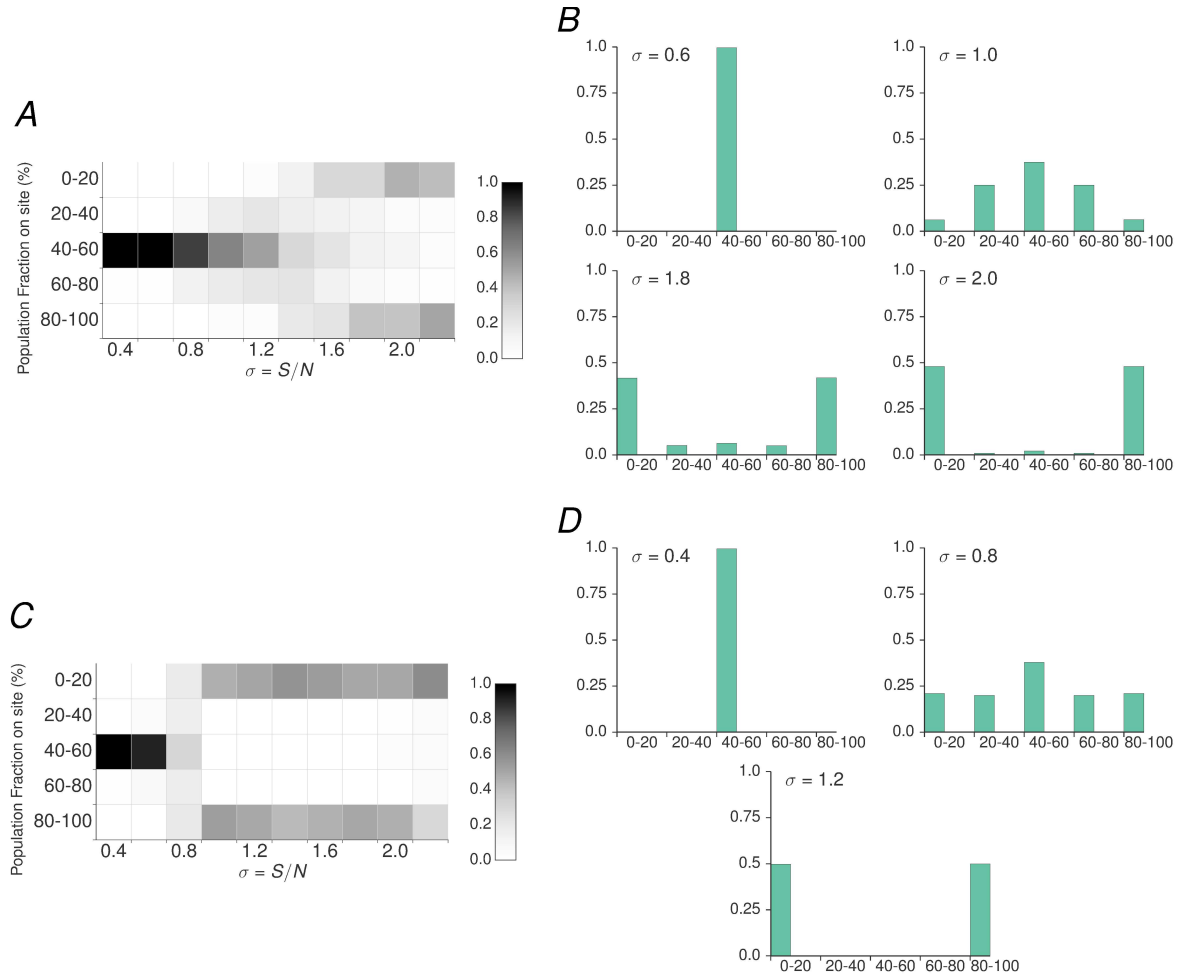
Figure 3: Bifurcation diagrams and distributions of 50 (*C*) ***B. germanica*** **(Panels A and B) or *P. americana* (Panels C and D) cockroaches in the first shelter as a function of** σ **[28].** The bifurcation diagrams are represented as bi-dimensional histograms of the results of using 1000 resolutions for each parameter set. In the bifurcation diagrams (Panels A and C), the (greyscale) colour intensity of each bin of the histograms corresponds to the frequency of observed experiments. The diagrams are symmetric for all tested values of σ, so only one shelter is represented. The bifurcation point is close to $\sigma = 0.8$ for *P. americana*, and $\sigma = 1.0$ for *B. germanica*. Before the bifurcation point ($0.4 \leq \sigma < 0.8$ for *P. americana*, $0.4 \leq \sigma < 1.0$ for *B. germanica*), only one configuration exists, an equipartition of the individuals between the two shelters ($x_1/C = x_2/C = 1/2, x_e = 0$). After the bifurcation point ($\sigma > 0.8$ for *P. americana*, $\sigma > 1.0$ for *P. americana*), two stable configurations exist, with all individuals concentrated in one of the two shelters (either $x_1 \approx 0, x_2 \approx 1, x_e \approx 0$ or $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$).
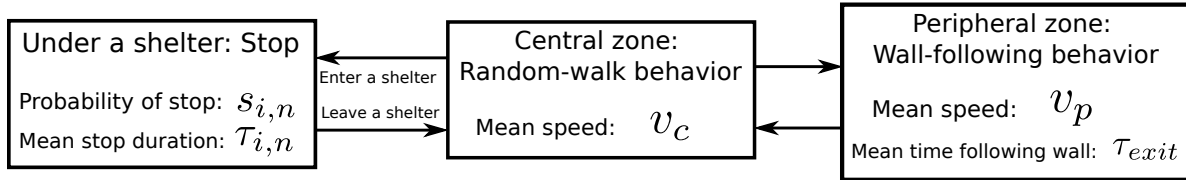
Figure 4: Markov chain model of the cockroach individual behaviours. The arena contains two zones: the peripheral zone (where agents display a wall-following behaviour), and the central zone (where agents display a random-walk behaviour). Shelters are in the central zone. When an agent enters a shelter, it has a probability of stopping for a random duration before exiting the shelter. The probability of stopping under a shelter depends on the number of neighbours present in the shelter, and can differ for each shelter. Only 10 neighbours are considered in our experiments. In set-ups with two shelters, this model has 46 parameters per population.

2.2. Markov chain model

We use the Markov chain described in [29] as an agent-based model of cockroach and robot behaviour. This model is inspired by the agent-based aggregation models in [31, 7] that describe the collective behaviour of cockroaches in a similar set-up.

Cockroaches tend to follow the walls of the arena when they are already close to them. The model defines two zones in the arena. The ring area that borders the walls of the arena is called the *peripheral zone*, while the rest of the arena is labelled as the *central zone*. In the peripheral zone, agents follow a wall-following behaviour for a random number of time steps (the mean time is denoted $\tau_{c,exit}$). In the central zone, agents follow a random-walk behaviour, with trajectories composed of a recurring alternation of straight lines (of randomly chosen length, with a mean length of l_c) and rotations (of randomly chosen angles, with a geometric mean of a_c). The shelters are all in the central zone. We do not model the actual trajectories of cockroaches.

When agents enter a shelter, they have a probability of stopping (parameter $s_{c,i,n}$) for a random duration (parameter $\tau_{c,i,n}$) before moving away from the shelter. Similarly to [7], this probability depends on the number of agents present under the shelter, as cockroaches are gregarious during their resting period. However, in this model (as opposed to [31, 7]), the probability of stopping when under a shelter differs between shelters: this model is more general, and can be used to describe more complex behaviours with asymmetric decision-making dynamics [29]. When the cockroaches are not under a shelter, their movements are not influenced by the presence or absence of neighbours.

Figure 4 represents the Markov chain used in this model. The relevant model parameters are found in Table. 2.

We use two different parameter sets of the MC model to describe either cockroaches or robot behaviour. However, all cockroaches are considered to exhibit an homogeneous

behaviour (all cockroach agents share the same parameters). Similarly, all robots agents share the same parameters. We make this choice for simplicity reasons: the main message of this paper can be explored without the need to take individual variability into account.

2.3. Hybrid model

Here, we introduce a model of the collective behaviour of cockroaches using information at both macroscopic and microscopic levels of abstraction. We call this multi-level model the 'Hybrid' model. This model was already used with manually defined parameters in [2], but was not formally described previously. This hybrid model was done to facilitate the development of the behavioural architecture of the robots [33, 2]. Compared to the MC model, which presents a biomimetic description of the insects trajectories, the Hybrid model is a compromise between biomimetism and ease of implementation as robotic controller. The robot control architecture is a behaviour-based controller [34] composed of a multi-level collection of behaviours. Each behavioural building block can take inputs from the robot sensors and/or from other behavioural building blocks, and send outputs to the robot actuators and/or to other behaviours. The behaviours are arranged in a hierarchy in which the behaviours on the higher levels integrate or arbitrate the ones on the lower levels. At the higher level the Hybrid model is used as a building block that takes into account the speciality of the agents, and thus allows to build the robot controller. The Hybrid model is a crossover between the macroscopic MF model, which easily describes collective behaviour and site occupation, and the microscopic MC model, which details the spatio-temporal behaviour of single agents. As such, it is a multi-agents model (like the MC model), but it also takes into account macroscopic information (like the MF model). For ease of implementation, the hybrid model does not include a wall-following behaviour, and only considers simple arenas with no distinctions between central zone and peripheral zone. The agents can have two states: moving, or resting under a shelter. In contrast to the MC model, the agents move with a constant speed v.

The Hybrid model builds on the MF model, introducing several parameters from the MF model (Table 2). The Hybrid model has a smaller dimensionality than the MC model: in set-ups with two shelters, the MC models has 46 parameters (43 without counting wall-following dynamics), while the Hybrid model has 20 parameters. It allows the Hybrid model to be easier to calibrate than the MC model.

Figure 6 describes the Hybrid model using a Markov chain representation of the behaviour of a single agent. When the agents are not under a shelter, they follow a random-walk behaviour (microscopic behaviour). As in the MC model, this random-walk behaviour involves trajectories composed of a recurring alternation of straight lines of randomly chosen length, with a mean length of l, and rotations of randomly chosen angles, with a geometric mean of a. When agents enter a shelter, they stop, and have a probability of leaving the shelter at each subsequent time-step. This probability, taken

from Eq. 1 and 2, is computed using macroscopic information. For the cockroaches agents, this probability of leaving the shelter is defined as:

$$\frac{\theta_i}{1 + \rho \frac{x_i + \beta r_i}{S_i}^n} \tag{4}$$

For the robotic agents, this probability of leaving the shelter is defined as:

$$\frac{\theta_{ri}}{1 + \rho_r \frac{\gamma x_i + \delta r_i}{S_i}^{n_r}} \tag{5}$$

This behaviour can be described as macroscopic, as it requires information about the density of agents under the shelter. This combination of microscopic and macroscopic components makes it a multi-level (or hybrid) model.

As in the MC model, we use two different parameter sets of the hybrid model to describe either cockroaches or robot behaviour. However, all cockroaches are considered to exhibit an homogeneous behaviour (all cockroach agents share the same parameters). Similarly, all robots agents share the same parameters.

Figure 5 presents examples of the trajectories of single cockroaches in a simulation with a population of 50 cockroaches with the Hybrid model.
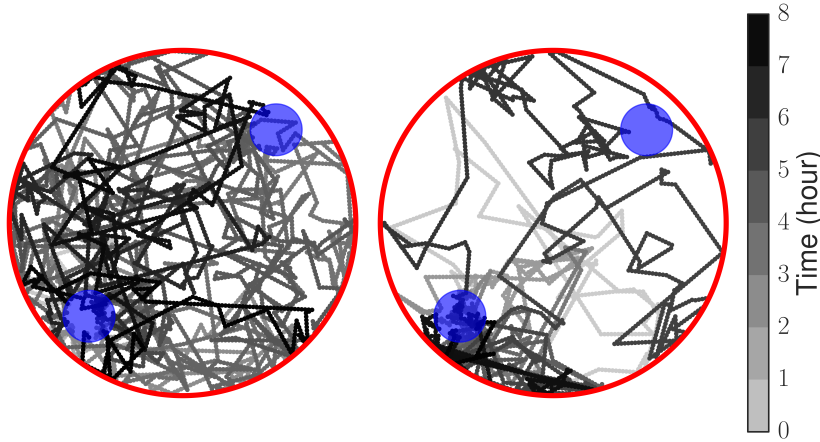

Figure 5: Two example trajectories of a one simulated cockroach, using the Hybrid model, in a population of 50 **cockroaches.** The arena contains two shelters. Each grey line represents the (random-walk) trajectory of one agent. These trajectories are not meant to fit the natural trajectories of actual cockroaches: we designed our models to reproduce qualitatively the observed random exploration. The opacity of the line reflects simulation time. The timeframe of all simulations is 8 hours.
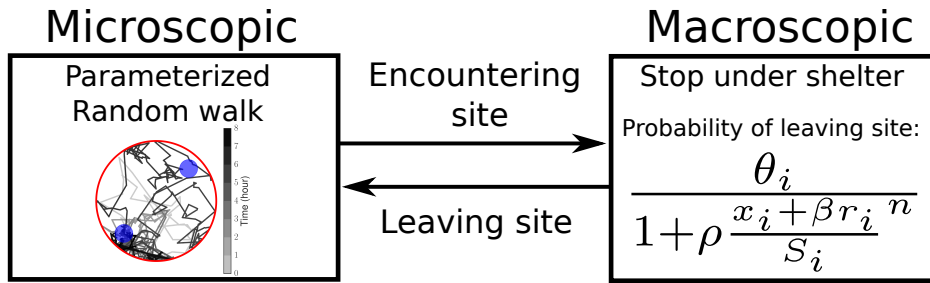
Microscopic

Parameterized Random walk

Macroscopic

Stop under shelter

Probability of leaving site:

$$\frac{\theta_i}{1+\rho\,\dfrac{x_i+\beta r_i}{S_i}^n}$$

Encountering site →

← Leaving site

Figure 6: Markov chain representation of the Hybrid behavioural model
Table 2 gives the parameters of the model. The model describes two kinds of behaviour: when the agents are not under a shelter, they will exhibit a random-walk behaviour, following a recurring alternation of straight lines and rotations. This behaviour can be described as microscopic because agents use only local information to determine their course of action. When agents encounter a shelter, they stop. At each subsequent time-step, the stopped agent has a probability of $\frac{\theta_i}{1+\rho\frac{x_i+\beta r_i}{S_i}^n}$ (for cockroaches) or $\frac{\theta_{ri}}{1+\rho_r\frac{\gamma x_i+\delta r_i}{S_i}^{n_r}}$ (for robots) of leaving the shelter and returning to random-walk behaviour. This behaviour can be described as macroscopic, as it requires information about the density of agents under the shelter. This combination of microscopic and macroscopic components makes it a multi-level (or hybrid) model.

2.4. Models calibration

To use the MC and Hybrid models describing animal behaviour in simulation, we must calibrate them to exhibit the same decision-making dynamics as the MF model. As the MF model is parametrized using experimental data, it allows the MC and Hybrid models to accurately describe the (macroscopic) site-selection dynamics of the cockroaches. The calibration process is described in Fig. 7.

We optimize the parameters for the individual cockroaches in the MC and Hybrid models. The optimization algorithm will identify interesting solutions (i.e. sets of model parameters). The performance of each proposed solution will then be tested ("evaluated"), by first computing a collection of simulations where agents are driven by the model with the parameters sets associated with the solution, and second quantifying how the agents behaviors in those simulations match the dynamics of the reference (MF) model. The latter is achieved as follows. We consider simulations with differing values of the number of robots (N) and of the sites' carrying capacities (S). This allows us to compute the bifurcation diagrams of each tested solution (w.r.t. $\sigma = S/N$). This bifurcation diagram will finally be compared to the bifurcation diagram of the reference (MF) model. The performance score ("Fitness") of each individual corresponds to the difference between the solution diagram and the reference diagram measured by the Hellinger distance. The optimization algorithm will iteratively search for high-performing solutions, based on this score.

Table 2 lists the parameters of these two optimized models. Instances of the MC

and Hybrid models using these parameters are simulated for different values of σ. This yields bifurcation diagrams for each optimized individual, similar to those in Fig. 3.

As there is little *a priori* information about the parameter space, and as it is relatively high-dimensional, we use the state-of-the-art CMA-ES evolutionary optimization method [35] to optimize the parameters of the MC and Hybrid models. To evaluate the difference between two parameter sets, we use a distance metric between the two resulting bifurcation diagrams. This method is described in the Supplementary S1.

3. Results

3.1. Models Calibration

Our goal is to find parameter sets of the MC and Hybrid models describing animal and robot behaviour so that the resulting collective dynamics, observed in simulations, fit the solutions of the MF model describing animal behaviour. We use use the methodology presented in Sec. 2.4. We consider two types of simulations, for both *P. americana* and *B. germanica* cockroach species. The first type describes a purely biological system, with only 50 cockroaches (either *P. americana* or *B. germanica*) and no robots. It is used as the biological reference case. The second type is devoted to biohybrid groups made up of 45 cockroaches (either *P. americana* or *B. germanica*) and 5 robots. The number of robots is kept small to reflect the settings used in a mixed-society experiment [2], where a minority of robots can control the whole mixed group behaviour. The parameters sets of models describing robot behaviour are chosen empirically.

We consider populations of 50 individuals. **Similar results are observed with populations of** 16 **and** 100 (results not shown).

Figure 8 shows to the distribution of agents in the two shelters, using parameters from the best-performing optimized individuals after 100 optimization runs. Panels A and C show results from simulations with 50 cockroaches and no robots. Panels B and D show results from simulations with 45 cockroaches and 5 robots. Only results from the bifurcation diagram at selected values of σ are shown. More generally, results before the bifurcation point ($\sigma < 0.8$) are similar to results at $\sigma = 0.4$, and results after the bifurcation point ($\sigma \geq 0.8$) are similar to results at $\sigma = 1.2$.

Both the MC and Hybrid models can be optimized to approximate correctly the decision-making dynamics described by the MF model, as shown in Fig. 8. Our methodology can generate many different parameter sets for the MC and Hybrid models. Optimized parameters that produce the collective dynamics described by the MF model can be associated to highly variable agent behaviour. In the MC model, the parameter d, the diameter of the central zone of the arena, is optimized: when this parameter is very close to the diameter of the peripheral zone, the resulting agents do not exhibit any wall-following behaviour. In the MC and Hybrid models, the parameters that influence stopping behaviour ($s_{c,i,n}$, $\tau_{c,i,n}$, θ_i) vary less than the other parameters, with only a few islands of relevant values in the explored ranges.
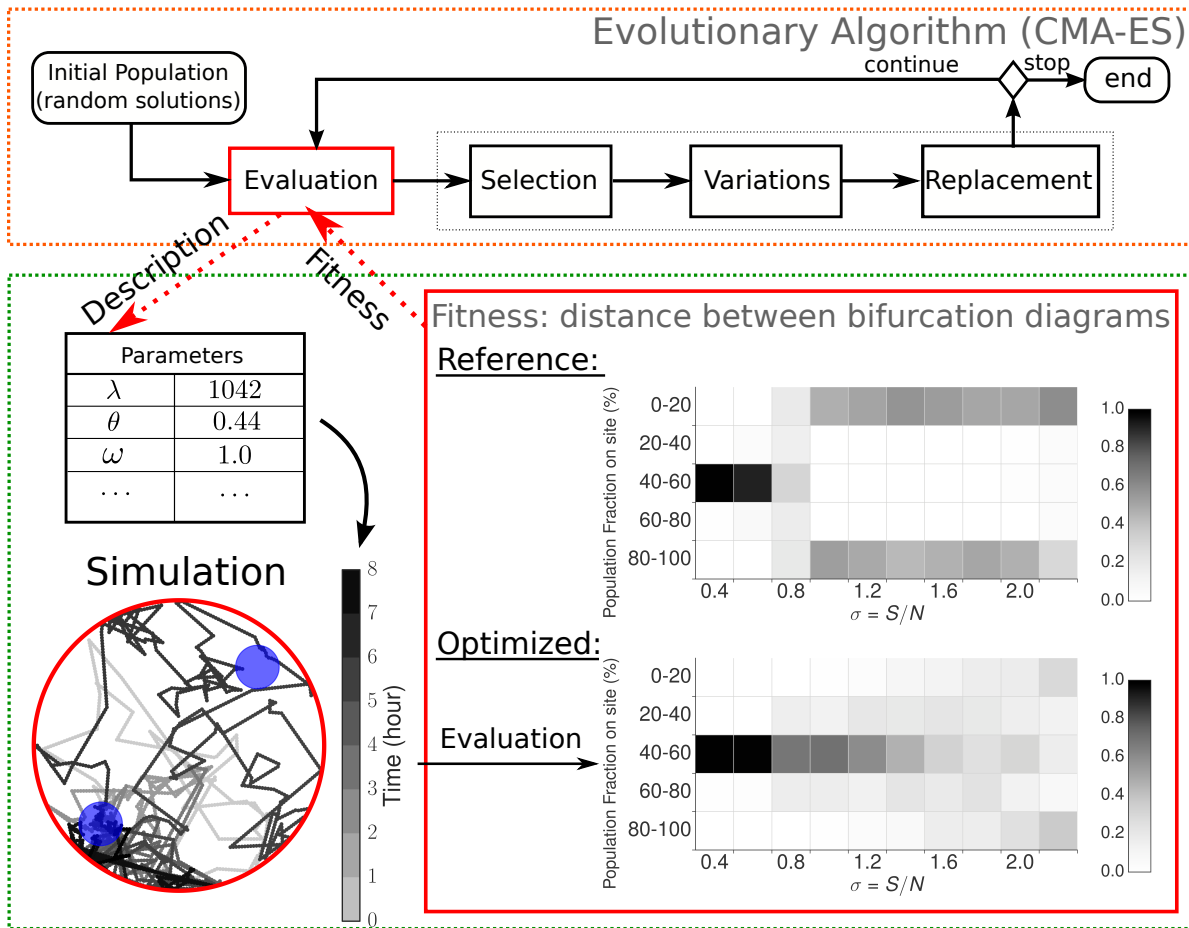
Figure 7: Workflow of the automated calibration of models by optimization. The optimized bifurcation diagram and the reference bifurcation diagram are both converted to one-dimensional histograms, by normalizing the sum of all bin values to 1.0. The optimizer will maximizes the fitness, which is computed by the formula: $Fitness = 1.0 - D_{hellinger}(B_{optimized}/N_u, B_{reference}/N_u)$ where N_u is the number of columns in the bifurcation diagrams (10) and $B_{optimized}$ and $B_{reference}$ are one-dimensional histogram versions of the respective bifurcation diagrams. The term N_u is a normalization term. $D_{hellinger}(P, Q) = \frac{1}{\sqrt{2}}\sqrt{\sum_{i=1}^{d}(\sqrt{P_i} - \sqrt{Q_i})^2}$ is the Hellinger distance [36]. This approach is described in detail in the Supplementary S1

We show that simulations performed with 45 cockroaches and 5 robots exhibit the same dynamics as the simulations of groups with 50 cockroaches and no robots (Fig. 8). In this case the robots are governed by the same behavioural models as the insects, but do not have the same parameter sets as those used to describe the natural behaviour of the cockroaches. The detailed microscopic behaviours of the robots, *e.g.* trajectories and movement patterns, can be very different from the microscopic behaviours of the animals. Nevertheless, we show that our methodology can be used to optimize the parameters of robot behavioural models in biohybrid systems to mimic correctly the decision-making dynamics of the animals.
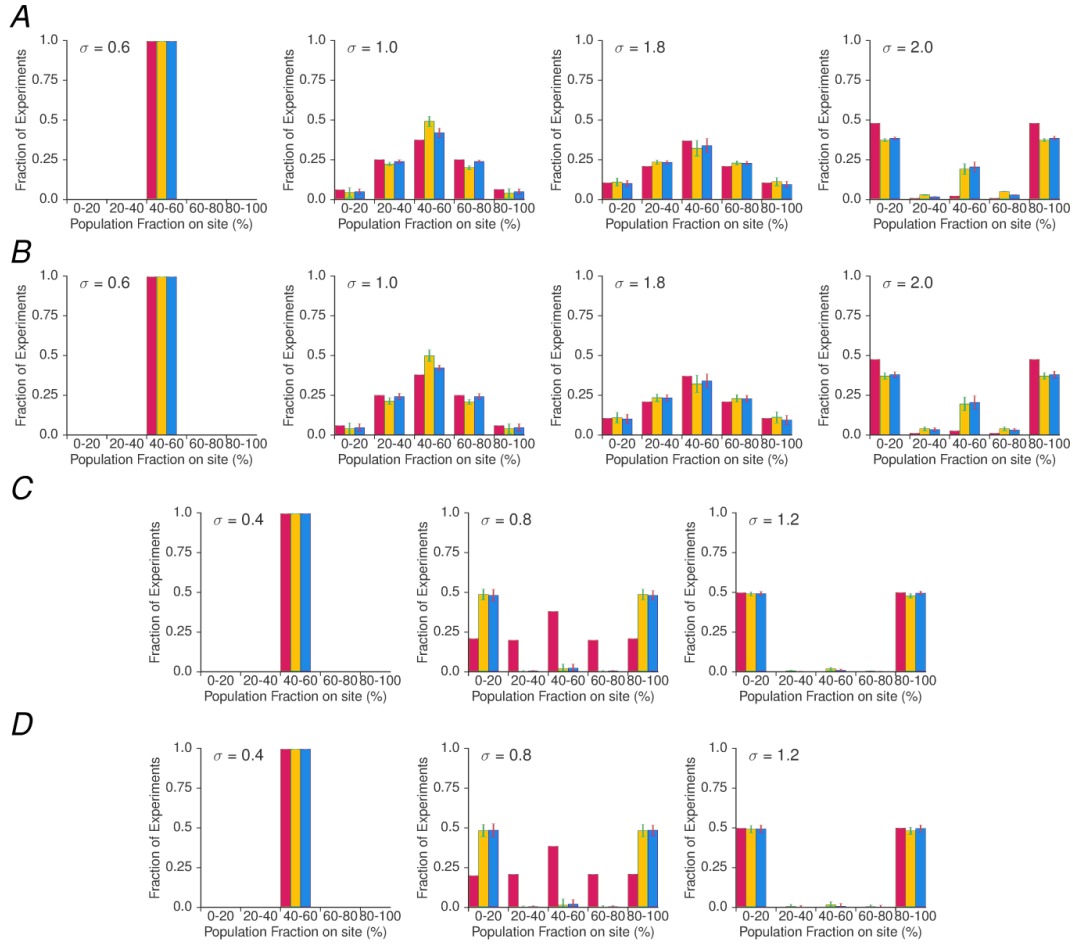
Figure 8: Proportion of 50 **agents in the first shelter for chosen values of** σ**, using three different models: MF, MC and Hybrid.** Panels A and C are obtained from simulations using 50 cockroaches (Panel A: *P. americana* ; Panel C: *B. germanica*). Panels B and D are obtained from simulations using 45 cockroaches and 5 robots (Panel B: *P. americana* ; Panel D: *B. germanica*). Results for MF, MC and Hybrid models results are shown respectively in red, green, and blue. The bifurcation point is close to $\sigma = 0.8$ for *P. americana*, and $\sigma = 1.0$ for *B. germanica*. The other σ parameter values chosen are before the bifurcation point ($\sigma = 0.4$ for *P. americana* , $\sigma = 0.6$ for *B. germanica*), and just after the bifurcation point ($\sigma = 1.2$ for *P. americana* , $\sigma = 1.8$ and $\sigma = 2.0$ for *B. germanica*). The best sets of optimized model parameters are used, after 100 runs of optimization. The diagram is symmetric for all tested values of σ, so only one shelter is represented. Calibrated versions of the MC and Hybrid models behave similarly to the MF model: (1) Before the bifurcation point ($0.4 \leq \sigma < 0.8$ for *P. americana*, $0.4 \leq \sigma < 1.0$ for *B. germanica*), only one configuration exists, an equipartition of the individuals between the two shelters ($x_1/N = x_2/N = 1/2, x_e = 0$); (2) After the bifurcation point ($\sigma > 0.8$ for *P. americana*, $\sigma > 1.0$ for *P. americana*), two stable configurations exist, with all individuals in only one of the shelters (either $x_1 \approx 0, x_2 \approx 1, x_e \approx 0$ or $x_1 \approx 1, x_2 \approx 0, x_e \approx 0$).
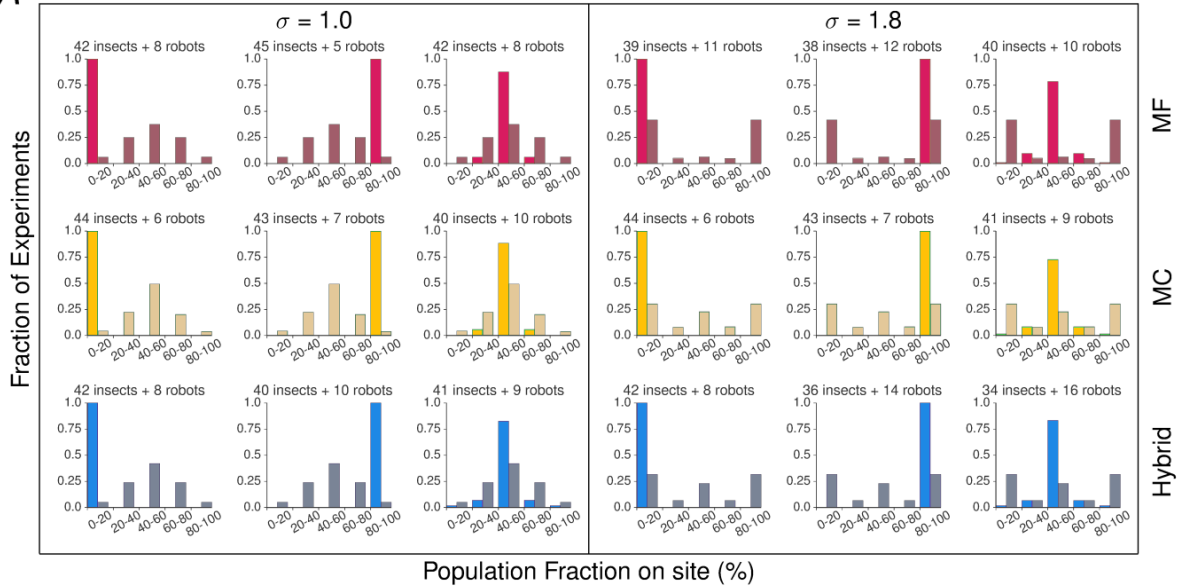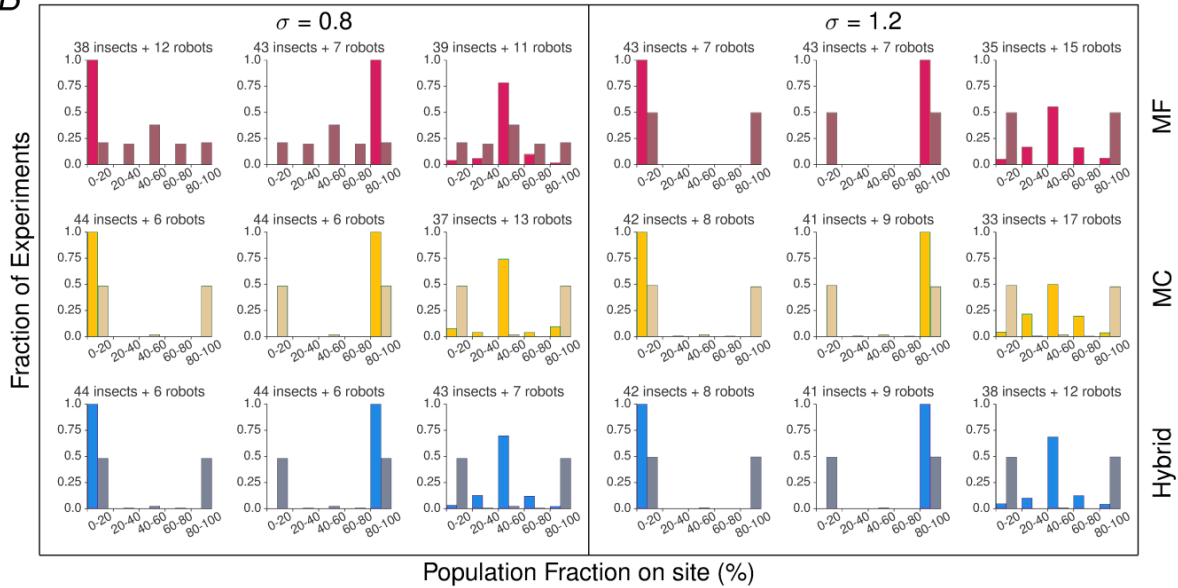
Figure 9: **Examples of modulation of the biohybrid group behaviour when robots are optimized to change the behaviour of cockroaches (A: *P. americana*, B: *B. germanica*)**. (red: MF model, green: MC model, blue: Hybrid model). Results in red, green and blue are the final states corresponding to the change of steady states induced by the robots. Results in dark red, dark green, and dark blue correspond to the reference results, from experiments with only insects and no robots (from Fig. 8). Values of σ are chosen around the bifurcation point (*P. americana*: $\sigma = 0.8$, *B. germanica*: $\sigma = 1.0$), and just after the bifurcation point (*P. americana*: $\sigma = 1.2$, *B. germanica*: $\sigma = 1.8$). Results before the bifurcation points are not shown.

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3.2. Modulation of collective behaviours

We also test if our methodology could be applied to calibrate robot models so that they can modulate the collective dynamics of a group of cockroaches and robots. We consider simulations, for both *P. americana* and *B. germanica* cockroach species. In these simulations, cockroach behaviour is described by the MC or Hybrid models calibrated to have the same collective dynamics as the reference MF model. Robot behaviour is also described by the MC or Hybrid models, but with different parameter sets. We find relevant parameters of models describing robot behaviour empirically, for different proportion of robots, and for different values of σ. These examples of results of the modulation of the mixed-society of cockroaches and robots are found in Fig. 9. This shows that our methodology could be also applied to optimize parameter sets of models describing robot behaviour for a modulation task. Additionally, Fig. 9 also presents examples of modulation of a mixed-society described by the MF model. In this case, we find empirically interesting robot behaviour related parameters of the MF model. These preliminary results suggest that a larger number of robots than 5 may be needed to modulate a population of 50 agents. We will investigate how robots models can be calibrated automatically to modulate the collective dynamics of a mixed-society in a subsequent study.

4. Discussion

We tackle the problem of moving between models of different levels of abstraction in the context of animal collective decision-making. Animal collective behaviour can be described macroscopically (analytical description of the behaviour of the population) or microscopically (explicit description of the behaviour and states of individuals and their interactions with the environment). The two types of models are complementary. Our methodology enables translation from one to the other: we automatically optimize the parameters of microscopic target models on the basis of a reference macroscopic model from the literature. We apply this methodology to the cockroach shelter-selection problem described in [28, 2]. The Mean Field macroscopic model used as a reference is described in [2].

We consider two target models, both agent-based. The MC model [29] is a microscopic model inspired by the literature on individual cockroach behaviour [32, 7]. The Hybrid model uses both macroscopic and microscopic information. Both the MC and Hybrid models can be used both to replay the behaviour of animals in simulation and for implementation as robot controllers. We automatically generate the parameters of the MC and Hybrid models for cockroach agents, calibrating them to display the collective behaviour and site-selection dynamics described in the Mean Field model.

The MC and Hybrid models presented in this study can directly be implemented into a robot. However, here our approach does not explain how to translate them automatically into robotic controllers. This question was tackled in [37] by using formal

methods and supervisory control theory to automatically generate robot controller code and to validate it so that it translates into robot behaviours matching a given formal specification.

Here, we use a user-defined metric (the bifurcation diagrams) to compare the results in simulation of two different pairs of models and parameter sets, during the optimisation process. As a result, the obtained models and parameter sets only approximate the collective dynamics of individuals, and not the behaviours (trajectories) of each individual. This could be further improved by considering the calibration of these models as a multi-objective process where the first objective would cater to the collective dynamics, and additional objectives would cater to the individual behaviour of the individuals. Alternatively, one could design a methodology similar as the like in [38], where no metric is specified, by co-evolving simultaneously models of robot behaviours and classifiers of the resulting behaviour in simulation. These classifiers would be trained to identify whether or not the resulting behaviours of the optimised models are distinct from the behaviours from reference experiments.

More generally, complex systems exhibit multi-level dynamics (hierarchical organisation), with both global and local behavioural patterns. Recent studies have investigated the *micro-macro link*: the relationship between macroscopic and microscopic descriptions of multi-level behavioural dynamics [39, 40, 41, 42]. This problem also applies to the design of swarm group robotic controllers [39, 41, 43, 44, 45]. Our methodology is a first step toward the automatic generation of controllers for robots in a mixed society of animals and robots. Mixing animals and robots can be useful for the study of animal behaviour, and even to modulate their individual or collective behaviour.

Few works in the literature on animals and robotics attempt to tackle the problem of transitioning from models of one level of abstraction (reference model) to another level of abstraction (target model). Moreover, these studies have generally considered the transition from microscopic to macroscopic models [41, 46, 47]. The transition methodology adopted by these studies is incremental, and relies on the creation of intermediate models, dealing with both macroscopic and microscopic information, and that share some parameters with both the reference and the target models. In [41], this methodology is applied to go from a microscopic model to a macroscopic model of the behaviour of a swarm of autonomous robots in a collaborative task. The resulting model outperforms human-calibrated macroscopic models. In [46], a time-continuous kinetic mean field version of the Couzin-Vicsek model is obtained from its discrete microscopic version. In [47], continuous macroscopic models of pedestrian behaviour are obtained from discrete microscopic agent-based models. Little work in the literature has investigated how to automate and generalize the transition between models at different levels of abstraction. The transition process can also be more challenging if the reference and target models have no (or few) common parameters, or if their formulation is too different.

Our approach can be applied to other modelling problems involving a transition

between different levels of description: either from a macroscopic one to a microscopic one, or the other way around, provided that the considered models at several levels of abstraction already represent the same kind of dynamics. This approach is illustrated here with three models that we designed to represent the same studied system: a macroscopic model that deals with the dynamics of site occupancy, and two models with microscopic components that mirror this problem by describing how a focal agent can move from a resting state under a site to a random walk in the middle or at the edge of the arena. To generalise to other systems, it is necessary to first design several models that would represent a particular system, but at different levels of abstraction. Then our approach can be used to calibrate the parameters of these models so that they exhibit the exact same dynamics, with respect to a given bifurcation diagram from a given reference model (that can be at any level of abstraction).

In particular, it may be possible to apply our approach to model, calibrate, and modulate the collective behaviour of other species. For instance, it could be used to calibrate models of fish behaviour to match what would be observed in collective decision making experiments. The work of Couzin et al. [48] is a good example of a fish collective behavioural study where models at different levels of abstraction are introduced to describe various features of the observed experiments. In the latter, the authors investigate consensus in fish groups, and asses whether a strongly opinionated minority can exert its influence on group movement decisions. The authors propose two models of the observed behaviours: an adaptive-network model (macroscopic and analytical) and a spatially explicit model (microscopic and in simulations). The authors present the phase diagram of the studied system based on the results of the adaptive-network model. Our approach could have been applied here to calibrate other models (for instance the spatially explicit model proposed by the authors) to directly match the dynamics of this phase diagram. Another example would be the work of Calovi et al. [49], that presents an in-depth analysis of three prominent collective decision-making dynamics of fish: swarming, schooling and milling. That study relies on a fish collective dynamics model from the literature [50] and the authors compute its phase diagram. In this setting, our approach could be used to calibrate another model (microscopic and/or macroscopic) to exhibit the dynamics of a reference phase diagram. These two studies are similar to the present article in the sense that they focus on dynamics with a co-existence of three states (two stables and one unstable states) that correspond to collective choices. All three works rely on bifurcation or phase diagrams to present the transition between these states. These diagrams could in turn be used as reference of our methodology to calibrate any models describing these dynamics.

In our simulation, both the MC and hybrid models exhibit relatively similar performances – however their differences in design imply different challenges to implement them as robotic controllers in experiments ("sim-to-real" task). Both models can easily be implemented and calibrated on robots, as the only major difference between the two models is the type of parameters used. Our algorithm does not use complex features in its implementation on robots: it is only required that each robot knows the

number of robots in its neighbourhood. In this case, the implementation of the Hybrid model and the MC model have approximately the same level of complexity. In a robot implementation, the parameters of the behavioural models often need to be adjusted to obtain the same results as in simulation. In the case of the MC model, all parameters will be related to the local interactions of the robot, which may make calibration easier than for the hybrid model (which deals with both macroscopic and microscopic information); however, the Hybrid model has fewer parameters than the MC model, which may make the Hybrid model easier to calibrate in robotic experiments. Overall difficulties will depend on the problem and personal preferences.

Another study could include an application of this methodology to more complex set-ups, with more than two shelters and more than two population types. Our methodology could also be extended by generating microscopic Markov Chain models from scratch, without *a priori* structural knowledge (*i.e.* the type and number of states).

Acknowledgement

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