Two Cascaded and Extended Kalman Filters Combined With Sliding Mode Control for Sustainable Management of Marine Fish Stocks

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Abstract:
This paper deals with a possible approach to controlling marine fish stocks using the prey-predator model described by the Lotka-Volterra equations. The control strategy is conceived using the sliding mode control (SMC) approach which, based on the Lyapunov theorem, offers the possibility to track desired functions, thus guaranteeing the stability of the controlled system. One of the most important aspects of this model is the identification of some parameters which characterizes the model. In this work two cascaded and Extended Kalman Filters (EKFs) are proposed to estimate them in order to be utilized in SMC. This approach can be used for sustainable management of marine fish stocks: through the developed algorithm, the appropriate number of active fishermen and the suitable period for fishing can be determined. Computer simulations validate the proposed approach.

Keywords: *Lotka-Volterra Model, Sliding Mode Control, Extended Kalman Filter*

1. Introduction

Marine ecosystems provide humanity with a multitude of goods and services, including water quality, flood control and food supply, all of which are critical for human welfare. Since the human population is growing continuously, the demand for these goods and services is also increasing and progressively exerting more pressure on aquatic ecosystems. As many fish species migrate frequently and the oceans are mostly defined as public areas, the definition of clear boundaries and property rights regarding marine resources is rather complicated. As a result, most natural resources exploited by the fishing industry are defined as common-pool resources. This has resulted in many pelagic ecosystems experiencing high levels of depletion and overexploitation [1], with 46 % of European community fish stocks currently below their minimum biological level (European Environment Agency, [2]). The increasing intensity of human fishing activities in turn diminishes the biodiversity within the affected systems, which is positively correlated with the provision of the goods and services of the ecosystem that are of benefit to the human population, see [3]. Levels of biodiversity have been shown to determine the stability of marine ecosystems and their ability to recover. Consequently, Worm et al. suggest that business as usual in the fishing industry could potentially threaten global food security and water quality, as well as ecosystem resilience, and thus jeopardise present and future generations, see [3]. The observed trend is thus of increasing concern, so the topic of the conservation and restoration of aquatic biodiversity through sustainable fishery management is increasingly visible in scientific and political agendas. The United Nations has included this issue in its sustainable development goals, dedicating goal number 14 to the conservation and sustainable usage of the planet's oceans, seas and marine resources, [4]. The successful implementation of this goal includes the adaptation of sustainable methods to manage marine and coastal ecosystems in order to avoid significant adverse effects, which is indicated by the proportion of national economic zones following ecosystem-based approaches. By 2020, the United Nations aims to regulate destructive fishing activities and end overfishing, alongside implementing a science-based management approach to restore natural fish stocks (United Nations, 2019). In addition, the European Union has conducted several reforms of the Common Fisheries Policy (CFP), establishing different approaches to attempt to bring the situation under control, with the goal of reaching and maintaining a sustainable level of fish in the oceans and in fishermen's nets. As common practice in this field, scientists estimate the existing level of fish stocks within an area and suggest a number of total allowable catches (TACs) to political fishery ministers. In turn, those ministers try to bargain and receive the highest shares for their regions, which often leads to the amount of TACs exceeding the maximum level recommended by scientists, rather than levels being allocated for mutual benefit and optimal conservation purposes. As a result, the methods of the EU are rather unsuccessful for maintaining a sustainable yield of fish and achieving the targets adopted by all member states of the United Nations: as [5] claims, the decision-making process within the catch allocation should be managed by scientists rather than by politicians. One possible approach to enhancing this decision-making process and expanding it based on an independent and objective component, driven by scientific data, is to translate the observed ecosystem into a mathematical model using MATLAB and simulate them with the integrated tool MATLAB/Simulink. MATLAB is a software package used to describe dynamic systems in a mathematical model and can be used to identify the interdependences, mutual interactions, information feedback loops and circular causalities existing in the observed system. This article is an extension of the research presented in [6]. In this work the estimate of some parameters which characterize the model taken into consideration using Extended Kalman Filters (EKF). Thus, this paper aims to offer a first attempt at exploring how MATLAB and Simulink can be utilised to facilitate the implementation of sustainable management approaches in the fishing industry through strategic policy testing. The software will be used to formulate a simple mathematical description of a marine ecosystem based upon the prey-predator system represented in the Lotka-Volterra equations. A number of papers dealing with simulated prey-predator systems have been published previously; however, adaptation of the model to a marine ecosystem including fish stocks and human fishers has not yet been covered. In order to simulate the consequences of various possible policies through different controllers, these have been incorporated into the code to eventually reach and maintain a certain setpoint equal to the maximum sustainable yield of fish. In terms of the proposed control technique, sliding mode control (SMC) is taken as one of the first possible approaches. In fact, the controllers obtained by an SMC approach show robust properties with respect to parameter uncertainties, as well with respect to more general dynamic uncertainties and to unknown signals. Another application for which SMC has suitable qualities is the field of fault-tolerant control (FTC). In this area, due to intrinsic robustness, SMC models are able to overcome faults and uncertainties. Nevertheless, large uncertainties in the model imply strong chattering effects. Therefore, one of the most important aspects of this approach is the identification of some parameters which characterize the model. In this work, two cascaded and EKFs are proposed to estimate them in order to be utilized in SMC. KF is one of the most important and used algorithms in the field of identification of states and parameters of a system of any nature. During the last years many different contributions appeared in many fields of applications and in different technical estimation and identification contexts, [7], [8]. Very often, to reduce problems of curse of dimensionality KFs are split and organized in cascaded forms as for instance in [9]. Just to recall very briefly, KF is one of the algorithms using series of the observed measurements over time and it also contains inaccuracies such as statistical noise. Estimates of unknown variables are produced by KF and they are more accurate than the estimates based on the only measurements by estimating a joint probability distribution over the variables for each time frame, see [10], [11] and [12]. In fact, the controllers obtained by an SMC approach show robust properties with respect to parameter uncertainties, as well with respect to more general dynamic uncertainties and to unknown signals. Another application for which SMC has suitable qualities is the field of fault-tolerant control (FTC). In this area, due to intrinsic robustness, SMC models are able to overcome faults and uncertainties. Concerning the measurements of the prey, recent research held at the University Laval and Quebec's Ministry of Forests, see [13], Wildlife and Parks treated the topic of DNA found in lake water which can be used for estimation of the fertility of fish which live there. This revolutionary approach presented in the Journal of Applied Ecology can contribute to understanding how fish stocks are managed in lakes. 10 one-liter samples of water from different areas of each lake under investigation were analysed by the researchers to be able to estimate the concentration of DNA of the lake trout. The water was filtered and particles for genomic analysis helped to measure the trout DNA in the water samples. A strong correlation between population estimates obtained by means of the traditional approach and the one based on the DNA concentration is presented in the results. The paper is organised in the following way. In Section 2 the Lotka-Volterra model is presented. Section 3 is devoted to the control design performed using SMC without and with using EKF. Section 5.1 presents the obtained results and the paper ends with the conclusions drawn.

2. Model Design

The designed model is inspired by the ecological concept of the prey and predator relationship. This concept was formulated by Lotka and Volterra, and is based upon different mathematical theorems.

2.1. Lotka-Volterra Equations

The assumptions of Lotka and Volterra are taken as a basis to describe the relationship between natural fish stocks and the fishing activities of humans. Lotka and Volterra first describe the population dynamics of two species in a prey and predator relationship through two first-order nonlinear differential equations, as follows:

$$\frac{dx(t)}{dt} = \alpha x(t) - \beta x(t)y(t), \tag{1}$$

$$\frac{dy(t)}{dt} = \delta x(t)y(t) - \gamma y(t), \tag{2}$$

where $x(t)$ represents the number of prey and $y(t)$ represents the number of predators. $\frac{dx(t)}{dt}$ and $\frac{dy(t)}{dt}$ represent the growth rates of the populations based on the respective changes within their population sizes over time, which is denoted by the term t. $\alpha, \beta, \delta, \gamma$ are positive real parameters and describe the interaction between the two populations. The expression (1) represents the dynamics of the prey population, which are calculated by subtracting the rate of predation from the population's intrinsic growth rate. Since it is assumed that the prey has an unlimited food supply, its population grows exponentially if the population of predators and the rate of predation equal zero, which is expressed by the term $\alpha x(t)$. In turn, the rate of predation upon the prey is assumed to be proportional to $\beta x(t)y(t)$. Thus, if either $x(t)$ or $y(t)$ equals zero, there is no predation.

Equation (2) describes the dynamics of the predator population, which are determined by the rate at which it consumes the prey population, minus its intrinsic death rate. Since the growth rate of the predator population does not necessarily equal the rate of predation of the prey, it is expressed by $\delta x(t)y(t)$, which is similar but not equal to the term representing the rate of predation in Eq. (1). In this equation, $\gamma y(t)$ denotes the loss rate of the predator population due to natural death or emigration. This results in an exponential decay if there is no prey available to be consumed. Since the main objective of designing this new approach is to achieve and maintain sustainable levels of fish stocks and harvests alike, an equilibrium point between the two populations is intended. This point is reached if:

$$\frac{dx(t)}{dt} = 0, \tag{3}$$

$$\frac{dy(t)}{dt} = 0. \tag{4}$$

As a result, putting the corresponding equations also equal zero, wherefore one has:

$$0 = \alpha x(t) - \beta x(t)y(t), \tag{5}$$

$$0 = \delta x(t)y(t) - \gamma y(t). \tag{6}$$

These equations yield two different solutions. One solution states that both populations become extinct:

$$x(t) = 0, \quad y(t) = 0. \tag{7}$$

Given the second solution, a fixed point can be achieved at which both populations sustain their current non-zero numbers, depending on the settings of the four parameters $\alpha, \beta, \delta, \gamma$. This yields:

$$y(t) = \frac{\alpha}{\beta}, \tag{8}$$

$$x(t) = \frac{\gamma}{\delta}. \tag{9}$$

Considering the Linearization Lyapunov Theorem it is possible to determine the nature of these two equilibrium points. The Jacobian matrix is as follows:

$$\mathbf{J} = \begin{bmatrix} \alpha - \beta y(t) & -\beta x(t) \\ \delta y(t) & \delta x(t) - \gamma \end{bmatrix}. \tag{10}$$

At the extinction point $(0, 0)$ the Jacobian matrix becomes:

$$\mathbf{J} = \begin{bmatrix} \alpha & 0 \\ 0 & -\gamma \end{bmatrix}, \tag{11}$$

with the following two eigenvalues $\lambda_1 = \alpha$ and $\lambda_2 = -\gamma$. This implies instable equilibrium points. Considering the second equilibrium point stated by (9), then

$$\mathbf{J} = \begin{bmatrix} 0 & -\frac{\beta\gamma}{\delta} \\ \frac{\alpha\delta}{\beta} & 0 \end{bmatrix}, \tag{12}$$

with the following two complex eigenvalues $\lambda_1 = j\sqrt{\alpha\gamma}$ and $\lambda_2 = -j\sqrt{\alpha\gamma}$. This implies oscillating point and no conclusion about the nature of this equilibrium point.

3. Sliding Mode Control

As the goal of the simulation is to realise and establish sustainable fishing activities in order to ensure the continuity of both marine ecosystems and the human species, the current situation of overfishing and ocean depletion has to be stopped and managed in a way that enables fish stocks to recover. Therefore, the error between the desired setpoint, being the equilibrium point of the fishery system, and the actual value, represented by the current level of fish, has to be ascertained, harmonised and stabilised. This is explored through application of the Lyapunov Theorem. With zero being the intended value for $\dot{x}(t) = f(x, u, t)$, the theorem defines that if:

$$V(x(t)) > 0, \forall x(t), \tag{13}$$

$$V(0) = 0, \tag{14}$$

the function is positive and if:

$$\dot{V}(x(t)) < 0, \forall x(t) \tag{15}$$

and one has:

$$\dot{x}(t) = f(x, u, t), \tag{16}$$

then $x(t) = 0$ is an asymptomatic stabile point for function $\dot{x}(t) = f(x, u, t)$.
In order to reduce the error and harmonise the actual value of fish with the desired value of fish associated with a sustainable population size, an SMC is used as follows:

$$S(t) = (x_d(t) - x(t)) + k_s \int_0^t (x_d(z) - x(z))d_z, \tag{17}$$

where k_s is a parameter to be designed. Since the V-function is a positive-define function of $x(t)$, it can be employed in the function above. Therefore, one gets:

$$V(S(t)) = \frac{1}{2}S^2(t). \tag{18}$$

Thereupon, the function is differentiated, which yields:

$$\dot{V}(S(t)) = \frac{1}{2}2S(t)\dot{S}(t), \tag{19}$$

$$= S(t)\left[(\dot{x}_d(t) - \dot{x}(t)) + k_s(x_d(t) - x(t))\right], \tag{20}$$

$$= S(t) \left[\dot{x}_d(t) - \big(\alpha x(t) - \beta x(t)y(t)\big) + k_s(x_d(t) - x(t))\right], \tag{21}$$

if: $y(t) = y_{eq}(t) =$

$$\frac{-\dot{x}_d(t) + \alpha x(t) - k_s(x_d(t) - x(t))}{\beta x(t)}, \tag{22}$$

then $\dot{V}(S(t)) = 0$ and if:

$$y(t) = y_{eq}(t) - \frac{\eta sgn(S(t))}{\beta x(t)}, \tag{23}$$

with

$$sgn(S(t)) = \begin{cases} 1 \text{ if } S(t) > 0 \\ 0 \text{ if } S(t) = 0 \\ -1 \text{ if } S(t) < 0, \end{cases} \tag{24}$$

then, if $\eta > 0$:

$$\dot{V}(S(t)) = S(t)[-\eta sgn(S(t))] \\ = -\eta S(t) sgn(S(t)) = -\eta|S(t)| < 0. \quad (25)$$

In order to accelerate the process and reach the desired value more quickly, term $\lambda S(t)$, with $\lambda > 0$, can be included in the equation. The resulting control law is as follows:

$$y(t) = y_{eq}(t) - \frac{\eta sgn(S(t))}{\beta x(t)} - \frac{\lambda S(t)}{\beta x(t)}. \quad (26)$$

Remark 1 *It is known that, if Δ represents the upper bound of the uncertainties of the cancellation through the equivalent part of the control, see (22), then to guarantee the convergence it is sufficient to impose $\eta > \Delta$.*

3.1. Euler Method

Since the system in question has a relatively slow dynamics, it is not intended to measure its state second-by-second, but rather on a monthly basis. Therefore, the equation is discretised according to the Forward Euler method, where k represents the known counting integer variable and T_s represents the known sampling time, which yields:

$$\dot{x}(t) = \frac{x(k) - x(k-1)}{T_s}$$

$$= \alpha x(k-1) - \beta x(k-1)y(k-1) \quad (27)$$

$$\rightarrow x(k) = x(k-1) + T_s\big(\alpha x(k-1) \\ - \beta x(k-1)y(k-1)\big). \quad (28)$$

At this point, the respective equations are integrated into Matlab. With the number of predators and respectively the number of fishermen represented by $y(t)$, being the leverage point to control the level of fish stocks in the regarded aquatic ecosystem, Eq. (26) represents one of the main equations in the SMC. Since the goal of the applied controller is to harmonise the desired and actual amounts of fish, measured in kilogram biomass, the desired amount of fish (denoted by $x_d(t)$) and the actual amount of fish (represented by $x(t)$) are the two main data inputs for the equation. Eq. (26) represents the main equation within the SMC strategy.

4. An Extended Kalman Filter in the Control Loop

The two KFs represeted in Fig. 1 consider the measured prey $x(k)$ as output measured signal and parameter $\alpha(k)$ and $\beta(k)$ are the two augmented state to be estimated and $y(k-1)$ is the number of predators which represents the measured input. The a priori estimation of the augmented state of EKF I is as follows:

$$\hat{\alpha}^-(k) = \hat{\alpha}(k-1), \quad (29)$$

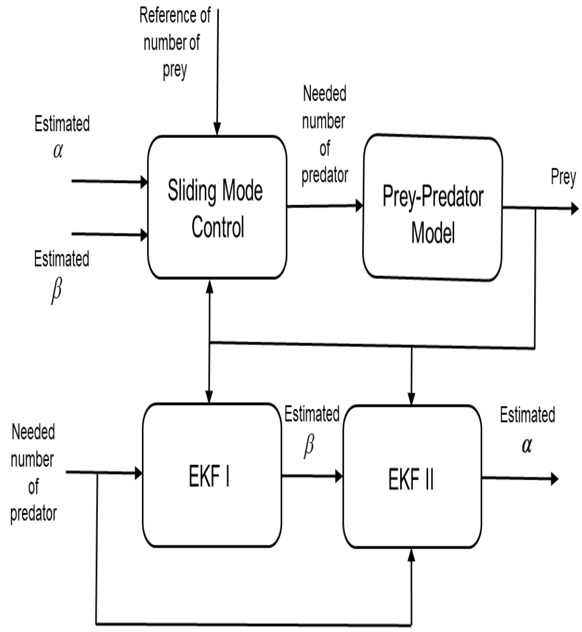

Fig. 1. Control Scheme

and the augmented state of EKF II is as follows:

$$\hat{\beta}^-(k) = \hat{\beta}(k-1). \quad (30)$$

The a priori predicted covariance matrix is

$$P^-(k-1) = J_{\mathrm{d}} P(k-1) J_{\mathrm{d}}^{\mathrm{T}} + Q_w, \quad (31)$$

where Q_w is the process noise covariance matrix and matrix J_{d} represents the discrete state Jacobian matrix which is an identity matrix and in our case is represented by the scalar for both EKFs:

$$J_{\mathrm{d}} = 1.$$

Considering that for EKF I which estimates parameter $\hat{\beta}^-(k) = \hat{\beta}(k-1)$ as a stochastic augmented state, the equation of the output prey state is as follows:

$$h_I(k) = (1 + T_s\hat{\alpha}(k-1))x(k-1) \\ - \hat{\beta}(k-1)T_s x(k-1)y(k-1), \quad (32)$$

where T_s represents the sampling time and $y(k-1)$ represents the input predator variable. The output Jacobian of $h_I(k)$ is as follows:

$$H_I(k) = -T_s x(k-1)y(k-1).$$

Considering that for EKF II which estimates parameter $\hat{\alpha}^-(k) = \hat{\alpha}(k-1)$ as a stochastic augmented state, the equation of the output is exactly the same as for EKF I:

$$h_{II}(k) = (1 + T_s\hat{\alpha}(k-1))x(k-1) \\ - \hat{\beta}(k-1)T_s x(k-1)y(k-1) \quad (33)$$

and its output Jacobian is as follows:

$$H_{II}(k) = -T_s x(k-1).$$

The following equations state the correction (a posteriori prediction) of for both EKF, EKF I and EKF II:

$$\begin{aligned} K_{(.)}(k) &= P^-(k-1)H_{(.)}^{\mathrm{T}}\big(H_{(.)}P^-(k-1)H_{(.)}^{\mathrm{T}}+\zeta\big)^{-1}, \\ \alpha(k) &= \hat{\alpha}(k-1)+K_{(.)}(k)\big(x(k)-h(k)\big), \\ \beta(k) &= \hat{\beta}(k-1)+K_{(.)}(k)\big(x(k)-h(k)\big), \\ P_{(.)}(k) &= P_{(.)}(k-1)-K_{(.)}(k)H_{.}P_{(.)}(k-1), \end{aligned} \tag{34}$$

where ζ is the measurement noise covariance variable and $\mathbf{K}(k)$ is the Kalman gain and $x(k)$ represents the measured biomass.

5. Simulation Results

It is known, that in the presence of uncertainties SMC should provide to switch with a sufficient large amplitude of η to guarantee the convergence, see (22). In this paragraph the use of EKF is proposed to relax the task of SMC. Tests without considering cancellation errors are shown at the beginning and after simulations using EKF in the presence of cancellation errors are shown.

5.1. Simulation Results Without Using EKF and Without Errors in α and β

In order to test the designed model it is assumed that a sustainable level of fish stocks is reached at a minimum of 10.000 kg of fish. The goal is then to test how the attendance of fishermen affects the dynamics of the prey population and how a meaningful policy designed to regulate the activities of the fishermen could be framed. Figure 2 shows the number of fishermen in a system that is not restricted by political regulations. The line graph shows the development of the number of fishermen over a period of 60 months. In the absence of political regulations, the number of fishermen immediately increases to 1.000 and remains stable over the entire period of time. The line graph depicted in Fig. 3 shows the corresponding dynamics of the fish population over a period of 60 months, given the same situation that no political regulation of fishing activities exists. In this scenario the amount of fish peaks at 11.000 kg after approximately three months and stabilises at the desired amount of 10,000 kg after 60 months. In order to test how a political regulation regarding the number of active fishermen affects the system, a hypothetical regulation has been assumed demanding that all fishing activities are prohibited between the 5^{th} and the 8^{th} month of the period in question. This regulation is realised through an if-clause in the m-file of Matlab, as follows: $if((T<5)|(T>8))$

$$y(t) = y_{eq}(t) - \frac{\eta sgn(S(t))}{\beta x(t)}. \tag{35}$$

As a result, the number of fishermen depicted in Fig. 4 rises to 1.000 and remains at that level until it drops

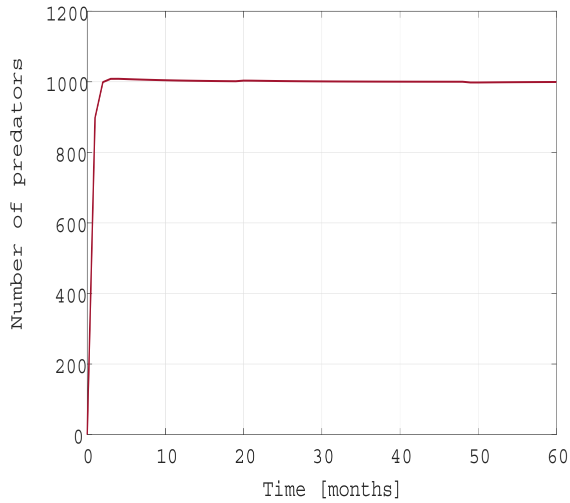

Fig. 2. Number of predators without regulation

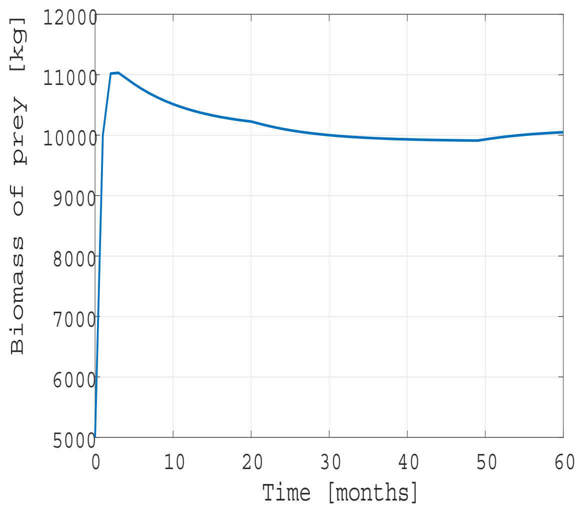

Fig. 3. Biomass of prey without regulation

to 0 at the five-month mark. It then remains at 0 until the 8^{th} month and temporarily increases to 1.100 after this point. Subsequently, the number slowly decreases again until it returns to a level of 1.000 after 60 months. The consequences of the regulation regarding the level of fish stocks in kilogram biomass is depicted in Fig. 5. At the beginning of the time period in question, when the number of fishermen is high, the fish biomass level is at 10.000 kg. As soon as the regulation takes effect, the fish biomass increases exponentially, peaking at 17.500 kg at eight months. Since the fishermen resume their activities from the 8^{th} month onwards, the biomass level decreases again, stabilising at the desired level of 10.000 kg after 60 months. The results show that the designed model is indeed sensitive to regulatory changes, and that it is able to depict the dynamics of the interdependent populations.

5.2. Simulation Without Using EKF and Including Errors in α and β

If an error is considered in the parameter of α, then it is possible that SMC needs to work with large gain η

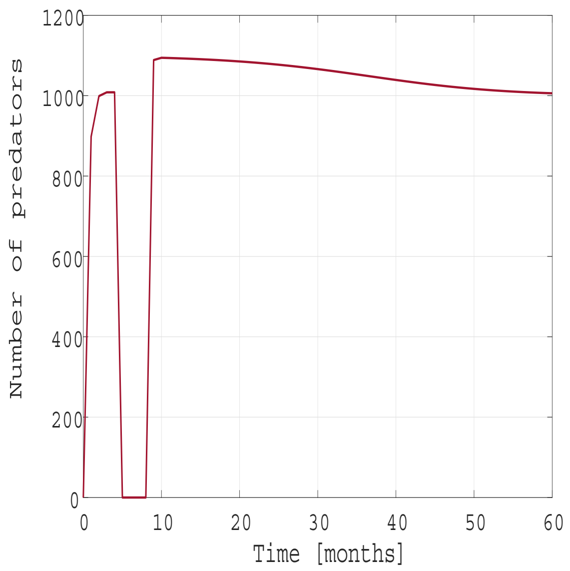

Fig. 4. Number of predators with regulation

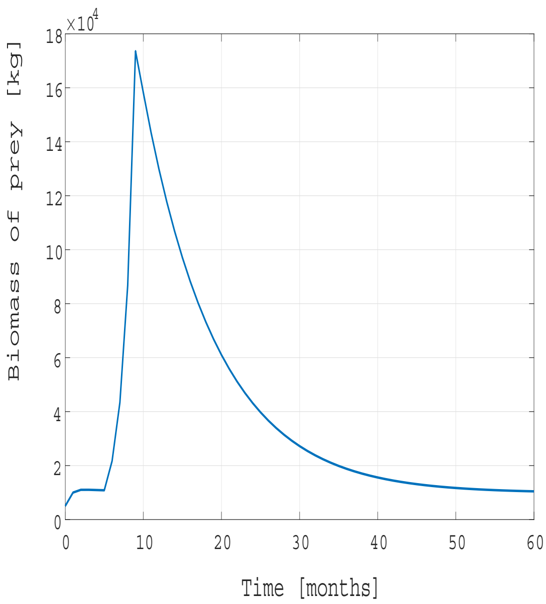

Fig. 5. Biomass of prey with regulation

and λ to obtain the same performances. Nevertheless, using large η the chattering phenomenon results to be increased. In Fig. 6, a possible result in term of control is shown in which an error of 20% is considered in the parameter α without increasing the tuning parameters of SMC. In Fig. 7, it is visible how the sliding surface does not reach zero.

5.3. Simulation Results Using EKF and Including Errors in α and β

Using the control scheme of Fig. 1 in which an EKF is utilized in the control loop the following results are obtained. Figures 8 and 9 show how the EKF can estimate parameters α and β even with an initial condition error on parameters α and β of 20%. Figure 10 shows the result of the controlled biomass inside the

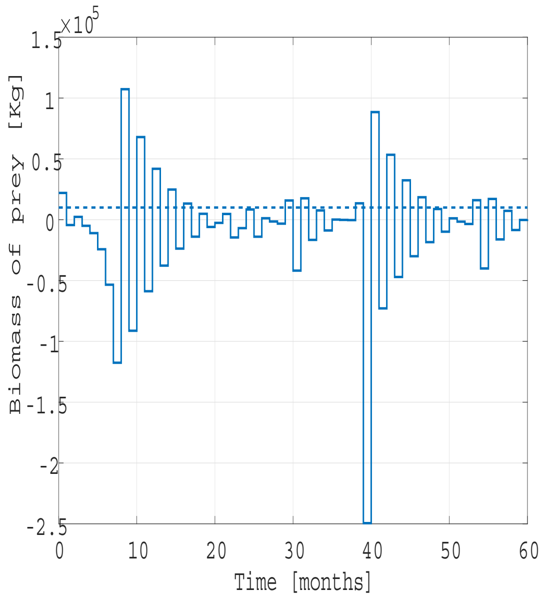

Fig. 6. Biomass of prey without Kalman estimator and with 20% of the error in parameter α

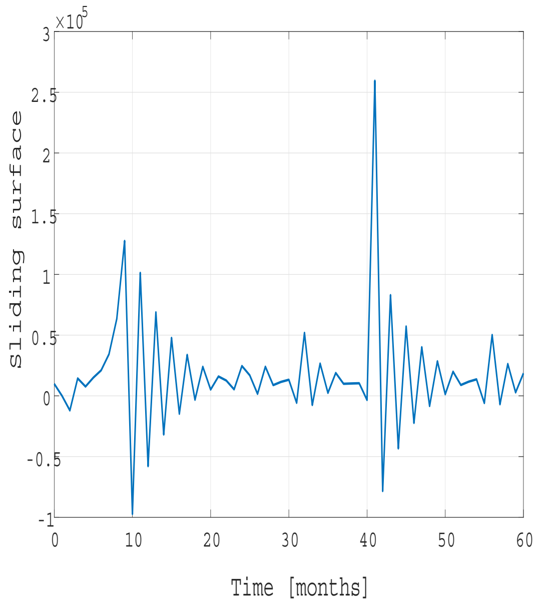

Fig. 7. Sliding surface without Kalman estimator and with 20% of the error in parameter α

described regulation in which the proposed EKF is utilised in the control loop. A biased error on parameters α and β of 20% is simulated with error in the initial value of biomass. Figure 11 shows the number of predators with regulation and using EKF in the control loop. Figure 12 indicates the sliding surface in the presence of the EKF estimation action.

6. Conclusion

Since the implementation of a regulating if-clause in the m-file yields a reasonable result, the model seems to work and to be appropriate for policy testing

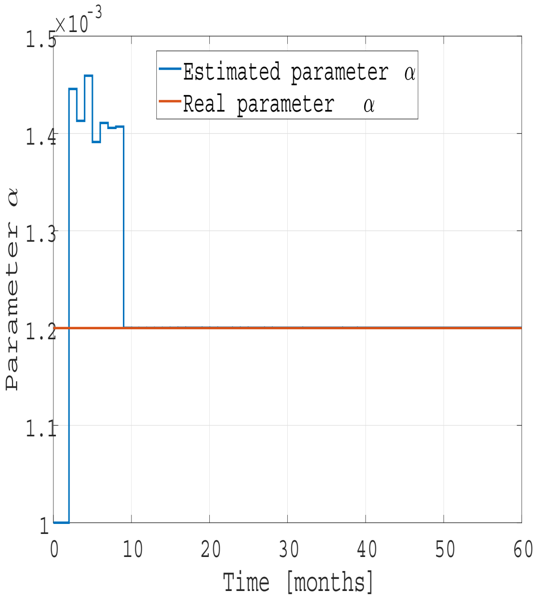

Fig. 8. Estimation of parameter α using EKF in the control loop with an initial error of 20% in parameter α

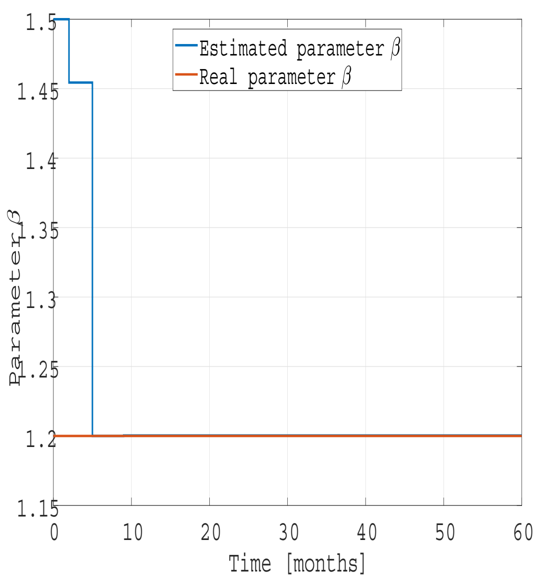

Fig. 9. Estimation of parameter β using EKF in the control loop with an initial error of 20% in parameter α

in the fishing industry. An algorithm is built in which the biomass of prey is controlled using an SMC strategy. To estimate the necessary parameter of the model, in this work two cascaded and Extended Kalman Filters (EKFs) are proposed to estimate them in order to be utilized in SMC. However, further research will be necessary in order to construct more complex models, and thus more realistic ones, by including additional variables that may influence the system. In addition, appropriate measurements must be taken and the values within the models must be adapted accordingly in order to obtain realistic and meaningful results.

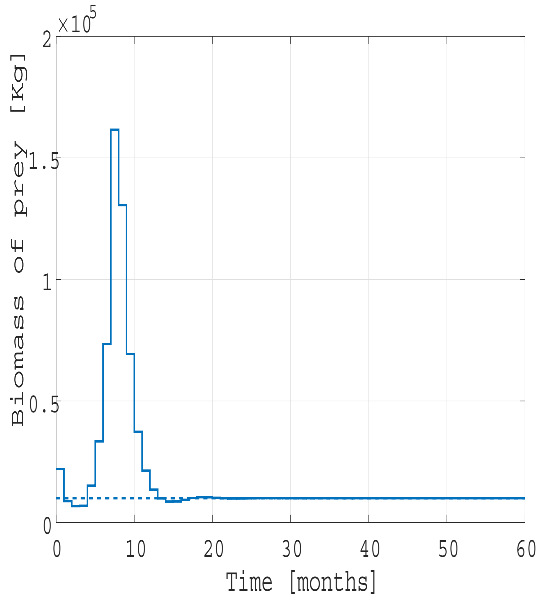

Fig. 10. Biomass of prey using EKF in the control loop with an initial error of 20% in parameter α

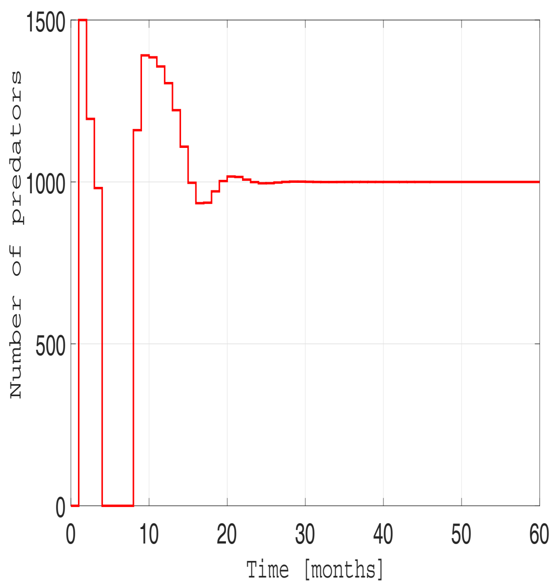

Fig. 11. Number of predators using EKF in the control loop with an initial error of 20% in parameter α

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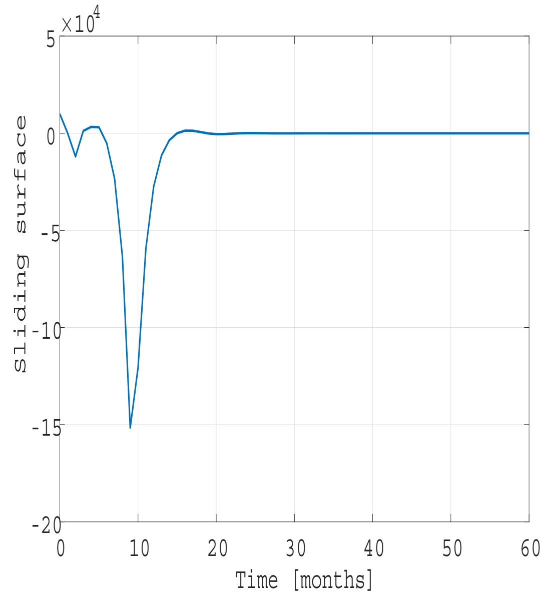

Fig. 12. Sliding surface with Kalman estimator and with 20% of the error in parameter α

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REFERENCES

[1] H. Gordon, "The economic theory of a common-property resource: The fishery", *The Journal of Political Economy*, vol. 62, no. 2, 1954, 124–142, www.jstor.org/stable/1825571.

[2] "EU 2010 biodiversity baseline". European Environment Agency (EEA), 2010. Accessed on: 2020.12.02.

[3] B. Worm, E. B. Barbier, N. Beaumont, J. E. Duffy, C. Folke, B. S. Halpern, J. B. C. Jackson, H. K. Lotze, F. Micheli, S. R. Palumbi, E. Sala, K. A. Selkoe, J. J. Stachowicz, and R. Watson, "Impacts of Biodiversity Loss on Ocean Ecosystem Services", *Science*, vol. 314, 2006, 787–790, 10.1126/science.1132294.

[4] United Nations. "Sustainable development goal 14". https://sustainabledevelopment.un.org/sdg14. Accessed on 2020.12.18.

[5] B. Leary, J. Smart, F. Neale, J. Hawkins, S. Newman, A. Milman, and C. Roberts, "Fisheries mismanagement", *Marine Pollution Bulletin*, vol. 62, no. 12, 2011, 2642–2648, 10.1016/j.marpolbul.2011.09.032.

[6] K. Benz, C. Rech, and P. Mercorelli, "Sustainable Management of Marine Fish Stocks by Means of Sliding Mode Control". In: *2019 Federated Conference on Computer Science and Information Systems (FedCSIS)*, vol. 18, 2019, 907–910, 10.15439/2019F221.

[7] P. Mercorelli, "A hysteresis hybrid extended Kalman filter as an observer for sensorless valve control in camless internal combustion engines", *IEEE Transactions on Industry Applications*, vol. 48, no. 6, 2012, 1940–1949, 10.1109/TIA.2012.2226193.

[8] P. Mercorelli, "A two-stage augmented extended Kalman filter as an observer for sensorless valve control in camless internal combustion engines", *IEEE Transactions on Industrial Electronics*, vol. 59, no. 11, 2012, 4236–4247, 10.1109/TIE.2012.2192892.

[9] B. Haus, H. Aschemann, and P. Mercorelli, "Tracking control of a piezo-hydraulic actuator using input-output linearization and a Cascaded Extended Kalman Filter structure", *Journal of the Franklin Institute*, vol. 355, no. 18, 2018, 9298 – 9320, 10.1016/j.jfranklin.2017.07.042.

[10] R. Kalman, "A New Approach to Linear Filtering and Prediction Problems", *Transactions of the ASME-Journal of Basic Engineering*, vol. 82, 1960, 35–45.

[11] P. S. Maybeck, *Stochastic Models, Estimation, and Control*, volume 1, Academic Press, Inc., 1979.

[12] F. L. Lewis, *Optimal Estimation with an Introduction to Stochastic Control Theory*, Wiley-Interscience, 1986.

[13] A. Lacoursière-Roussel, G. Côté, V. Leclerc, and L. Bernatchez, "Quantifying relative fish abundance with edna: a promising tool for fisheries management", *Journal of Applied Ecology*, 2016.