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# Simulating collective intelligence of bio-inspired competing agents

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ABSTRACT

In this paper, a comprehensive model is introduced to investigate the influence of energy flow on the lifetime of stochastic multi-species prey–predator artificial ecosystems. The model consists of a non-stationary hosting environment with food sources and a few species of competing herbivore and carnivore birds that can perform several individual and collective behaviors such as flocking, breeding, competing, resting, hunting, escaping, seeking, and foraging. The experimental results of 11,000 simulations analyzed by Cox univariate analysis and hazard function suggest that only a fraction of associated energy variables and pairwise interactions between them influence the lifetime. The proposed stochastic model can be utilized to simulate the complex multi-agent systems and their emergent behavior. Also, the proposed statistical analysis of energy flow to estimate the system stability and lifetime can be generalized to other physical and economical complex systems.



## 1. Introduction

A complex system is a hierarchical self-organizing system featuring a large number of interacting agents whose collective behavior cannot be identified by observing the individual behavior of the agents independently (Axelrod & Cohen, 2001). The nonlinearity of the collective behavior (i.e. aggregate behavior is not the summation of the agents' individual behaviors) is referred as emergence property of a complex system (Mitchell & Newman, 2002). This emergent behavior in social swarms of biological organisms such as bacteria groups, fish schools, bird flocks and ant colonies is known as collective intelligence which plays an important role in survival of the social species. An example of this phenomenon appears in bird groups in which dynamics of density and structure of flocking alongside with its choreographed motion is a mechanism for confusing predators (Milinski, 1986; Parrish, Viscido, & Grünbaum, 2002). One important interactional channel within a collective intelligence system affecting its stability is energy flow (i.e. the process of generating, transforming and consuming energy). An agent within an ecosystem competes with other agents to absorb energy in order to survive, evolve, breed, and reshape its environment. Observing the energy flow of a given system in both macro- and micro-levels can provide a deep inside into the emergent behaviors and optimizing it can enhance the stability of the system (Abbott, 2011).

There are two general approaches for modeling the complex systems including bottom-up and top-down – analytical–reductionist approaches. It is suggested that due to the dynamics and complexity of the complex systems, the top-down approach is more suitable for modeling these systems (Lima et al., 2011). Conventional modeling tools are not suitable for simulating heterogeneous complex systems with nonlinear and discontinued interactions (Gilbert & Terna, 2000). On the other hand, simulating complex systems based on multi-agent system (MAS) methodology improves the comprehensibility of interactions within aggregated phenomena occurring in the ecosystem (Singh, Gautam, Singh, & Gupta, 2009). In a complex system modeled using MAS approach, the emergence can originate from agent properties, environmental influence, inter-agent interactions, or evolutionary processes. There are five major categories for simulating complex systems based on MAS methodology as follows: (i) a set of agents with stationary behaviors interact within a static environment; (ii) the environment plays an active role and influences the agents; (iii) the agents evolve through the time within a static environment; (iv) the environment plays an active role in the evolution of agents; and (v) both the agents and the environment evolve concurrently (Kubík, 2002). A comprehensive overview of MAS simulation of ecosystems can be found in Bousquet and Le Page (2004).

In this paper, we propose a stochastic scheme for modeling a multi-species prey–predator artificial ecosystem with two levels of food chain to investigate the influence of energy flow on the ecosystem lifetime. The proposed model consists of a stationary hosting environment with dynamic weather conditions and non-stationary food sources. Inhabitants of this environment are a few species of herbivore and carnivore birds inspired by Reynolds'

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Boids model (Reynolds, 1987). In the proposed model collective behavior emerges in terms of flocking, breeding, competing, resting, hunting, escaping, seeking, and foraging behaviors. The ecosystem is defined as a combination of prey and predator species with inter-competition among species within the same level of the food chain and intra-competition among those belonging to different levels of the food chain. Some energy variables are also introduced as functions of behaviors to model the energy within the ecosystem. Furthermore, a simulation and visualization environment is developed for implementing the proposed model. As far as the authors' knowledge is concerned, there is no comprehensive model in literature that investigates the lifetime of a stochastic multi-species prey–predator artificial ecosystem based on energy flow analysis. The paper is organized as follows: in Section 2, a comprehensive survey on related works is presented. Section 3 presents the proposed model for simulating a multi-species prey–predator artificial ecosystem, whereas the simulation and visualization environment is discussed in Section 4. Section 5 explains the survival analysis in detail, and Section 6 provides the evaluations on experimental results. Finally, Section 7 concludes the paper.

## 2. Related works

An artificial ecosystem is inhabited by abstract or embodied agents interacting autonomously within a dynamic environment. An early simulation of an artificial ecosystem is introduced in Heleno and Próspero dos Santos (1998) in which virtual animals are modeled using a set of internal states including hunger, health, and energy, and a set of prioritized behavioral rules. In Nishimura and Ikegami (1997) the emergence of collective strategies in prey–predator ecosystems based on reward mechanism is studied. Species gain rewards based on feeding and hunting behaviors which increase their reproduction chances proportional to the gained rewards. Simulation results on this mechanism suggest that swarm behavior allows both preys and predators to maximize their lifetime. Reynolds' bird-imitating MAS (Reynolds, 1987) was proposed to visualize the flocking behavior based on cohesion, alignment, and separation rules for computer animation applications. Since then various extensions of this model have been studied including but not limited to adding: phase transitions (Vicsek, Czirók, Ben-Jacob, Cohen, & Shochet, 1995), distributed behaviors (Olfati-Saber, 2006), leadership in alignment behavior (Hartman & Benes, 2006), self-occlusion model (Silva, Lages, & Chaimowicz, 2010), pseudo-leadership mechanism (Zhou, Wu, Yu, Small, & Lu, 2012), and direction selection capability (Ben-Shahar, Dolev, Dolgin, & Segal, 2014). Some research works investigate evolutionary modeling of artificial ecosystems to evolve the agents in a way that they can exhibit emergent behavior (Dorin, 2005; Husbands, Harvey, Cliff, & Miller, 1997; Lee, 2013; Woodberry, Korb, & Nicholson, 2007). In the system proposed in Ward, Gobet, and Kendall (2001), individuals learn how to optimize their energy consumption while increasing their survival chance through an evolutionary process. Results indicate that preys learn to build swarms while predators learn to seek for preys. Gras, Devaurs, Wozniak, and Aspinall (2009) exploited a fuzzy cognitive map (FCM) to track and analyze the agents' behaviors such as keeping distance from predators and moving toward resources, and their internal states such as hunger and fear. They suggested that diversity of emergent patterns within species is explicitly associated with environmental information and internal states.

Stability analysis of prey–predator ecosystems has also been extensively investigated in literature. It is shown that both sensitivity analysis and analyzing structural robustness can investigate the robustness of a given prey–predator ecosystem in respect to its population dynamics (Weisberg & Reisman, 2008). It is also shown that chaotic behavior of such ecosystem can be estimated using Lyapunov exponent to analyze the signal transitions (Golestani & Gras, 2010). Furthermore, various works have investigated how the local stability and chaotic behavior are affected by internal parameters such as growth rate and external factors such as competition (Cooper & Ofria, 2003; Elsadany, EL-Metwally, Elabbasy, & Agiza, 2012). On the other hand, energy flow analysis is only addressed in a few studies. It is shown that energy flow plays a crucial role in emergence of collective behaviors (Dorin & Korb, 2007) and analyzing its corresponding data enhances the modeling process (Dorin, Korb, & Grimm, 2008). Yaeger (1994) investigated energy inheritance in an evolutionary ecosystem in which offspring inherit the parents' energies. Scogings and Hawick (2008) studied the correlation between energy conservation and reproduction. The energy flow is also investigated in physical multi-agent systems. For example, it is shown that using a nonlinear dynamic model it is possible to enhance the energy consumption within a swarm of micro-robots exhibiting collective behaviors (Kernbach & Kernbach, 2011). As far as the authors' knowledge is concerned, there is no comprehensive model in literature that investigates the lifetime of a stochastic multi-species prey–predator artificial ecosystem based on energy flow analysis.

## 3. Modeling artificial ecosystems

Data collection for energy flow analysis of artificial ecosystems necessitates the development of a simulator with a proper degree of complexity. In order to address this demand, we develop a stochastic model to simulate a multi-species prey–predator ecosystem. To do so, we expand Reynolds' Boids model (Reynolds, 1987) in three directions. First, we extend the original model from a single species ecosystem to a multi-species prey–predator system. In our system, it is possible to define an arbitrary number of species in any preferred configuration. For example, we can define only one species to simulate the original Boids model. Also, we can define a few prey species with similar diets to simulate competition among species within the same level of food chain. At the most general configuration, we can define the ecosystem as a combination of prey and predator species with inter-competition among species within the same level of food chain and intra-competition among those belonging to different levels of the food chain. The second enhancement is regarding the behavioral model. In Reynolds' original system, only three rules are defined to govern the flocking behavior, including separation, alignment, and cohesion, whereas in our model behaviors such as breeding, competing, resting, hunting, and seeking are defined in addition to flocking. Furthermore, we define some random variables such as weather conditions and disease that affect the inhabitants' behavior. Finally, we introduce energy variables to model the energy flow within the ecosystem.

### 3.1. Environmental parameters

The ecosystem is modeled within a stationary hosting environment with two features defined as $E = \langle W,T \rangle$ where $W$ denotes the weather condition and $T$ presents a set of fruit trees within the environment. Weather condition affects the dynamics of flocking, whereas fruit trees provide the herbivore birds (i.e. preys) with required energy. Weather condition is defined as a set of state-probability pairs in which each pair presents the probability of a particular weather condition. In simulations, we consider three possible conditions including rainy, windy and sunny states. Hence, we can define weather as a triple $W = \langle (r,p_r),(w,p_w),(S,p_s) \rangle$ representing rainy, windy and sunny conditions along with their associated probabilities, respectively. Fruit trees represented by $T$ occupy the bottom level of the food chain and are considered as energy resources of the ecosystem. A tree is defined as a triple $T_i = \langle P,T_c,F_c \rangle$, where $P$ denotes the position of the tree within the environment, $T_c$ represents the age of the tree, and $F_c$ denotes the