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On the stock estimation for some fishery systems

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Abstract

In this work we address the stock estimation problem for two fishery models. We show that a tool from nonlinear control theory called "observer" can be helpful to deal with the resource stock estimation in the field of renewable resource management. It is often difficult or expensive to measure all the state variables characterising the evolution of a given population system, therefore the question arises whether from the observation of certain indicators of the considered system, the whole state of the population system can be recovered or at least estimated. The goal of this paper is to show how some techniques of control theory can be applied for the approximate estimation of the unmeasurable state variables using only the observed data together with the dynamical model describing the evolution of the system. More precisely we shall consider two fishery models and we shall show how to build for each model an auxiliary dynamical system (the observer) that uses the available data (the total of caught fish) and which produces a dynamical estimation $\hat{x}(t)$ of the unmeasurable stock state $x(t)$. Moreover the convergence speed of $\hat{x}(t)$ towards $x(t)$ can be chosen.

Keywords: Fishery models, Stage-structured population models, Estimation, Harvested Fish Population, Observers.

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1 Introduction and a short survey of *observers* design

The stock estimation is one of the most important problem in fishery science. One can quote J.A. Gulland [17]: *A major emphasis in fishery science has been on the problems of estimating current and past level using catch levels and fishing effort data.*

To make a policy decision about the exploitation of renewable ressources, it is necessary to take into account the state of the resource stocks. This implies the need of a good estimate of the available resource. Mathematical models are more and more used to describe the evolution of biological systems. Here, we consider two mathematical models for fishery resources. The first one is a "stage structured" model [43, 44] that describes the dynamics of a population divided in stage-classes (according to age, length or weight) and submitted to the fishing action. The second model is a "global" model that describes the evolution of a fish population that can move between an area where it can be harvested and a reserve area where no fishing is allowed [9]. Both models are given by systems of differential equations of the form

$$\dot{x} = f(x, E), \quad (1)$$

where E is the fishing effort (it can be seen as a control or an input) and $x(t)$ is the state of the system at time t . The state variable $x(t)$ represents the density of the population or the number of individuals by stage. For both models, the state $x(t)$ is not available for measurement. In practice, the only available information at time t is the value of the captures: this means that one can measure the total catch at each time t . The value of the captures can be seen as the measurable output of system (1). The output is in general a function of the state variable and the input, that is, $y(t) = h(x(t), E)$.

Now assuming that (1) is a "good" model of the system under consideration, if it is possible to have the value of the state at some time t_0 then it is possible to compute $x(t)$ for all $t \geq t_0$ by integrating the differential equation with the initial condition $x(t_0)$. Unfortunately, it is often not possible to measure the whole state at a given time and therefore it is not possible to integrate the differential equation because one does not know an initial condition. One can only have a partial information of the state and this partial information is precisely given by $y(t)$ the output of the system. Therefore we shall show how to use this partial information $y(t)$ together with the given model in order to have a dynamical estimate $\hat{x}(t)$ of the real unknown state variable $x(t)$. This estimate will be produced by an auxiliary dynamical system which uses the information $y(t)$ provided by the system (1). This dynamical system is generally of the form

$$\dot{\hat{x}} = g(\hat{x}, E, y). \quad (2)$$

It can be represented by Schema 1 The estimate error is given by $e(t) = \hat{x}(t) - x(t)$ and it satisfies the following "error equation"

$$\dot{e} = g(\hat{x}, E, y) - f(x, E) \quad (3)$$

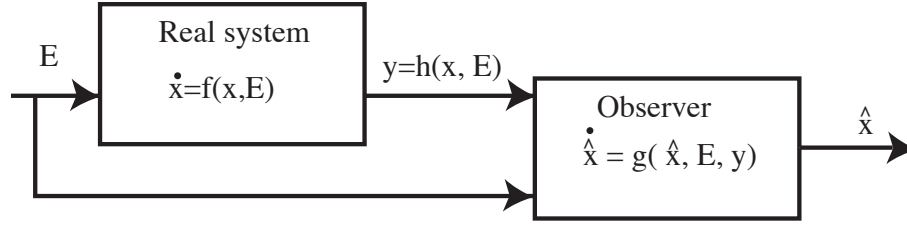


Figure 1: A schematic representation of an observer

39 The function g has to be determined in such a way that the solutions of (1) and (2)
 40 satisfy $x(t) - \hat{x}(t) \rightarrow 0$ as $t \rightarrow +\infty$ regardless of the respective initial conditions of
 41 system (1) and system (2).

42 A dynamical system (2) satisfying this conditions is called an "observer" for sys-
 43 tem (1). When the convergence of $\hat{x}(t)$ towards $x(t)$ is exponential, the system (2) is
 44 an "exponential observer". More precisely, system (2) is an exponential observer for
 45 system (1) if there exists $\lambda > 0$ such that, for all $t \geq 0$ and for all initial conditions
 46 $(x(0), \hat{x}(0))$, the corresponding solutions of (1) and (2) satisfy

$$\|\hat{x}(t) - x(t)\| \leq \exp(-\lambda t) \|\hat{x}(0) - x(0)\|.$$

47 In this situation a good estimate of the real unmeasured state is rapidly obtained.
 48 One must notice that we need not care about the choice of the initial condition of the
 49 observer since the convergence of $\hat{x}(t)$ towards the real state $x(t)$ does not depend
 50 on this choice.

51 When the system under consideration is a linear system, i.e., it can be written as
 52 follows

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t), \\ y(t) = Cx(t), \\ x(t) \in \mathbb{R}^n, u(t) \in U \subset \mathbb{R}^m, y(t) \in \mathbb{R}^q, \\ A, B, \text{ and } C \text{ are respectively } n \times n, n \times m \text{ and } q \times n \text{ matrices,} \end{cases} \quad (4)$$

53 then an exponential observer (called *Luenberger Observer*) [30] for this system is
 54 given by

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K(y(t) - C\hat{x}(t)) \quad (5)$$

55 where the $n \times q$ matrix K has to be computed. The Luenberger observer converges,
 56 i.e., $\|\hat{x}(k) - x(k)\|$ tends to zero exponentially fast if it is possible to find a matrix K
 57 in such a way that the eigenvalues of the matrix $A - KC$ are all with negative real
 58 part. It has been proved that such a matrix K exists if the pair (C, A) is observable.

59 The pair (C, A) is observable if and only if the matrix:

$$O_{(C,A)} = \begin{pmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{n-1} \end{pmatrix}$$

60 is of rank n . In this case we say that the system (4), or the pair (C, A) , satisfies the
 61 Kalman rank condition for observability (one can see for more details and examples
 62 [39] or [20]).

63 The construction of observers for highly nonlinear systems is still a very active
 64 research area in Control Theory. Several methods have been developed for some
 65 classes of systems (one can see for instance the references [30, 27, 28, 26, 47, 13] that
 66 represent different approaches). This is not an exhaustive list, because the literature
 67 on the subject is very extensive. This active research has resulted in the emergence
 68 of many nonlinear observer design techniques. The most classical one is based on
 69 the "feedback linearization" and the observer normal form (see for instance [6], [22],
 70 [27], [46]) Roughly speaking, this method consists in finding change of coordinates
 71 $x = \kappa(z)$, $u = \zeta(E)$, $y = \eta(w)$ in the state space as well as in the input space and in
 72 the output space in such a way that equation (1) is transformed into

$$\begin{cases} \dot{x} = Ax + \chi(w, u), \\ w = Cx. \end{cases} \quad (6)$$

73 In this case a Luenberger type observer can be easily constructed. However the
 74 conditions under which the appropriate changes of coordinates exist are restrictive.
 75 These changes of coordinates often exist only locally and hence the derived observer
 76 design works only locally.

77 The second famous method is the high gain construction ([41],[7],[13],[14], [15], [21],
 78 [4]). A short survey is given in [4]. This method is developed hereafter and will be
 79 used in this paper.

80 Another design method uses an on-line optimization approach ([24] , [2], [33], [34],
 81 [47]) such as moving horizon observers that use the integral output prediction error
 82 in the estimation process, and the observer using Newtons method. In this case,
 83 the state is estimated by minimizing a certain norm of the difference between the
 84 ob- server output and the measured output. The advantage of the online optimiza-
 85 tion method is the capability of dealing with a variety of nonlinear systems includ-
 86 ing time-varying systems, chaotic systems, and systems with unknown parameters.
 87 Moreover this method does not require the use of any canonical form. However, the
 88 corresponding observer computations are generally quite heavy and may prevent the
 89 use of these observers for systems with very fast dynamics.

90 Historically observability theory and observers design have been developed for arti-
 91 ficial engineering systems but nowadays they are more and more applied to "natural

systems". We outline here some applications of nonlinear observers to biological models. Once again the list is not exhaustive.

In [5] the well-known Droop model which describes the growth of a population of phytoplanktonic cells is considered. Observers for this model are built and are used to discuss the validity of this model by comparing the prediction of the state computed by the observer with direct measurements of this state.

In [10], observers are used to estimate the kinetic rates in bioreactors. The efficiency of the observer design is illustrated with examples dealing with the microbial growth and biosynthesis reactions.

A robust nonlinear asymptotic observer with adjustable convergence rate has been proposed in [1]. This observer has been applied to a model of an anaerobic digestion process used for wastewater treatment.

The authors of [29] consider a system of populations described by the classical Lotka-Volterra model with one predator and two preys. The only available information is the total quantity of population preys without distinction between them. An observer is constructed that allows to estimate all the state variables. It is also shown how the observer can be used for the estimation of the level of an abiotic effect on the population system. It must be, however, noticed that the proposed observer in [29] is a local observer, i.e., its convergence is guaranteed only if the initial estimate error is small.

A high gain observer is used in [42] to study a system describing a one-gene regulation circuit. The observer is used to rebuild the non-measured concentrations of the mRNA and the protein.

The use of observer theory in fishery is scarce, we have done some works in this sense (see [35], [16]). In [35], an observer has been constructed for a stage structured discrete-time fishery model that exhibits an unknown recruitment function. In [16], a stage structured continuous model is considered and it is assumed that only the last class (mature individuals) is harvested. The present work is a continuation and a generalization of [16].

The goal of this paper is twofold. First we shall show that some tools from control theory are helpful to address the stock estimation problem for an exploited fish population. More precisely we shall build exponential observers for the two models under consideration. These observers will allow to give an estimate of the respective stocks. The second is to show that the application of mathematical tools to biological systems has to be done carefully. One of the most efficient way to build an observer for a nonlinear system has been given in [13]. We briefly recall the method developed in [13]. To simplify matters we consider systems without control. Roughly speaking, the result of [13] concerns systems that can be written (possibly after a coordinates

130 change):

$$\left\{ \begin{array}{l} \dot{z}(t) = \underbrace{\begin{pmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & \dots & 0 & 0 \end{pmatrix}}_A z(t) + \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ \psi(z(t)) \end{pmatrix} = X(z(t)) \\ y(t) = z_1(t) = \underbrace{(1, 0, \dots, 0)}_C z(t). \end{array} \right. \quad (7)$$

131 The state of the system at time t is $z(t) = (z_1(t), z_2(t), \dots, z_n(t)) \in \mathbb{R}^n$, and its
 132 measurable output is $y(t)$. The fact that $y(t) = z_1(t)$ means that one can measure
 133 only the first component of the state and hence the other components are not avail-
 134 able for measurement. Assume that the function ψ is globally Lipschitz on $\mathbb{R}^n$, that
 135 is, there exists $K > 0$ such that $|\psi(z) - \psi(x)| \leq K|z - x|$ for all $(z, x) \in \mathbb{R}^n \times \mathbb{R}^n$.
 136 It has then been proved in [13] that for $\theta \geq 1$ large enough, an exponential observer
 137 (a *Luenberger type observer*) for the system (7) is given by the following dynamical
 138 system:

$$\dot{\hat{z}} = X(\hat{z}) - S_\theta^{-1} C^T (C \hat{z} - y), \quad (8)$$

139 with S_θ being the solution of

$$\theta S_\theta + A^T S_\theta + S_\theta A = C^T C.$$

140 System (8) is an exponential observer for system (7) means that the solutions of
 141 (8) converge to the solutions of system (7) with an exponential speed regardless the
 142 values of the respective initial conditions $z(0)$ and $\hat{z}(0)$. To prove this result the
 143 authors of [13] use the fact that the function ψ is globally Lipschitz on the **whole**
 144 state space $\mathbb{R}^n$. The global Lipschitz assumption is very restrictive. Biological
 145 systems always evolve in a bounded domain $\mathcal{D}$ of $\mathbb{R}^n$ and hence the global Lipschitz
 146 assumption is satisfied on $\mathcal{D}$. However, it must be noticed that the fact that the
 147 domain $\mathcal{D}$ is positively invariant for system (7) and that the map ψ is globally
 148 Lipschitz on $\mathcal{D}$ does not guarantee the convergence of the observer (8) even if one
 149 take the initial values inside $\mathcal{D}$. Indeed, the domain $\mathcal{D}$ is positively invariant for the
 150 system (7) but it is **not** a positively invariant set for the system (8) defining the
 151 equations of the observer. More precisely, for a given initial condition $(z(0), \hat{z}(0)) \in$
 152 $\mathcal{D} \times \mathcal{D}$, the corresponding solution $(z(t), \hat{z}(t))$ of (7-8) can leave the set $\mathcal{D} \times \mathcal{D}$ in
 153 finite time: the component $z(t)$ will actually belong to $\mathcal{D}$ for all positive time but
 154 there is no reason that the same property will be true for $\hat{z}(t)$. In order to built
 155 an exponential observer for the considered system in this situation, one has first to
 156 extend the function ψ from $\mathcal{D}$ to the whole $\mathbb{R}^n$ by a function $\tilde{\psi}$ which is globally
 157 Lipschitz on $\mathbb{R}^n$ and then to consider the systems (7-8) defined on $\mathbb{R}^n \times \mathbb{R}^n$ after
 158 replacing the function ψ by its prolongation $\tilde{\psi}$. The stage-structured fishery model
 159 we consider here will illustrate this fact. For this model, there is a domain $\mathcal{D} \subset \mathbb{R}^3$
 160 which is positively invariant, and the system dynamics are defined by a vector field
 161 X which is globally Lipschitz on $\mathcal{D}$. We shall show that the observer works well

when we extend the vector field X to the whole space $\mathbb{R}^3$ and it fails to work when the prolongation is not done. The same things are valid for the global model. This shows that the Lipschitz extension of the vector field mentioned in [13] is not only for mathematical sophistication purpose but it is also necessary for application purpose. Here we construct simply a continuous Lipschitz extension of the function ψ . For more details concerning the design of Lipschitz extensions one can see for instance [38].

The paper is organized as follows. In Section 2, we present the stage-structured model and we built an observer for this system. The construction is made for a three stages model. It can be done for an arbitrary number of stages but the calculus are longer and more complicated. Section 3 is devoted to the stock estimation problem for a "global" model. Once again, for clarity reasons, we have preferred to deal with a model with two fishing areas but the observer construction can be done for a system describing the dynamics of a fish population that can move between different fishing zones (an example of such a system has been considered in [32]).

2 A Stage-structured model

In this section, we consider a class of a structured model in fishery with three classes. The first class x_0 is constitute of the pre-recruits i.e the eggs, larvae and the juveniles. The second and the third classes are the post-recruits or the exploited phase of the population.

The dynamics of the system are modeled by the following three dimensional system (see [43, 44], [36]) :

$$\begin{cases} \dot{x}_0(t) = -\alpha_0 x_0(t) + \sum_{i=1}^2 f_i l_i x_i(t) - \sum_{i=1}^2 p_i x_i(t) x_0(t) - p_0 x_0^2(t) \\ \dot{x}_1(t) = \alpha x_0(t) - (\alpha_1 + q_1 E) x_1(t) \\ \dot{x}_2(t) = \alpha x_1(t) - (\alpha_2 + q_2 E) x_2(t) \end{cases} \quad (9)$$

where :

x_i :	the number of fish in the stage i .	
α :	linear aging coefficient	(in time ⁻¹)
m_i :	natural mortality rate of class i	(in time ⁻¹)
$\alpha_i = m_i + \alpha$		(in time ⁻¹)
p_0 :	juvenile competition parameter	(in time ⁻¹ .number ⁻¹)
f_i :	fecundity rate of class i	(no dimension)
l_i :	reproduction efficiency of class i	(in time ⁻¹)
p_i :	predation rate of class i on class 0	(time ⁻¹ .num ⁻¹)
q_i :	capturability coefficient of class i	(in unit effort ⁻¹)
E :	instantaneous fishing effort.	(in unit effort × time ⁻¹).

We assume that the total catch is available for measurement. This total catch can

196 be considered as a measurable output of the system(9) and it is given by

$$y(t) = q_1 E x_1(t) + q_2 E x_2(t) \quad (10)$$

197 We then obtain the following coupled system:

$$\begin{cases} \dot{x}_0(t) = -\alpha_0 x_0(t) + \sum_{i=1}^2 f_i l_i x_i(t) - \sum_{i=1}^2 p_i x_i(t) x_0(t) - p_0 x_0^2(t) \\ \dot{x}_1(t) = \alpha x_0(t) - (\alpha_1 + q_1 E) x_1(t) \\ \dot{x}_2(t) = \alpha x_1(t) - (\alpha_2 + q_2 E) x_2(t) \\ y(t) = q_1 E x_1(t) + q_2 E x_2(t) \end{cases} \quad (11)$$

198 We consider system (11) which is a nonlinear system. Our aim is to construct an
199 observer (estimator) i.e an auxiliary system which will give a dynamical estimate
200 $(\hat{x}_0(t), \hat{x}_1(t), \hat{x}_2(t))$ of the state $(x_0(t), x_1(t), x_2(t))$ of system (9). For the construction
201 of such auxiliary system, we shall use a method called High Gain construction (see
202 for instance [13]). This construction provide an exponential observer; the estimation
203 error will converges to zero with exponential speed, i.e.,

$$\|\hat{x}(t) - x(t)\| \leq \exp(-\lambda t) \|\hat{x}(0) - x(0)\|.$$

204 2.1 High Gain observer design for (11)

205 The system (11) is the system (9) coupled with the output (10). For the observer
206 design, we will use the High Gain observer techniques (Gauthier et al.([13])) to
207 construct a High Gain observer for system (9).

208 It has been proved in [43] that there is a positively invariant compact set for sys-
209 tem (9). This set is of the form $D = [a_0, b_0] \times [a_1, b_1] \times [a_2, b_2]$, where the numbers a_i
210 can be chosen as small as we need and the numbers b_i are function of the parameters
211 f_i, l_i and p_i . More precisely:

$$\begin{aligned} b_i &= \pi_i \mu \\ \text{with } \pi_i &= \frac{\alpha^i}{\prod_{j=1}^i (\alpha_j + q_j E)}, \\ \text{and } \mu &= \min_{i: p_i \neq 0} \left\{ \frac{f_i l_i}{p_i} \right\} \end{aligned}$$

212 Let us denote by F the vector field defining the dynamics of the system (9), and h
213 the output function, that is $y(t) = h(x(t)) = q_1 E x_1(t) + q_2 E x_2(t)$ and

$$214 \quad F(x(t)) = \begin{pmatrix} -\alpha_0 x_0(t) + \sum_{i=1}^2 f_i l_i x_i(t) - \sum_{i=1}^2 p_i x_i(t) x_0(t) - p_0 x_0^2(t) \\ \alpha x_0(t) - (\alpha_1 + q_1 E) x_1(t) \\ \alpha x_1(t) - (\alpha_2 + q_2 E) x_2(t) \end{pmatrix}$$

215 Let Φ be the function $\Phi : \overset{\circ}{D} \rightarrow \mathbb{R}^3$ ($\overset{\circ}{D}$ is the interior of D), defined as follows:

216 $\Phi(x) = \begin{pmatrix} h(x) \\ L_F h(x) \\ L_F^2 h(x) \end{pmatrix}$, where L denotes the Lie derivative operator with respect to
 217 the vector field F . Thus,

$$\Phi(x) = E \begin{pmatrix} q_1 x_1 + q_2 x_2 \\ \alpha q_1 x_0 + \left(\alpha q_2 - q_1(\alpha_1 + q_1 E) \right) x_1 - q_2(\alpha_2 + q_2 E) x_2 \\ \left(-\alpha_0 \alpha q_1 + \alpha^2 q_2 - \alpha q_1(\alpha_1 + q_1 E) \right) x_0 \\ + \left(\alpha q_1 f_1 l_1 - \alpha q_2(\alpha_1 + q_1 E) + q_1(\alpha_1 + q_1 E)^2 - \alpha q_2(\alpha_2 + q_2 E) \right) x_1 \\ + \left(\alpha q_1 f_2 l_2 + q_2(\alpha_2 + q_2 E)^2 \right) x_2 \\ - \alpha q_1 p_0 x_0^2 - \alpha q_1 p_1 x_1 x_0 - \alpha q_1 p_2 x_2 x_0 \end{pmatrix}$$

218 The Jacobian of Φ can be written:

$$\frac{d\Phi}{dx} = \begin{pmatrix} 0 & q_1 E & q_2 E \\ \alpha q_1 E & \gamma_1 & \gamma_2 \\ \gamma_3 & \gamma_4 & \gamma_5 \end{pmatrix},$$

and

$$\left[\frac{d\Phi}{dx} \right]^{-1} = \frac{1}{\Gamma} \begin{pmatrix} \beta_1 & \beta_2 & \beta_3 \\ \beta_4 & \beta_5 & \beta_6 \\ \beta_7 & \beta_8 & \beta_9 \end{pmatrix},$$

219 where:

$$\begin{aligned} 220 \quad \Gamma &= \text{Det} \left(\frac{d\Phi}{dx} \right) = q_1 E \gamma_2 \gamma_3 + \alpha q_1 q_2 E^2 \gamma_4 - q_2 E \gamma_1 \gamma_3 - \alpha q_1^2 E^2 \gamma_5 \\ 221 \quad \gamma_1 &= \alpha q_2 E - q_1 E(\alpha_1 + q_1 E) \\ 222 \quad \gamma_2 &= -q_2 E(\alpha_2 + q_2 E) \\ 223 \quad \gamma_3 &= \alpha^2 q_2 E - \alpha_0 \alpha q_1 E - \alpha q_1 E(\alpha_1 + q_1 E) - 2\alpha q_1 E p_0 x_0 - \alpha q_1 E p_1 x_1 - \alpha q_1 E p_2 x_2 \\ 224 \quad \gamma_4 &= q_1 E(\alpha_1 + q_1 E)^2 - \alpha q_2 E(\alpha_1 + q_1 E) - \alpha q_2 E(\alpha_2 + q_2 E) + \alpha q_1 f_1 l_1 E - \alpha q_1 E p_1 x_0 \\ 225 \quad \gamma_5 &= q_2 E(\alpha_2 + q_2 E)^2 + \alpha q_1 f_2 l_2 E - \alpha q_1 E p_2 x_0 \\ 226 \quad \beta_1 &= \gamma_1 \gamma_5 - \gamma_2 \gamma_4 \\ 227 \quad \beta_2 &= -q_1 E \gamma_5 + q_2 E \gamma_4 \\ 228 \quad \beta_3 &= q_1 E \gamma_2 - q_2 E \gamma_1 \\ 229 \quad \beta_4 &= -\alpha q_1 E \gamma_5 + \gamma_2 \gamma_3 \\ 230 \quad \beta_5 &= -q_2 E \gamma_3 \\ 231 \quad \beta_6 &= \alpha q_1 q_2 E^2 \\ 232 \quad \beta_7 &= \alpha q_1 E \gamma_4 - \gamma_1 \gamma_3 \\ 233 \quad \beta_8 &= q_1 E \gamma_3 \end{aligned}$$

$$\beta_9 = -\alpha q_1^2 E^2.$$

The determinant of $\frac{d\Phi}{dx}$ can be written

$$\Gamma(x_0, x_1, x_2) = \text{Det}\left(\frac{d\Phi}{dx}\right) = (c + a_0x_0 + a_1x_1 + a_2x_2) E^3,$$

where c and a_i are functions of the parameters. The map $(x_0, x_1, x_2) \mapsto \Gamma(x_0, x_1, x_2)$ is affine on the polyhedron D , hence it reaches its extrema on the vertexes of D . For a given set of parameters, it is then sufficient to compute the values of $\Gamma(x_0, x_1, x_2)$ on the vertexes of D in order to see if $\Gamma(x_0, x_1, x_2)$ vanishes in D or not.

We assume that the parameters are such that the map Φ is a diffeomorphism from $\overset{\circ}{D}$ to $\Phi(\overset{\circ}{D})$. This implies that system (11) is observable.

In the new coordinates defined by $(z_1, z_2, z_3)^T = z = \Phi(x) = (h(x), L_F h(x), L_F^2(x))^T$, our system can be written in the canonical form as follow:

$$\begin{cases} \dot{z}(t) = \underbrace{\begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix}}_A z(t) + \begin{pmatrix} 0 \\ 0 \\ \psi(z(t)) \end{pmatrix} \\ y(t) = z_1(t) = \underbrace{(1, 0, 0)}_C z(t). \end{cases} \quad (12)$$

where : $\psi(z) = L_F^3 h(\Phi^{-1}(z)) = L_F^3 h(x) = \varphi(x)$

The function φ is smooth (it is a polynomial function of $x = (x_0, x_1, x_2)$) on the compact set D . Hence, it is globally Lipschitz on D . Therefore it can be extended by $\tilde{\varphi}$, a Lipschitz function on $\mathbb{R}^3$ which satisfies $\tilde{\varphi}(x) = \varphi(x)$, for all $x \in D$. In the same way we define $\tilde{\psi}$ the Lipschitz prolongation of the function ψ . So we have the following system (13) defined on the whole space $\mathbb{R}^3$. The restriction of (13) to the domain D is the system (12):

$$\begin{cases} \dot{z} = Az + \begin{pmatrix} 0 \\ 0 \\ \tilde{\psi}(z) \end{pmatrix}, \\ y = Cz. \end{cases} \quad (13)$$

Hence, we have shown that system (11) satisfies the conditions of the following result which provides the observer construction.

Proposition 2.1 ([13]) *Under the assumptions that*

H1: Φ is a diffeomorphism from $\overset{\circ}{D}$ to $\Phi(\overset{\circ}{D})$. ($\overset{\circ}{D}$ is the interior of D).

H2: φ can be extended from D to $\mathbb{R}^3$ by a C^∞ function, globally Lipschitz on $\mathbb{R}^3$.

256 Then an exponential observer for system (13) is given by the following system :

$$\dot{\hat{z}} = A\hat{z} + \psi(\hat{z}) + S^{-1}(\theta)C^T(y - C\hat{z}). \quad (14)$$

257 where $S(\theta)$ is the solution of

$$0 = -\theta S(\theta) - A^T S(\theta) - S(\theta)A^T + C^T C,$$

258 and θ is large enough.

259 Here, $S(\theta) = \begin{pmatrix} \theta^{-1} & -\theta^{-2} & \theta^{-3} \\ -\theta^{-2} & 2\theta^{-3} & -3\theta^{-4} \\ \theta^{-3} & -3\theta^{-4} & 6\theta^{-5} \end{pmatrix}.$

260 Precisely $\theta \geq 2ncK\sqrt{S}$, where K is the lipschitz coefficient of the function ψ , n is
261 the dimension of the space, and $S = \sup_{i,j} |S(1)_{i,j}|$.

262 For the proof one can see [13].

263 Going back to the our original system (9) via the transformation Φ^{-1} , we have :

$$\dot{\hat{x}} = \tilde{F}(\hat{x}) + \left[\frac{d\Phi}{dx} \right]_{x=\hat{x}}^{-1} \times S(\theta)^{-1}C^T(y - h(\hat{x})) \quad (15)$$

264 The restriction of this system to D is the following system :

$$\begin{cases} \dot{\hat{x}}_0 = -\alpha_0 \hat{x}_0 + \sum_{i=1}^2 f_i l_i \hat{x}_i - \sum_{i=1}^2 p_i \hat{x}_i \hat{x}_0 - p_0 \hat{x}_0^2 \\ \quad + (3\theta\beta_1 + 3\theta^2\beta_2 + \theta^3\beta_3)(y - q_1 E \hat{x}_1 - q_2 E \hat{x}_2) \\ \dot{\hat{x}}_1 = \alpha \hat{x}_0 - (\alpha_1 + q_1 E) \hat{x}_1 \\ \quad + (3\theta\beta_4 + 3\theta^2\beta_5 + \theta^3\beta_6)(y - q_1 E \hat{x}_1 - q_2 E \hat{x}_2) \\ \dot{\hat{x}}_2 = \alpha \hat{x}_1 - (\alpha_2 + q_2 E) \hat{x}_2 \\ \quad + (3\theta\beta_7 + 3\theta^2\beta_8 + \theta^3\beta_9)(y - q_1 E \hat{x}_1 - q_2 E \hat{x}_2) \end{cases} \quad (16)$$

265 which is the observer for the fishery model (9). This observer is particularly simple
266 since it is only a copy of (9), together with a corrective term depending on θ .

267 2.2 Simulations and comments

268 We present here some simulation results that show the efficiency of the observer of
269 system (9). The simulations have been done with the free software SCILAB.

270 **Remarque 2.1** For the simulations we extend the function φ by continuity in order
271 to make it globally lipschitz on $\mathbb{R}^3$ in the following way: We denote $\tilde{\varphi}$ the prolonga-
272 tion of φ to $\mathbb{R}^3$ and the function π the projection on the domain D and we construct
273 $\tilde{\varphi} = \varphi \circ \pi$. The extended function $\tilde{\varphi}$ has the same Lipschitz coefficient as φ . The
274 projection π is defined as follows: for $x \in \mathbb{R}^3$, $\pi(x) = \bar{x}$, where $\bar{x} \in D$ is such that
275 $\text{dist}(x, D) = \|x - \bar{x}\|$, i.e., $\bar{x}$ satisfies $\|x - \bar{x}\| = \min_{u \in D} \|u - x\|$. The extension algorithm
276 is described in *Appendix B.*

277 We use the following fishery parameters [36], [43].

278 $\alpha_0 = 1.3; \alpha_1 = 0.9;$

279 $\alpha_2 = 0.85; p_0 = 0.2;$

280 $p_1 = 0.1; p_2 = 0.1;$

281 $q_1 = 0.07; q_2 = 0.15;$

282 $f_1 = 0.5; f_2 = 0.5;$

283 $l_1 = 10; l_2 = 10;$

284 $E = 0.5; \alpha = 0.8.$

285 For these parameter the Jacobian of the function Φ is expressed as:

286

$$\frac{d\Phi}{dx} = \begin{pmatrix} 0 & 0.035 & 0.075 \\ 0.028 & 0.027275 & -0.069375 \\ -0.01458 - 0.0112x_0 & 0.0589979 - 0.0028x_0 & 0.191338 - 0.0028x_0 \\ -0.0028x_1 - 0.0028x_2 & & \end{pmatrix}$$

The determinant of this matrix is:

$$\text{Det}\left(\frac{d\Phi}{dx}\right) = 1.612 \times 10^{-6} + 0.00004697x_0 + 0.0000125265x_1 + 0.0000125265x_2.$$

287 The states x_0, x_1 and x_2 are time varying but remain in the positive orthant; so the
 288 $\text{Det}\left(\frac{d\Phi}{dx}\right)$ does not vanish. Therefore $\frac{d\Phi}{dx}$ is invertible and then $\Phi(x)$ is a diffeomor-
 289 phism.

290 With the parameters defined in the top of this section, we compute the coor-
 291 dinates of the higher corner B of the parallelepiped D ([43]) and we get $B =$
 292 $(25; 20.639; 17.868).$

293 The nontrivial equilibrium point is $x^* = (18.572; 15.89; 13.743).$

294 The construction of the high gain observer (15) is done with $\theta = 17$. For the
 295 simulations we have taken $x(0) = [21; 20; 15]$ and $\hat{x}(0) = [35; 40; 10]$.

296 **Comments:** Using the same parameters values, when we do not use the Lipschitz
 297 prolongation of the function φ to the whole $\mathbb{R}^3$, the state estimation $\hat{x}(t)$ computed
 298 by the observer tends to infinity in finite time. This actually happens in the begin-
 299 ning of the integration process as it can be seen in Figures 2, 4 and 6. When the
 300 Lipschitz prolongation of the function φ to the whole $\mathbb{R}^3$ is done, the convergence
 301 of the estimates delivered by the observer is quite fast (Figures 3, 5 and 7).

302 3 A global model

303 3.1 The model and the observer

304 Here we consider the dynamics of a fish population moving between two zones (see
 305 [9]). The first zone is a free fishing area, and the second zone is a reserve area

where no fishing is allowed. Let $x_1(t)$ be the biomass density at time t of the fish population in the free fishing area and $x_2(t)$ be the biomass density at a time t of the fish population in the reserved areas. For $(i, j) \in \{1, 2\}^2$, we denote by m_{ij} the migration rate from the zone i to the zone j . In the free fishing area, the total fishing effort is denoted by E . The growth of the two sub-population in each zone follows logistic model. The dynamics of the fish subpopulations in unreserved and reserved areas are then assumed to be governed by the following autonomous system of differential equations [9].

$$\begin{cases} \dot{x}_1 = r_1 x_1 \left(1 - \frac{x_1}{K_1}\right) - m_{12} x_1 + m_{21} x_2 - q E x_1 \\ \dot{x}_2 = r_2 x_2 \left(1 - \frac{x_2}{K_2}\right) + m_{12} x_1 - m_{21} x_2. \end{cases} \quad (17)$$

r_1 and r_2 represent the intrinsic growth of each fish sub-population, respectively, K_1 and K_2 are the carrying capacities of fish species in the unreserved and reserved areas, respectively; q is the catchability coefficient of fish species in the unreserved area. The parameters $r_1, r_2, q, m_{12}, m_{21}, K_1$ and K_2 are positives constants.

To the system (17) we associate the capture (i.e. the output) $y = q E x_1$ (the total of caught fish in the unreserved area), with this output, we show the observability condition of system (17) and construct an auxiliary system that will give a dynamical estimation of the state of system (17).

It is possible to find a positive real number w_0 in such a way that for any $w \geq w_0$ the following compact set D_w is positively invariant for system (17). This compact set is given

$$D_w = \{(x_1, x_2) \in \mathbb{R}_+^2 : x_1 + x_2 \leq w\},$$

The proof of this fact as well as the computation of w_0 as a function of the parameters are given in [Appendix A.](#)

Let us denote by f the vector field that defines the system (17):

$$f(x) = \begin{pmatrix} r_1 x_1 \left(1 - \frac{x_1}{K_1}\right) - (m_{12} + qE)x_1 + m_{21} x_2 \\ r_2 x_2 \left(1 - \frac{x_2}{K_2}\right) + m_{12} x_1 - m_{21} x_2 \end{pmatrix}.$$

Let $z = \begin{pmatrix} z_1 \\ z_2 \end{pmatrix}$, $y(t) = h(x) = q E x_1(t)$ and

$$\Phi(x) = \begin{pmatrix} y \\ \dot{y} \end{pmatrix} = \begin{pmatrix} q E x_1 \\ r_1 q E x_1 \left(1 - \frac{x_1}{K_1}\right) - (m_{12} + qE)q E x_1 + m_{21} q E x_2 \end{pmatrix}.$$

$$\text{Therefore } \frac{d\Phi}{dx} = \begin{pmatrix} qE & 0 \\ r_1 qE - \frac{2r_1 q E x_1}{K_1} - (m_{12} + qE)qE & m_{21} qE \end{pmatrix}$$

331 and $\text{Det}\left(\frac{d\Phi}{dx}\right) = q^2 E^2 m_{21}$.

332 As the parameters q , E and m_{21} are positive ($\neq 0$), we can conclude that $\text{Det}\left(\frac{d\Phi}{dx}\right) \neq$
 333 0, and then, Φ is a diffeomorphism from $\mathbb{R}^2$ to $\Phi(\mathbb{R}^2)$, thus system (17) is observable.
 334 Thanks to ([13]) the observer can be expressed as follows:

$$\dot{\hat{x}} = \tilde{f}(\hat{x}) + \left(\frac{d\Phi}{dx}\right)^{-1} \times S(\theta)^{-1} C^T (y - h(\hat{x})), \quad (18)$$

335 where $\tilde{f}$ is a Lipschitz extension of the function f from the invariant domain D_w to
 336 the whole $\mathbb{R}^2$ space, $C = (1, 0)$ and

$$337 S(\theta)^{-1} = \begin{pmatrix} 2\theta & \theta^2 \\ \theta^2 & \theta^3 \end{pmatrix}, \text{ with } \theta \geq 1.$$

338 The restriction of the estimator (18) to the invariant domain D_w is given by the
 339 equations:

$$\begin{cases} \dot{\hat{x}}_1 = r_1 \hat{x}_1 \left(1 - \frac{\hat{x}_1}{K_1}\right) - m_{12} \hat{x}_1 + m_{21} \hat{x}_2 - qE \hat{x}_1 + 2\theta(x_1 - \hat{x}_1) \\ \dot{\hat{x}}_2 = r_2 \hat{x}_2 \left(1 - \frac{\hat{x}_2}{K_2}\right) + m_{12} \hat{x}_1 - m_{21} \hat{x}_2 \\ \quad + 2\theta \left(\frac{qE}{m_{21}} - \frac{1}{m_{21}} + \frac{m_{12}}{qEm_{21}} + \frac{2r_1 x_1}{m_{21}} + \frac{\theta}{m_{21}} \right) (x_1 - \hat{x}_1), \end{cases} \quad (19)$$

340 3.2 Simulation

341 Simulations for the model (17) together with its observer (18) have been done with
 342 the following parameters :

$$343 r_1 = \frac{7}{10}; r_2 = \frac{5}{10},$$

$$344 q = \frac{25}{100}, E = \frac{9}{10},$$

$$345 K_1 = 10, K_2 = \frac{22}{10},$$

$$346 m_{12} = \frac{2}{10}, m_{21} = \frac{1}{10},$$

347 Thanks to formula (20) we compute $w_0 = 8.987$ and we take $w = 20$.

348 With these parameters, the invariant domain is the triangle defined by $O(0, 0)$,
 349 $A(w, 0) = A(20, 0)$ and $B(0, w) = B(0, 20)$, and we take $\theta = 4$.

350 Using the SCILAB free software, the time evolution of the states as well as the
 351 respective estimates when the Lipschitz extension is done are drawn in Figures 8
 352 and 10. When the Lipschitz extension has not been done, the simulations are given
 353 in Figures 9 and 11.

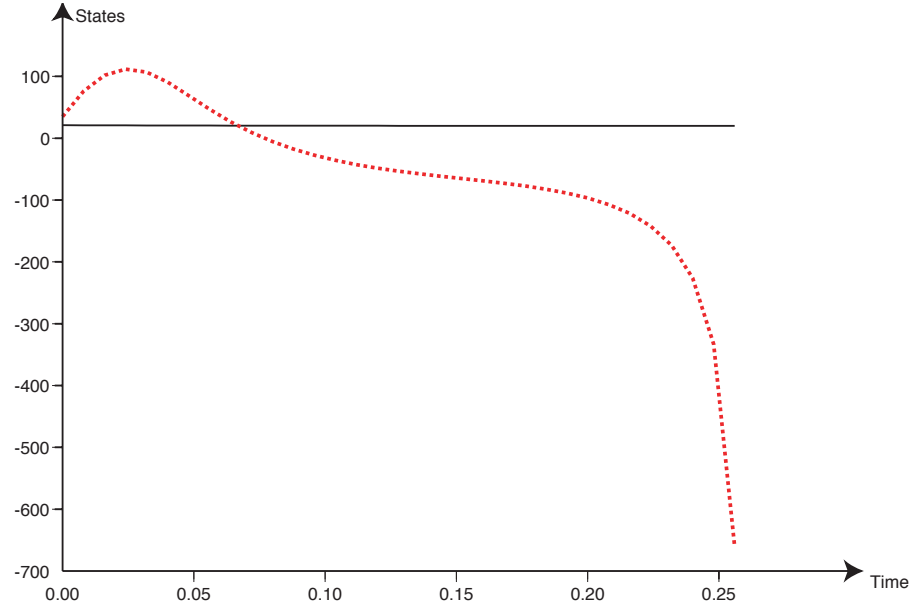


Figure 2: Simulation of system (9) with its observer (15): x_0 (solid line) and its estimate $\hat{x}_0$ (dashed line) when φ is not extended

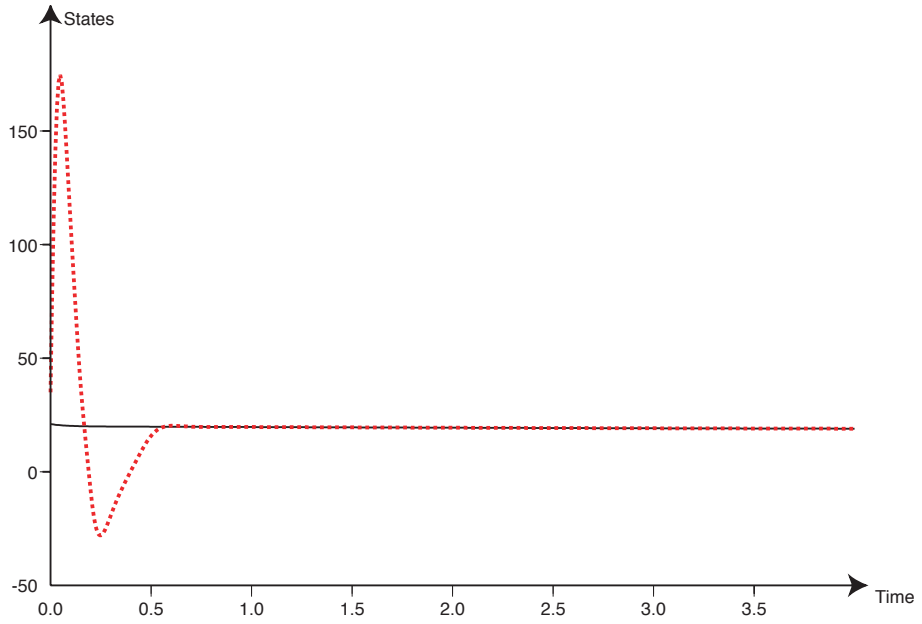


Figure 3: Simulation of system (9) with its observer (15): x_0 (solid line) and its estimate $\hat{x}_0$ (dashed line) when φ is extended

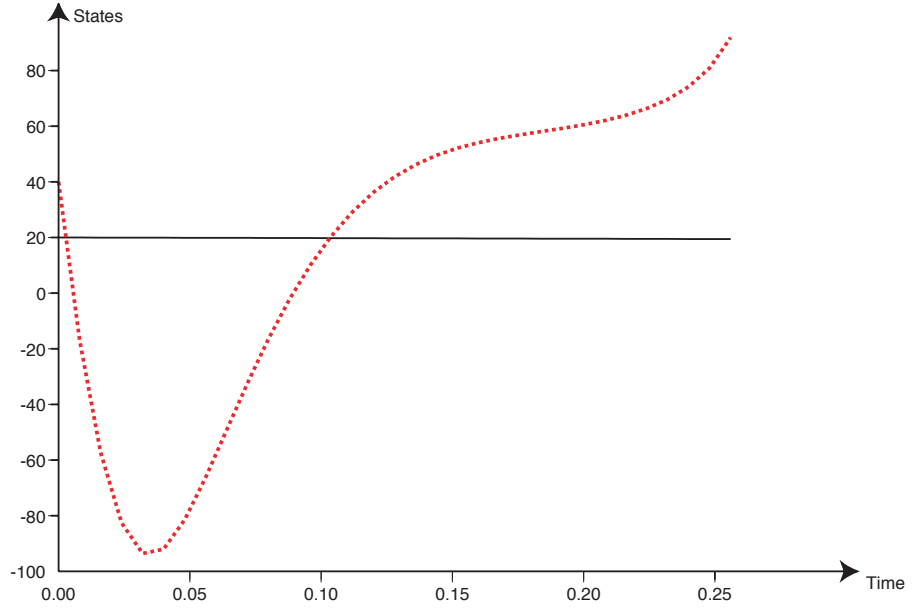


Figure 4: Simulation of system (9) with its observer (15): x_1 (solid line) and its estimate $\hat{x}_1$ (dashed line) when φ is not extended

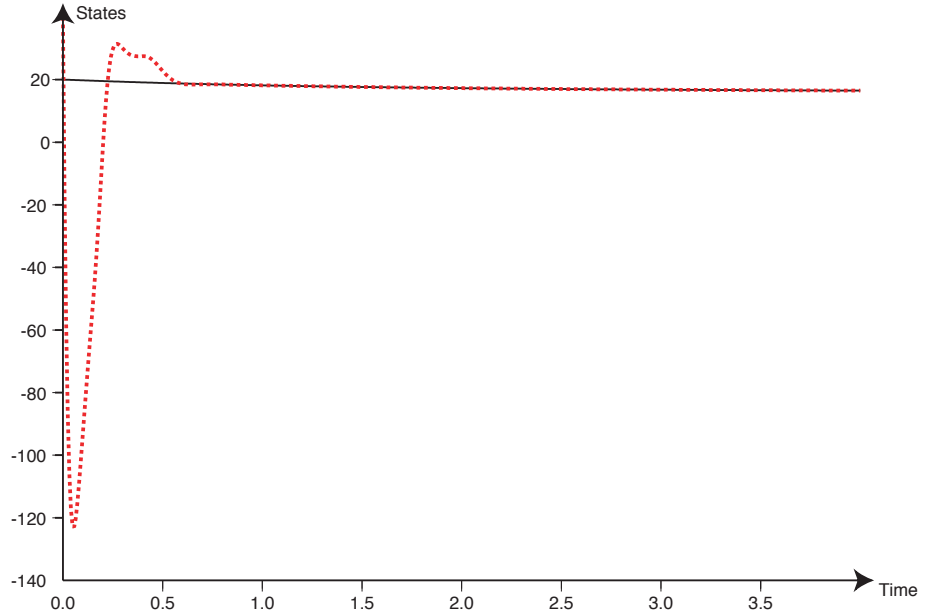


Figure 5: Simulation of system (9) with observer (15): x_1 (solid line) and its estimate $\hat{x}_1$ (dashed line) when φ is extended

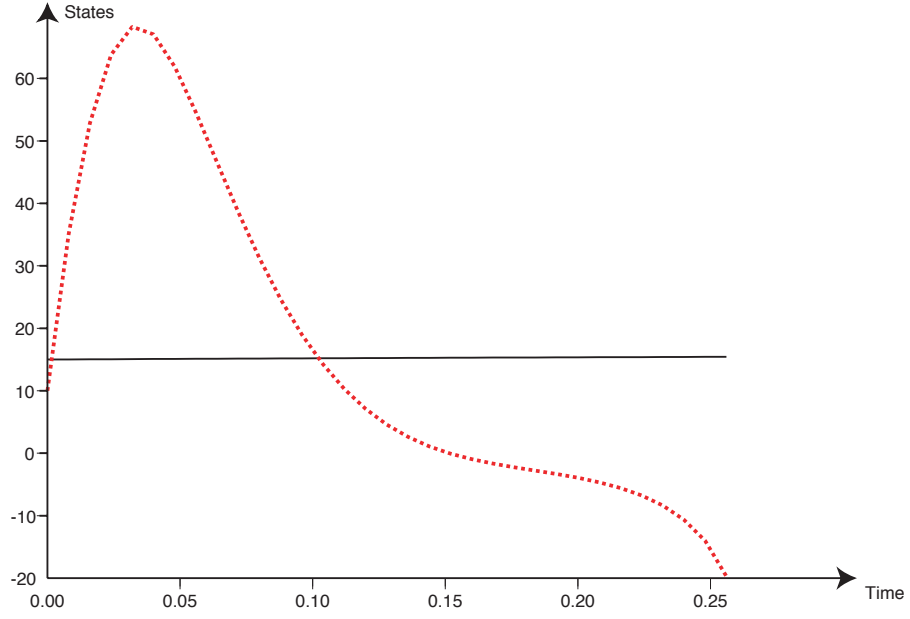


Figure 6: Simulation of system (9) with its observer (15): x_2 (solid line) and its estimate $\hat{x}_2$ (dashed line) when φ is not extended

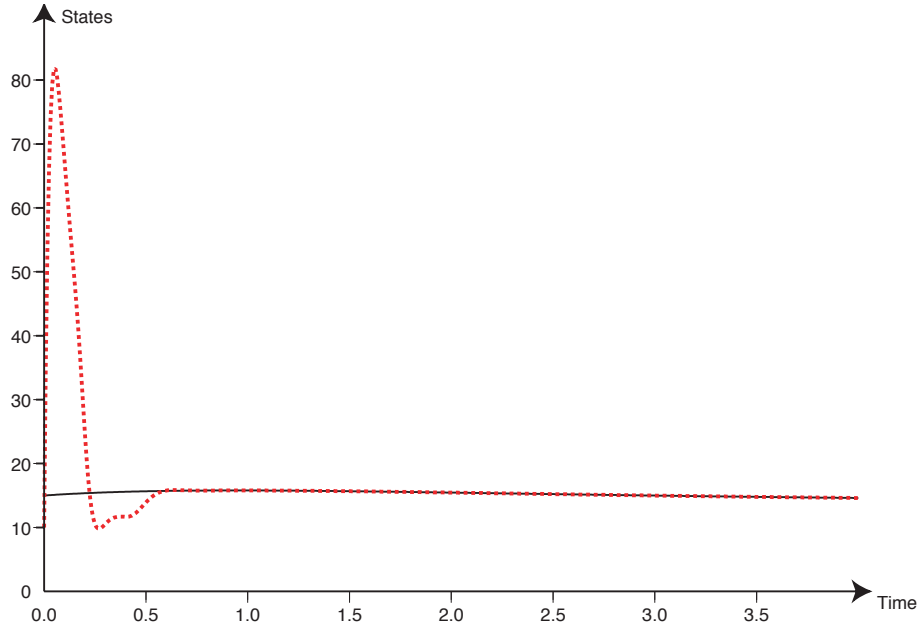


Figure 7: Simulation of system (9) with its observer (15): x_2 (solid line) and its estimate $\hat{x}_2$ (dashed line) when φ is extended

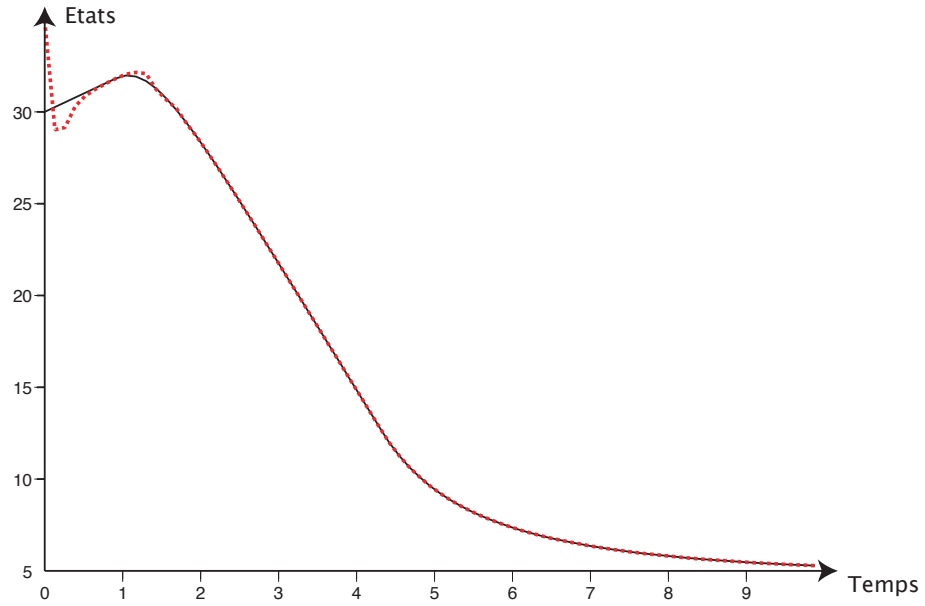


Figure 8: Simulation of system (17) with its observer (18): x_1 (solid line) and its estimate $\hat{x}_1$ (dashed line) when f is extended

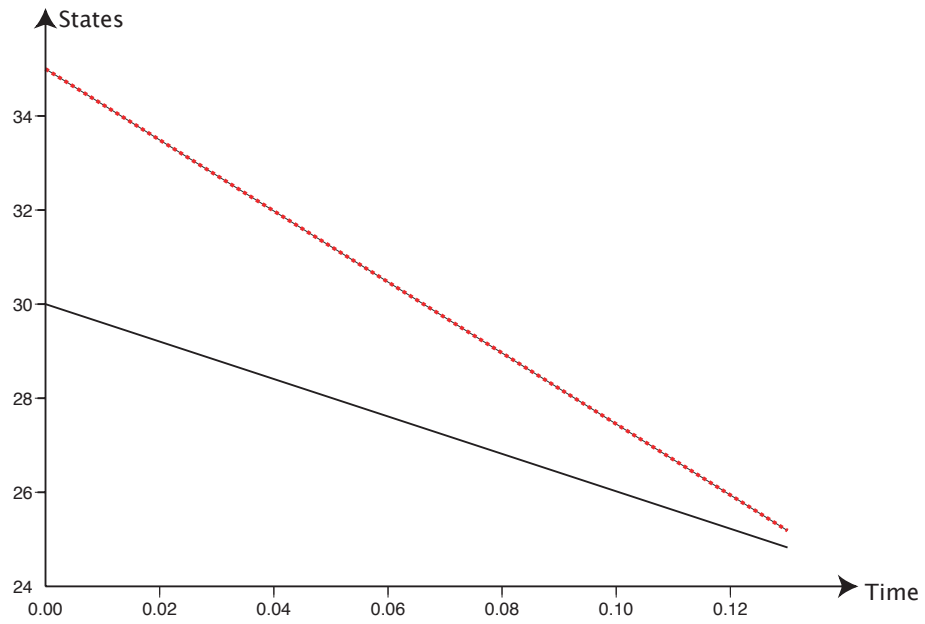


Figure 9: Simulation of system (17) with its observer (18): x_1 (solid line) and its estimate $\hat{x}_1$ (dashed line) when f is not extended

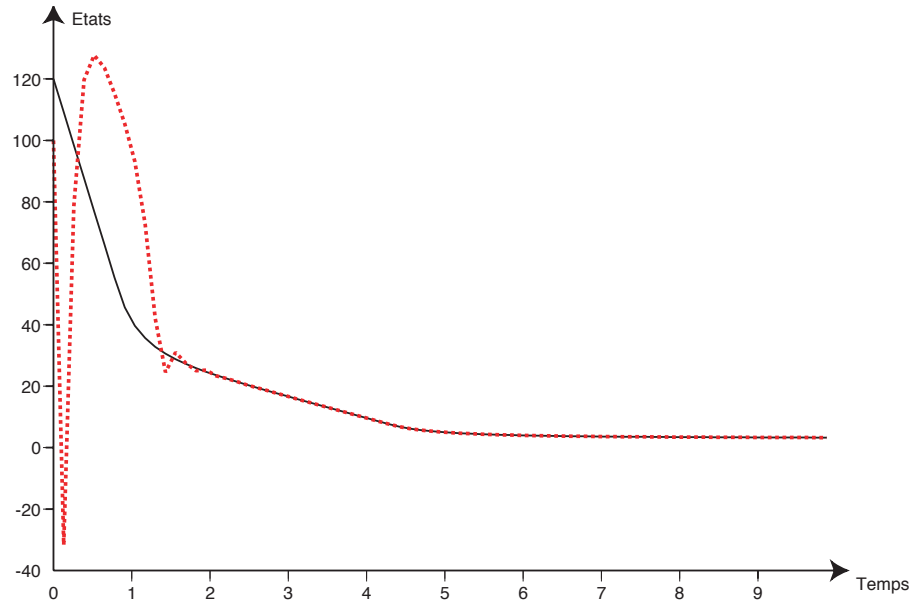


Figure 10: Simulation of system (17) with its observer (18): x_2 (solid line) and its estimate $\hat{x}_2$ (dashed line) when f is extended

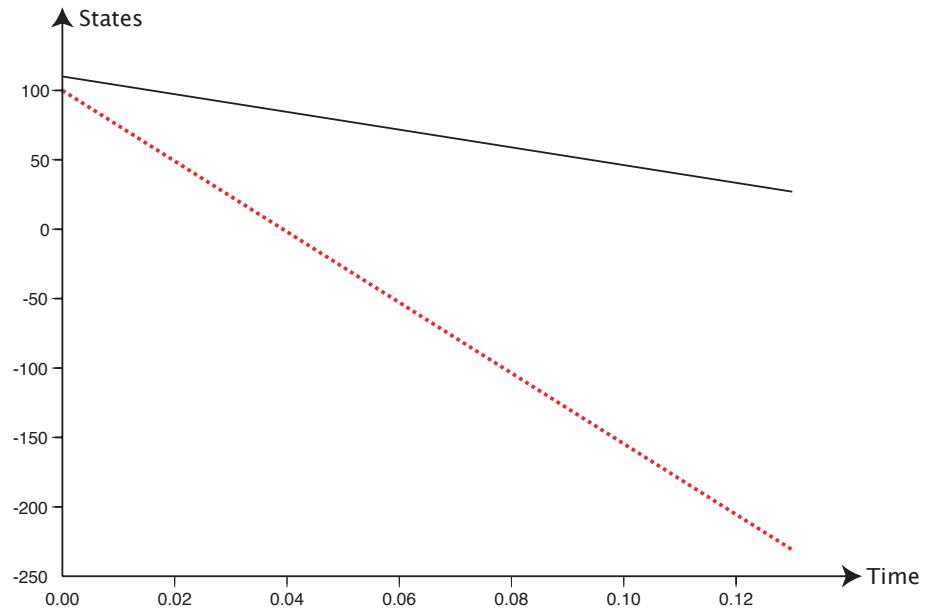


Figure 11: Simulation of system (17) with its observer (18): x_2 (solid line) and its estimate $\hat{x}_2$ (dashed line) when f is not extended

4 Conclusion

We have tried to combine modern Control Theory, Computer Science and Mathematics to address the state estimation problem for systems that model the dynamics of fish populations submitted to a fishing action. Indeed one of the important problems in fishery sciences is to estimate the state of the resource using the available data, in order to produce scientific opinions that can be helpful for developing management policies that need to have a good estimate of the available resource.

In this work, we have constructed High Gain observers for some fishery models. With the use of judicious value of the gain parameter θ we obtain satisfactory estimation of the real state. The observer's convergence is quite fast and does not depend on the initial conditions choice. Therefore one can get a "good" estimate of the unmeasurable real state very quickly. It is interesting to notice that the state estimator built in this paper for the stage-structured model use only the total catch to give not only an estimate of the total stock but also an estimate of the number of individuals in each stage class. The classical techniques like the Cohort Analysis (CA) or the Virtual Population Analysis (VPA) use the total catch for each stage-class in order to give estimates of the number of individuals in each stage class. In practice it is easier to measure the total catch (without doing any distinction between individuals) then to measure the catch for each stage class. However the observers given in this paper assume that the model is good enough and that the parameters values are available.

Nonlinear control techniques are useful for studying and controlling complex systems. Although they have been initially developed for mechanical and electrical systems their applications to biological and environmental problems are growing. Tools of optimal control theory have been extensively used in renewable resource management ([8], [3], [23], [18], [25], [31], [45], [12], [32]). The present paper shows that the estimation problem in fisheries management can also be investigated from the point of view of control engineering.

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Appendix A. Positive invariance of D_w

Let $N = x_1 + x_2$.

$$\dot{N} = -qEx_1 + r_1 \left(1 - \frac{x_1}{K_1}\right) x_1 + (N - x_1) \left(1 - \frac{N - x_1}{K_2}\right) r_2$$

Let w be a positive real number, for $N = w$, we have

$$\dot{N} = -qEx_1 + r_1 \left(1 - \frac{x_1}{K_1}\right) x_1 + (w - x_1) \left(1 - \frac{w - x_1}{K_2}\right) r_2 = g(x_1)$$

The function g is defined for $0 \leq x_1 \leq w$.

$$g(0) = w \left(1 - \frac{w}{K_2}\right) r_2$$

$$g(w) = -quw + w \left(1 - \frac{w}{K_1}\right) r_1$$

$$g'(x_1) = r_1 - r_2 - qu + \frac{2wr_2}{K_2} - 2 \left(\frac{r_1}{K_1} + \frac{r_2}{K_2} \right) x_1$$

$$g'(x_1) = 0 \Leftrightarrow x_1 = \bar{x}_1 = \frac{K_1(K_2r_1 - K_2r_2 - quK_2 + 2wr_2)}{2(K_2r_1 + K_1r_2)}$$

The maximum value of the function g is then given by the expression

$$\frac{K_1K_2(qu - r_1 + r_2)^2 + (4K_2r_1r_2 + K_1(-4qur_2 + 4r_1r_2))w - 4(r_1r_2)w^2}{4(K_2r_1 + K_1r_2)}$$

It is therefore clear that this maximum is non positive if $w \geq w_0$ with

$$w_0 = \frac{r_1r_2(K_1 + K_2) - quK_1r_2 + \sqrt{r_2(K_2r_1 + K_1r_2)(K_1(-qu + r_1)^2 + K_2r_1r_2)}}{2r_1r_2} \quad (20)$$

This shows that for any real number $w \geq w_0$, the compact set

$$D_w = \{(x_1, x_2) \in \mathbb{R}_+^2 : x_1 + x_2 \leq w\}$$

is positively invariant for system (17).

Appendix B. Construction of the Lipschitz extension of φ

The function φ is Lipschitz on the compact set $D = [a_0, b_0] \times [a_1, b_1] \times [a_2, b_2]$. Our aim is to extend it to a function $\tilde{\varphi}$ which is Lipschitz with the same Lipschitz coefficient in the whole $\mathbb{R}^3$.

Let $a(a_0, a_1, a_2)$, (respectively $b(b_0, b_1, b_2)$), the lower corner, (respectively the upper corner) of the domain D and $x(x_0, x_1, x_2)$ an unspecified point of $\mathbb{R}^3$.

The problem of the extension is set for point $x \notin D$; in this situation we have 26 possibilities according to the situation of x . The different situations correspond to $x_i \leq a_i$, $a_i \leq x_i \leq b_i$, or $x_i \geq b_i$.

The principle of this prolongation is to compose the function φ with the function π (the projection function of the point x on the domain D).

The extension of function φ is described by the following algorithm:

if $x_0 \leq a_0$ then

if $x_1 \leq a_1$ then

```

527         if  $x_2 \leq a_2$  then
528              $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(a_0, a_1, a_2)$ 
529         else
530             if  $x_2 \leq b_2$  then
531                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(a_0, a_1, x_2)$ 
532             else
533                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(a_0, a_1, b_2)$ 
534             end.
535         end.
536     else
537         if  $x_1 \leq b_1$  then
538             if  $x_2 \leq a_2$  then
539                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(a_0, x_1, a_2)$ 
540             else
541                 if  $x_2 \leq b_2$  then
542                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(a_0, x_1, x_2)$ 
543                 else
544                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(a_0, x_1, b_2)$ 
545                 end.
546             end.
547         else
548             if  $x_2 \leq a_2$  then
549                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(a_0, b_1, a_2)$ 
550             else
551                 if  $x_2 \leq b_2$  then
552                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(a_0, b_1, x_2)$ 
553                 else
554                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(a_0, b_1, b_2)$ 
555                 end.
556             end.
557         end.
558     end.
559 else
560     if  $x_0 \leq b_0$  then
561         if  $x_1 \leq a_1$  then
562             if  $x_2 \leq a_2$  then
563                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(x_0, a_1, a_2)$ 
564             else
565                 if  $x_2 \leq b_2$  then
566                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(x_0, a_1, x_2)$ 
567                 else
568                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(x_0, a_1, b_2)$ 
569                 end.
570             end.
571         else
572             if  $x_1 \leq b_1$  then

```

```

573         if  $x_2 \leq a_2$  then
574              $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(x_0, x_1, a_2)$ 
575         else
576             if  $x_2 \leq b_2$  then
577                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(x_0, x_1, x_2)$ 
578             else
579                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(x_0, x_1, b_2)$ 
580             end.
581         end.
582     else
583         si  $x_2 \leq b_2$  then
584              $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(x_0, b_1, x_2)$ 
585         else
586              $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(x_0, b_1, b_2)$ 
587         end.
588     end.
589 end.
590 else
591     if  $x_1 \leq a_1$  then
592         if  $x_2 \leq a_2$  then
593              $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(b_0, a_1, a_2)$ 
594         else
595             if  $x_2 \leq b_2$  then
596                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(b_0, a_1, x_2)$ 
597             else
598                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(b_0, a_1, b_2)$ 
599             end.
600         end.
601     else
602         if  $x_1 \leq b_1$  then
603             if  $x_2 \leq a_2$  then
604                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(b_0, x_1, a_2)$ 
605             else
606                 if  $x_2 \leq b_2$  then
607                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(b_0, x_1, x_2)$ 
608                 else
609                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(b_0, x_1, b_2)$ 
610                 end.
611             end.
612         else
613             if  $x_2 \leq a_2$  then
614                  $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(b_0, b_1, a_2)$ 
615             else
616                 if  $x_2 \leq b_2$  then
617                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(b_0, b_1, x_2)$ 
618                 else

```

```

619                                      $\tilde{\varphi}(x_0, x_1, x_2) = \varphi(b_0, b_1, b_2)$ 
620                                     end.
621                               end.
622       end.
623   end.
624 end.
625 end.

```