Article

Exogenous control of biological and ecological systems through evolutionary modelling

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Abstract
The controllability of network-like systems is a topical issue in ecology and biology. It relies on the ability to lead a system's behaviour towards the desired state through the appropriate handling of input variables. Up to now, controllability of networks is based on the permanent control of a set of driver nodes that can guide the system's dynamics. This assumption seems motivated by real-world networks observation, where a decentralized control is often applied only to part of the nodes. While in a previous paper I showed that ecological and biological networks can be efficaciously controlled from the inside, here I further introduce a new framework for network controllability based on the employment of exogenous controllers and evolutionary modelling, and provide an exemplification of its application.

Keywords external nodes; genetic algorithms; system control; system dynamics.

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1 Introduction

Network controllability is the ability to guide a system's behaviour towards the desired state through the appropriate handling of input variables (Caldarelli, 2007, Dorogovtsev and Mendes, 2003; Ferrarini, 2011; Ferrarini, 2013; Kim and Motter, 2009; Slotine and Li, 1991).

To date, the controllability of ecological and biological networks is based on the identification of a subset of nodes that are selected to be permanently controlled (Liu et al., 2011). This assumption seems motivated by real-world networks observation, where a decentralized control is often applied only to part of the nodes in order to make the problem computationally tractable.

Instead, genetic algorithms can reasonably lower the seemingly intractable problem of network control (Ferrarini, 2011). The application of genetic algorithms to network dynamics allows to act on the highest number of switches, while maintaining the computational effort to tameable levels (Ferrarini, 2013). In addition I showed that they allow to control multiple nodes and edges at the same time (Ferrarini, 2013).

While I previously showed that ecological and biological networks can be efficaciously controlled from the inside (Ferrarini, 2013), here I further introduce a new framework for network controllability based on the use of exogenous controllers and evolutionary modelling, and provide an exemplification of its application.

2 Mathematical Formulation

As noted by numerous authors (e.g., Liu et al., 2011; Slotine and Li, 1991) most real systems' dynamics can be modelled and simulated using a system of canonical, linear equations, as follows:

$$\begin{cases} \frac{dS_1}{dt} = a_{11}S_1 + ... + a_{1n}S_n + I_1 + O_1 \\ ... \\ \frac{dS_n}{dt} = a_{n1}S_1 + ... + a_{nn}S_n + I_n + O_n \end{cases} \quad (1)$$

where S_i is the number of individuals (or the total biomass) of the generic i-th species, while I and O represent inputs and outputs from outer universe. The previous system has initial values

$$\vec{S}_0 = <S_1(0), S_2(0)...S_n(0)> \quad (2)$$

and co-domain limits

$$\begin{cases} S_{1\min} \le S_1(t) \le S_{1\max} \\ ... \\ S_{n\min} \le S_n(t) \le S_{n\max} \end{cases} \quad (3)$$

If we hypothesize to add k exogenous controllers (external nodes; Fig. 1), eq. (1) becomes:

$$\begin{cases} \frac{dS_1}{dt} = a_{11}S_1 + ... + a_{1n}S_n + I_1 + O_1 + c_{11}C_1 + ... + c_{1k}C_k \\ ... \\ \frac{dS_n}{dt} = a_{n1}S_1 + ... + a_{nn}S_n + I_n + O_n + c_{n1}C_1 + ... + c_{nk}C_k \end{cases} \quad (4)$$

with initial values

$$<\vec{S}_0, \vec{C}_0> = <S_1(0), S_2(0)...S_n(0), C_1(0), C_2(0),...C_k(0)> \quad (5)$$

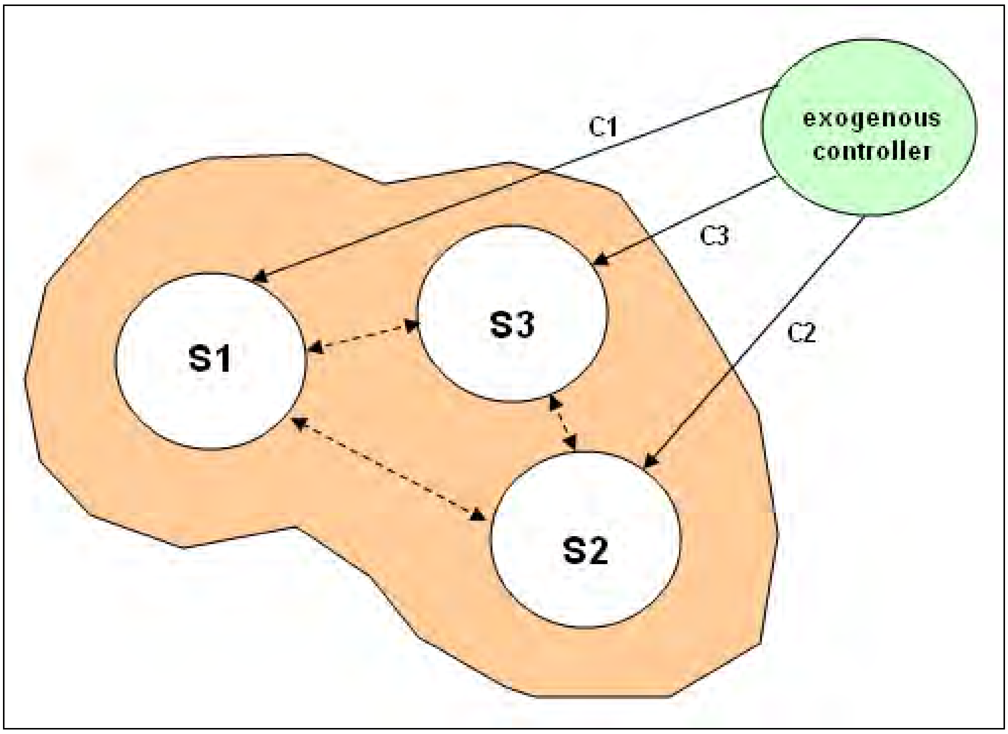

Fig. 1 An ecological system with 3 actors (S1, S2, S3) is controlled by an exogenous node.

In this form, nodes $C_1 \ldots C_k$ are effectively exogenous because they can act upon the network but they do not receive feedbacks from the network itself. We could also think of just 1 controller C_1 that, in some cases, can also receive feedbacks from the network, thus eq. (4) becomes:

$$\begin{cases} \dfrac{dS_1}{dt} = a_{11}S_1 + \ldots + a_{1n}S_n + I_1 + O_1 + c_{11}C_1 \\ \ldots \\ \dfrac{dS_n}{dt} = a_{n1}S_1 + \ldots + a_{nn}S_n + I_n + O_n + c_{n1}C_1 \\ \dfrac{dC_1}{dt} = f_1S_1 + \ldots + f_nS_n \end{cases} \tag{6}$$

with initial values

$$<\vec{S}_0, C_0> = <S_1(0), S_2(0) \ldots S_n(0), C_1(0)> \tag{7}$$

Under genetic optimization (Holland, 1975; Goldberg, 1989, Parolo et al., 2009; Ferrarini, 2012a) of the exogenous inputs to the network, eq. (6) becomes (Ferrarini, 2013):

$$\begin{cases} \left(\frac{dS_1}{dt}\right)_{OPT} = a_{11}S_1 + ... + a_{1n}S_n + I_1 + O_1 + c_{11*}C_{1*} \\ ... \\ \left(\frac{dS_n}{dt}\right)_{OPT} = a_{n1}S_1 + ... + a_{nn}S_n + I_n + O_n + c_{n1*}C_{1*} \\ \frac{dC_1}{dt} = f_1S_1 + ... + f_nS_n \end{cases} \quad (8)$$

with initial values

$$<\vec{S}_0, C_{0*}> = <S_1(0), S_2(0)...S_n(0), C_1(0)_*> \quad (9)$$

where asterisks stand for the genetic optimization of the exogenous node's edges (i.e., coefficients of interaction with the inner system) and exogenous node's stock, i.e. the modification of such values at the beginning of the network dynamics in order to get a certain goal (e.g., maximization of the final value of a certain variable). It's clear that also the feedback dC_1/dt to the controller could be subject to genetic control by taming $<f_1 \ldots f_n>$ and/or $\vec{S}_0$. By the way, I prefer considering a situation where the exogenous controller does not receive feedbacks from the inner system, otherwise it would resemble an *a posteriori*-appended endogenous node, rather than an exogenous one. Hence I set:

$$f_1 = f_2 = \ldots = f_n = 0 \quad (10)$$

3 An Applicative Example

Fig. 1 depicts an ecological network borrowed with modifications from Ferrarini (2012b). Greenish nodes represent positive actors or events for the goal of the network control, i.e. the increase of individuals of the target species (centre of the network). Reddish nodes represent ecological actors or events with negative impact on the target species. Blueish nodes represent resources needed by the target species. The goal is to preserve target species' occurrence in the study area. Stocks stand for the starting amounts of individuals or biomass. Updates stand for yearly internal dynamics (i.e., intraspecific gains due to births and/or immigration rates minus losses due to deaths and/or emigration rates). Minimum and maximum values stand for lowest and highest values of stock values. For the sake of simplicity, the maximum possible value for each actor (in italic hereafter) has been set to 100. The percent value associated to links represents the percentage of the receiver that is yearly consumed by the transmitter at the beginning of the simulation. Road mortality and re-introductions account for 15 and 20 individuals per year respectively.

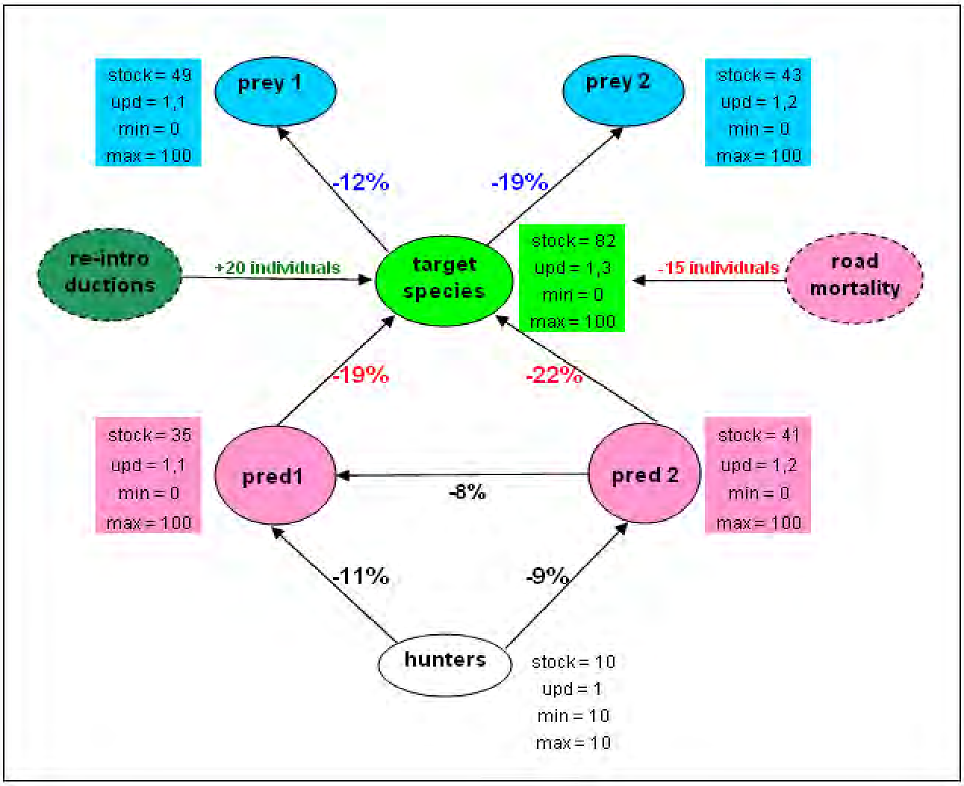

Fig. 2 The ecological network on which exogenous control has been applied.

Since data are yearly-based, I expressed eq. (1) using a system of difference recurrent equations, instead of differential ones. I have also used eq. (8) in terms of difference recurrent equations in order to find the way to control the network from outside.

Table 1 The interactions matrix relative to the ecological network of Fig. 2. The matrix has been calculated using Quant-Lab (Ferrarini, in preparation).

INTERACTIONS MATRIX (per-cycle changes to receivers per-unit of transmitters)											
		Receivers									
		target	prey1	prey2	pred1	pred2	hunters	var G	var H	var I	var J
Transmitters	target	1.3	-0.071	-0.099	0	0	0	0	0	0	0
	prey1	0	1.1	0	0	0	0	0	0	0	0
	prey2	0	0	1.2	0	0	0	0	0	0	0
	pred1	-0.445	0	0	1.1	0	0	0	0	0	0
	pred2	-0.44	0	0	-0.068	1.2	0	0	0	0	0
	hunters	0	0	0	-0.385	-0.369	1	0	0	0	0
	var G	0	0	0	0	0	0	0	0	0	0
	var H	0	0	0	0	0	0	0	0	0	0
	var I	0	0	0	0	0	0	0	0	0	0
	var J	0	0	0	0	0	0	0	0	0	0

The previous ecological network has the following inertial dynamics (Fig. 3), with the *target species* (green line) expected to go extinction after 8 years.

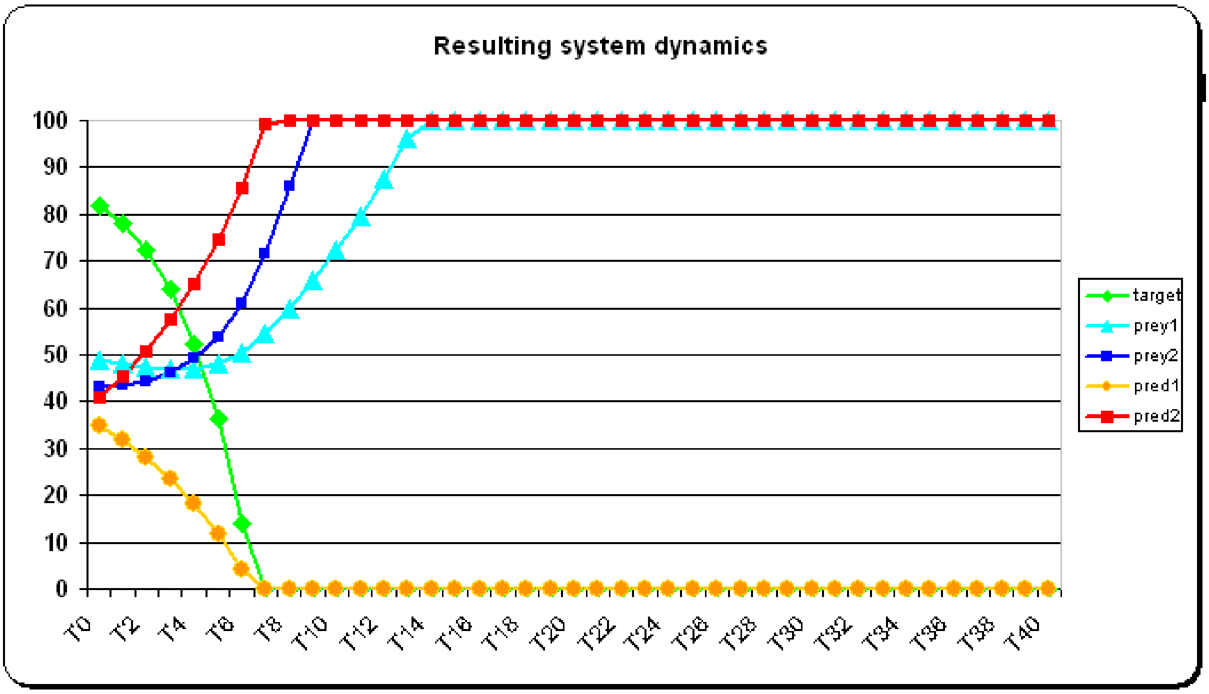

Fig. 3 Resulting dynamics for the network of Fig. 2. X-axis measures time in years. Dynamics have been calculated using Quant-Lab (Ferrarini, in preparation).

4 Exogenous Control

Now, I'll add an exogenous controller in order to drive the above ecological network to the desired equilibrium state (e.g., *target species*' stock=100).

Since GAs are based on random searching for solutions, I performed iterative processes for determining appropriate parameters. Previous research revealed that the optimal solution may be to search at a high rate of crossover, a low rate of mutation and proper population size (Kuo et al., 2000). In this study, crossover was set at a probability of 60% while mutations occur with a probability of 5%. This low setting helps to avoid getting trapped local optima during the search. The initial population consisted of 500 chromosomes that were evolved over minimal 10,000 generations. These parameters were set after preliminary experiments. I applied a steady-state genetic algorithm with a one-point crossover operator to accomplish crossover. In this case the parent genome strings are cut at some random position to produce two "head" and two "tail" segments. The "tail" segments are swapped to produce two new genomes. For parent selection the roulette wheel selection method was used (Goldberg, 1989), where the likelihood of selection is proportionate to the fitness score given by the performance criterion. After crossover and mutation, the individuals with the lowest fitness scores were removed.

I have found many solutions by acting on species' stocks. Figure 4 shows 6 of the detected solutions using bio-manipulations upon predators. The red node represents the exogenous controller. The number close to the red node represents the required *controller*'s stock, which is here constant (*controller*'s update rate= 1). Numbers close to relations represent the required effects of the *controller* upon the predators. These 6 solutions all lead to the desired goal: equilibrium value of the *target species* equal to 100. It's clear that red node behaves like an exogenous actor (e.g., a top-predator, a competitor that excludes predators' individuals, park guards etc.) that acts upon the two predators at each cycle (year here), and not only at the beginning of the dynamic simulation like in Ferrarini (2013).

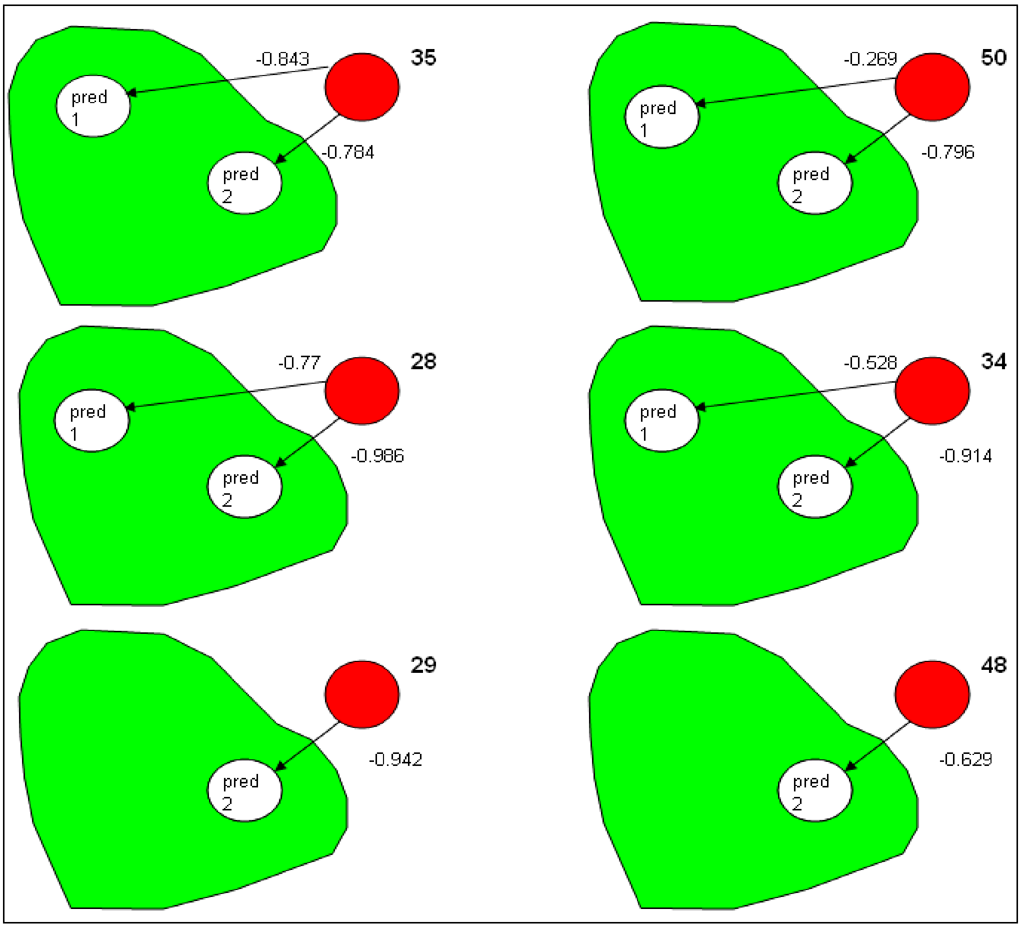

Fig. 4 Six detected solutions to the goal of network control acting upon the two *target species*' predators. Dynamics have been calculated using Quant-Lab (Ferrarini, in preparation).

It's not the goal of this paper to discuss the ecological meaning of such control, here just theoretical and methodological topics are focussed. Of course, it's also possible to externally act upon the *target species* itself. It's also feasible to externally act upon relations among actors or seek multiple goals (e.g. *target species* maximization and *pred1*>*m*).

It's clear that the more the external nodes C_i the higher the chance to externally drive the ecological or biological system toward the desired way. But the higher the number of external nodes, the more computationally challenging is the work of external control. In this view, I propose the following operative framework:

- goal setting (e.g. *target species* maximization);
- network setup;
- addition of an external node;
- application of 1-node framework to network control;
- multiple solutions detection via evolutionary modelling;
- in case of need, addition of further external nodes;
- multiple solutions detection via evolutionary modelling;

- setup of cost-benefit ratio (CBR) to each detected solution;
- choice of the action (or actions) that minimize CBR.

In my experience on ecological networks with up to 15 actors and up to 100 relations (Ferrarini, 2012b), one external node is enough in order to find feasible solutions to network control with also low CBRs. But it could be that, with a higher number of nodes or relations, one exogenous node is not enough.

5 Conclusions

Ecological and biological networks can be efficaciously controlled by coupling network dynamics and evolutionary modelling. While in a previous paper I showed that ecological and biological networks can be efficaciously controlled from the inside (Ferrarini, 2013), here I have further introduced a new framework for network controllability based on the use of an exogenous controller and evolutionary modelling. These two approaches are different both from a theoretical and methodological approach. The endogenous control requires that the network is optimized at the beginning of its dynamics (by acting upon nodes, edges or both) and then it will go inertially to the desired state. I call this the “soft way” to the network control. Instead, the exogenous control proposed here requires that exogenous controllers act upon the network at each cycle, and hence I call this the “constrained way”. *A priori*, it’s hard to say which of the two approaches is more effective, it mainly depends on the kind of ecological or biological network we are dealing with.

From a computational viewpoint, in the “soft way” we have to optimize n nodes and up to $n*(n-1)$ links (or $n*n$ links if we also consider self-links) in order to subdue the network; instead in the “constrained way” the problem of network controllability is translated into the control of up to n edges plus the exogenous node’s stock (in case one controller is enough), or $k*n$ edges and k nodes in case k controllers are required. In my experience based on ecological networks with up to 15 actors and up to 100 relations (Ferrarini, 2012b) it always happened that k=1, hence the “constrained way” is less intensive from a computational viewpoint than the “soft” one.

The framework proposed here might also be applied to semi-quantitative, qualitative ecological and biological networks (Ferrarini, 2011b; Ferrarini, 2011c).

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