Dynamic Output Feedback Fault Tolerant Controller for a Harvested Fish Population System

ACHRAF AIT KADDOUR, NOUREDDINE ELALAMI
Electrical Engineering Department
Ecole Mohammadia d’Ingénieurs
Rabat
MOROCCO
achraff@gmail.com

Abstract: - This paper addresses the problem of robust fault estimation and fault tolerant control of a continuous age structured model of a harvested fishery system. The harvested fish population is represented by Takagi-Sugeno fuzzy systems, where the effort is used as a control term, the age classes as a states and the quantity of captured fish per unit of effort as a measured output. Under some biological satisfied assumptions, we design a fuzzy augmented fault estimation observer to achieve fault estimation with actuator faults. Furthermore, based on the information of fault estimation, an observer based dynamic output feedback fault tolerant controller is designed to compensate for the effect of faults by stabilizing the closed loop system. The simulation results demonstrate the effectiveness of the proposed method.

Key-Words: - Dynamic output feedback, harvested fish population, Takagi-Sugeno multimodel, fault-tolerant control.

1 Introduction
Heavy use of the world’s marine fisheries is a severe concern. Significant increases in human population and rapid technological advances during the past decades have resulted in a vast increase in global production of marine capture fisheries. Today, these fisheries are in trouble as their populations are being depleted to dangerously low levels, which are affecting national economies and local communities’ socio-economic well-being. The optimal management of renewable resources, which has a direct relationship to sustainable development, must receive much attention. It requires further discussion in order to understand short and long term exploitation patterns. Therefore, it is very important for key stakeholders to plan a suitable pattern that sustains fisheries at a good level of productivity and meets economic goals.

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 [1,2,3,4,7].

Recently, there has been a growing interest in the Takagi-Sugeno T-S fuzzy system since it is a powerful solution that bridges the gap between linear and nonlinear control systems. The most important advantage of the T-S fuzzy system is its universal approximation of any smooth nonlinear function by combining some local linear system models, which greatly facilitates the analysis and synthesis of the complex nonlinear system. Many important results on analysis and synthesis for the T-S fuzzy system have been reported [9,10,11,12]. Considering the advantage of the T-S fuzzy system to approximating complex nonlinear systems, we will use it to describe the harvested fish population dynamics in this paper. Because of their nonlinearity and their complexity that are associated with biological phenomena (birth, death, growth, cannibalism, intra-stage competition for food and space, etc.), and because also of massive over exploitation, breakdown of regulatory and enforcement systems, harvested fish populations dynamics are inevitably subjected to disturbances which have as origin the noises due to the environment and the model uncertainties. Moreover, sensors and/or actuators can be corrupted by different faults or failures. To improve fish resources sustainability, FTC scheme must be considered in designing good harvesting policies. FTC allows controlling system in such a way that it fulfills desired objectives (perhaps with a possible performance degradation) in the presence of non-critical faults in components of the system[5,6].

This paper addresses the problem of controlling exploited fish population systems through dynamic output feedback fault tolerant controller and using T-S fuzzy models, based on the idea given in [5]. To the best of our knowledge, this problem has not been studied in the literature.

The rest of this paper is organized as follows. In the second section, a fuzzy-augmented fault estimation observer design is proposed to achieve fault estimation of T-S models with actuator faults. Based on the information of online fault estimation, an observer based dynamic output feedback fault tolerant controller is designed to compensate the effect of faults by stabilizing the closed-loop system. Sufficient conditions for the existence of both observer and controller are given in terms of linear matrix inequalities. The third section is dedicated to the description of the continuous stage structured model, which is transformed to a T-S fuzzy model. Finally, simulation results are presented to demonstrate the effectiveness of the proposed technique.

2 Observer And Controller Design And Analysis
Restrictive constraints are relaxed through a general observer-based dynamic output feedback-fault tolerant controller design for a class of T–S fuzzy systems under actuator faults. In this section, a multi objective fuzzy augmented fault-estimation observer, including a regional pole placement and a $H_\infty$ performance level, is proposed, to guarantee the convergence speed of fault estimation and to restrict the influence of disturbances as much as possible as well. Then, using the online fault estimate, a fuzzy observer-based dynamic output feedback-fault tolerant controller is designed to guarantee the system stability in the presence of actuator faults. In the design process, the observer and the controller are independently designed, and their performances are considered simultaneously, which is convenient for calculating the design parameters.

2.1 Model Representation
The design procedure describing in this section begins with representing a given nonlinear plant by the so-called T-S fuzzy
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A dynamic T-S fuzzy model is described by a set of fuzzy “IF … THEN” rules with fuzzy sets in the antecedents and dynamic linear time-invariant systems in the consequents. A generic T-S plant rule can be written as follows [10]:

\[ \text{IF } z(t) \text{ is } M_{ij} \text{ and } ... \text{ and } z_p(t) \text{ is } M_{ip}, \]

\[ \text{THEN } \]

\[ \dot{x}(t) = A(z(t))x(t) + B(z(t))u(t) + f(t) + D_{2i}w(t) \]

and \( z(t) \in \mathbb{R}^p \) is the output vector, \( u(t) \in \mathbb{R}^m \) is the input vector, \( y(t) \in \mathbb{R}^p \) is the output vector, \( x(t) \in \mathbb{R}^n \) is the state vector, and \( f(t) \in \mathbb{R}^q \) is the disturbance, which is assumed to belong to \( L_\infty q \). \( A, B, C, D \) are constant real matrices of appropriate dimensions. It is supposed that matrices \( B, C, D \) are of full column rank, i.e., rank(\( B \)) = m, the pairs \((A, B)\) are controllable, and the pairs \((A, C)\) are observable. \( 1 \leq i \leq p, 1 \leq j \leq m \) are known premise variables that may be functions of the state variables, external disturbances, and/or time.

Each linear consequent equation represented by \( A_i(z(t))x(t) + B_i(z(t))u(t) + f(t) + D_{2i}w(t) \) can be written as follows:

\[ \dot{x}(t) = \sum_{i=1}^{p} \mu_i(z(t)) (A_i(z(t))x(t) + B_i(z(t))u(t) + f(t) + D_{2i}w(t)) \]

where \( \mu_i(z(t)) = \frac{w_i(z(t))}{\sum_{i=1}^{p} w_i(z(t))} \). Since 

\[ \sum_{i=1}^{p} w_i(z(t)) > 0 \]

and 

\[ w_i(z(t)) \geq 0, \quad i = 1, 2, ..., p \]

we have:

\[ \sum_{i=1}^{p} \mu_i(z(t)) = 1 \]

and \( \mu_i(z(t)) \geq 0, \quad i = 1, 2, ..., p \) for all \( t \). The global output of T-S model is interpolated as follows:

\[ y(t) = \sum_{i=1}^{p} \mu_i(z(t)) C_i x(t) + D_{2i}w(t) \]

For simplicity, we introduce the following notations:

\[ \mu_i = \mu_i(z(t)) \quad \mu_i = \sum_{i=1}^{p} \mu_i A_i \quad \mu_i = \sum_{i=1}^{p} \mu_i B_i \]

\[ C_i = \sum_{i=1}^{p} \mu_i C_i \quad D_i = \sum_{i=1}^{p} \mu_i D_{2i} \]

and \( D_2 = \sum_{i=1}^{p} \mu_i D_{2i} \)

Then, the T-S fuzzy model (2) and (3) can be rewritten as:

\[ \dot{x}(t) = A(x(t))x(t) + B(x(t))u(t) + f(t) + D_2w(t) \]

\[ y(t) = C(x(t))x(t) + D_2w(t) \]

2.2 Fuzzy augmented fault-estimation observer design

In order to detect and estimate faults, the following fault estimation observer is constructed:

\[ \dot{x}(t) = A(\mu)\dot{x}(t) + B(\mu)(u(t) + f(t)) + L(\mu)(y(t) - \hat{y}(t)) \]

(6)

\[ \hat{y}(t) = C\hat{x}(t) \]

(7)

\[ f' = -F(\mu)(\hat{y}(t) - y(t)) \]

(8)

where \( \hat{x}(t) \) is the observer state, \( \hat{y}(t) \) is the observer output, and \( f(t) \) is an estimate of the fault \( f(t) \).

\( L(\mu) = \sum_{i=1}^{p} \mu_i L_i \) and \( F(\mu) = \sum_{i=1}^{p} \mu_i F_i \) are the gain matrices to be determined.

Now, we use the error dynamics:

\[ \dot{e}_x(t) = (\hat{A}(\mu) - L(\mu)C)\dot{x}(t) + (L(\mu)D_2 - D_2\hat{x}(t)) y(t) \]

(9)

\[ e_y(t) = C(\mu)\hat{e}(t) - D_2(\mu) y(t) \]

(10)

where

\[ \hat{e}(t) = (\hat{A}(\mu) - L(\mu)C)\hat{x}(t) + (L(\mu)D_2 - D_2\hat{x}(t)) y(t) \]

and \( e_y(t) = \hat{y}(t) - y(t) \). Then, the error dynamics is ruled by:

\[ \dot{e}_x(t) = \hat{A}(\mu)\dot{x}(t) + \hat{B}(\mu)u(t) + \hat{f}(t) + D_{2i}(\mu)w(t) \]

\[ e_y(t) = C(\mu)\dot{e}(t) - D_2(\mu) y(t) \]

\[ \dot{z}(t) = \hat{A}(\mu)z(t) + \hat{B}(\mu)u(t) + \hat{f}(t) + D_{2i}(\mu)w(t) \]

(11)

\[ e_y(t) = C(\mu)\dot{z}(t) - D_2(\mu) y(t) \]

(12)

\[ \mu_i = \mu_i(z(t)) \quad \mu_i = \sum_{i=1}^{p} \mu_i A_i \quad \mu_i = \sum_{i=1}^{p} \mu_i B_i \]

\[ C_i = \sum_{i=1}^{p} \mu_i C_i \quad D_i = \sum_{i=1}^{p} \mu_i D_{2i} \]

and \( D_2 = \sum_{i=1}^{p} \mu_i D_{2i} \)

Then, the T-S fuzzy model (2) and (3) can be rewritten as:

\[ \dot{x}(t) = A(x(t))x(t) + B(x(t))u(t) + f(t) + D_2w(t) \]

and \( e_y(t) = C(x(t))x(t) + D_2w(t) \)

\[ \dot{z}(t) = \hat{A}(\mu)\dot{x}(t) + \hat{B}(\mu)u(t) + \hat{f}(t) + D_{2i}(\mu)w(t) \]

(16)

\[ e_y(t) = C(\mu)\dot{x}(t) - D_2(\mu) y(t) \]

(17)

where \( \hat{A}(\mu) \) is the state, \( \hat{B}(\mu) = \sum_{i=1}^{p} \mu_i A_{ki} \), \( \hat{C}(\mu) = \sum_{i=1}^{p} \mu_i C_{ki} \) and \( D_K \) are the designed controller matrices.

Substituting (5) into (16) and (17), one obtains
Then, one gets
\[ \hat{y}(t) = \hat{A}(\mu, \lambda)\hat{x}(t) + \hat{B}(\mu, \lambda)\pi(t) \]
where:
\[ \hat{A}(\mu, \lambda) = \left[ A(\mu) + B(\mu)D_2(C(\mu)) \right] \]
\[ \hat{B}(\mu, \lambda) = \left[ B_2(\mu)C(\mu) \right] \]

Theorem 2: Assume a fault \( f(t) \) occurs at some unknown time \( t_f \), and let \( \alpha \) and \( r \) be two positive scalars. The eigenvalues of \( \hat{A}(\mu, \lambda) \) belong to \( D(\alpha, r) \), and the system dynamics (20) and (21) satisfy the H\( \infty \) performance index
\[ \| y(t) \|_2 < \gamma \| \mu(t) \|_2 \]
if there exist two symmetric positive definite matrices \( X, Y \) and matrices \( \hat{A}, \hat{B}, \hat{C} \) and \( \hat{D} \) such that
\[ \min \theta \text{ subject to } \]

where:
\[ P_{ij} = \begin{bmatrix} -X & -I_n & 0 & 0 \\ * & -\hat{A}_{ij} & Y & 0 \\ * & * & -r^2X & -r^2I_n \\ * & * & * & -r^2Y \end{bmatrix} \]
and
\[ \Xi_{ij} = \begin{bmatrix} X_{11} & X_{12} & 0 & 0 \\ * & X_{22} & YD_{21} & 0 \\ * & * & -YD_{21} & 0 \\ * & * & * & -YD_{21} \end{bmatrix} \]
with
\[ \pi_{13} = A_iX + B_iC_i - \alpha X \]
\[ \pi_{11} = A_iX + \alpha X \]
and
\[ X_{22} = A_i \hat{A} + B_i \hat{D} \]

The parameter matrices of the controller are given by
\[ D_K = \hat{D} \]
\[ C_{RI} = (\hat{A}_i - D_KC_iX)M^{-T} \]
\[ B_{Ki} = N_i^{-1}(\hat{B}_i - D_KD_2C_i) \]
\[ C_{Rij} = N_i^{-1}(\hat{A}_i - Y(\hat{A}_i + B_iD_2C_i)X)M^{-T} - B_{Ki}C_iX \]
where \( M, N \) satisfy \( MN^T = I_n - XY \).

Proof: See [5]

3 Fish Population System and T-S Modelling
3.1 Problem Formulation and Assumptions
We consider a population of exploited fish which is structured in \( n \) age classes (\( n \geq 2 \)), where every stage \( i \) is described by the evolution of its biomass \( X_i \) for \( 0 \leq i \leq n \). Each stage in the stock (\( i = 1 \ldots n \)) is characterized by its fecundity, mortality and predation rates. In addition, a fishing effort is included in the global mortality term. The dynamic of the fish population can be represented by the following system of ordinary differentials
\[ \dot{X}(t) = A_i X(t) + B_i \]
\[ u(t) = C_i X(t) + D_i \]
\[ \dot{X}(t) = A_i X(t) + B_i \]
\[ y(t) = C_i X(t) + D_i \]
where:
\[ \alpha_i = \alpha + M_i \]
\[ M_i \]
\[ \alpha \]
\[ p_0 \]
\[ f_i \]
\[ l_i \]
\[ q_i \]
\[ a \]
\[ q \]
\[ E \]
\[ Y \]
\[ \gamma \]

The nonlinearity at least must be considered.
\[ \sum_{i=1}^{n} f_i x_i > 0 \]

The spawning coefficient must be big enough so as to avoid extinction.
\[ \sum_{i=1}^{n} f_i x_i > 0 \]

where:
\[ \pi_i = \frac{a_i}{\prod_{j=1}^{n} (x_j + q_i)} \]

Assumption 3:
All age classes are subject to catch and the oldest one yield eggs, \( n = 1 \ldots n \).

A. State Transformation
Let \( E \) a constant fishing effort. Using the change of coordinate \( X_i = X_i - X_0 \) and \( u = u - E \) the system (26) can be transformed into:
\[ \dot{x} = A(x)x + B(x)u \]
where:
\[ a_i = a + M_i \]
\[ M_i \]
\[ \alpha \]
\[ p_0 \]
\[ f_i \]
\[ l_i \]
\[ q_i \]
\[ a \]
\[ q \]
\[ E \]
\[ Y \]
\[ \gamma \]

Theorem 2: Assume a fault \( f(t) \) occurs at some unknown time \( t_f \), and let \( \alpha \) and \( r \) be two positive scalars. The eigenvalues of \( \hat{A}(\mu, \lambda) \) belong to \( D(\alpha, r) \), and the system dynamics (20) and (21) satisfy the H\( \infty \) performance index
\[ \| y(t) \|_2 < \gamma \| \mu(t) \|_2 \]
if there exist two symmetric positive definite matrices \( X, Y \) and matrices \( \hat{A}, \hat{B}, \hat{C} \) and \( \hat{D} \) such that
\[ \min \theta \text{ subject to } \]

where:
\[ P_{ij} = \begin{bmatrix} -X & -I_n & 0 & 0 \\ * & -\hat{A}_{ij} & Y & 0 \\ * & * & -r^2X & -r^2I_n \\ * & * & * & -r^2Y \end{bmatrix} \]
and
\[ \Xi_{ij} = \begin{bmatrix} X_{11} & X_{12} & 0 & 0 \\ * & X_{22} & YD_{21} & 0 \\ * & * & -YD_{21} & 0 \\ * & * & * & -YD_{21} \end{bmatrix} \]
with
\[ \pi_{13} = A_iX + B_iC_i - \alpha X \]
\[ \pi_{11} = A_iX + \alpha X \]
and
\[ X_{22} = A_i \hat{A} + B_i \hat{D} \]

The parameter matrices of the controller are given by
\[ D_K = \hat{D} \]
\[ C_{RI} = (\hat{A}_i - D_KC_iX)M^{-T} \]
\[ B_{Ki} = N_i^{-1}(\hat{B}_i - D_KD_2C_i) \]
\[ C_{Rij} = N_i^{-1}(\hat{A}_i - Y(\hat{A}_i + B_iD_2C_i)X)M^{-T} - B_{Ki}C_iX \]
\[ MN^T = I_n - XY \]

Proof: See [5]

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Therefore the membership functions can be calculated as represented by:

\[
\begin{align*}
\text{For simplicity, we consider that } n=2, \text{ and } x_i \in [-a, a]. \\
\text{The system (27) has two non constant terms: } x_0, \text{ and } x_1. \text{ For non constant terms, define:}
\end{align*}
\]

\[
\begin{align*}
Z_i(t) = x_1, \quad i = 0, 1.
\end{align*}
\]

Next, calculate the minimum and maximum values of \( z_i(t) \) under \( x_i \in [-a, a] \). They are obtained as follows:

\[
\begin{align*}
\max z_i(t) = a, \quad \min z_i(t) = -a
\end{align*}
\]

From the maximum and minimum values, \( z_i(t) \) can be represented by:

\[
\begin{align*}
z_i(t) = M^i_1(z_i(t)) \cdot a + M^i_2(z_i(t)) \cdot (-a)
\end{align*}
\]

where \( M^i_1(z_i(t)) + M^i_2(z_i(t)) = 1 \)

Therefore the membership functions can be calculated as:

\[
\begin{align*}
M^i_1(z_i(t)) = \frac{z_i(t) + a}{2a} ; \quad M^i_2(z_i(t)) = \frac{a - z_i(t)}{2a}
\end{align*}
\]

We name the membership functions “Positive,” “Negative,” “Zero,” “Not Zero,” “Big,” and “Small,” respectively.

Then, the nonlinear system (16) is represented by the following fuzzy model.

Model Rule 1:

IF \( z_i(t) \) is “Negative” and \( z_i(t) \) is “Not Zero” and \( z_i(t) \) is “Big”
THEN \( \dot{x}(t) = A_2z(t) + B_2u(t) \)

Model Rule 2:

IF \( z_i(t) \) is “Negative” and \( z_i(t) \) is “Not Zero” and \( z_i(t) \) is “Small”
THEN \( \dot{x}(t) = A_2z(t) + B_2u(t) \)

Model Rule 3:

IF \( z_i(t) \) is “Negative” and \( z_i(t) \) is “Zero” and \( z_i(t) \) is “Big”
THEN \( \dot{x}(t) = A_3z(t) + B_3u(t) \)

Model Rule 4:

IF \( z_i(t) \) is “Negative” and \( z_i(t) \) is “Zero” and \( z_i(t) \) is “Small”
THEN \( \dot{x}(t) = A_3z(t) + B_3u(t) \)

Model Rule 5:

IF \( z_i(t) \) is “Positive” and \( z_i(t) \) is “Not Zero” and \( z_i(t) \) is “Big”
THEN \( \dot{x}(t) = A_4z(t) + B_4u(t) \)

Model Rule 6:

IF \( z_i(t) \) is “Positive” and \( z_i(t) \) is “Not Zero” and \( z_i(t) \) is “Small”
THEN \( \dot{x}(t) = A_4z(t) + B_4u(t) \)

Model Rule 7:

IF \( z_i(t) \) is “Positive” and \( z_i(t) \) is “Zero” and \( z_i(t) \) is “Big”
THEN \( \dot{x}(t) = A_5z(t) + B_5u(t) \)

Model Rule 8:

IF \( z_i(t) \) is “Positive” and \( z_i(t) \) is “Zero” and \( z_i(t) \) is “Small”
THEN \( \dot{x}(t) = A_6z(t) + B_6u(t) \)

Here, \( z_i(t), x(t) \) and \( u(t) \) are premise variables and \( A_i, B_i \) are activation functions of the eight-rule fuzzy model.

The activation functions of this eight-rule fuzzy model are:

\[
\begin{align*}
\mu_1(z(t)) &= M^i_2(z_i(t)) \times M^i_1(z_i(t)) \times M^i_2(z_i(t)) \\
\mu_2(z(t)) &= M^i_2(z_i(t)) \times M^i_1(z_i(t)) \times M^i_2(z_i(t)) \\
\mu_3(z(t)) &= M^i_2(z_i(t)) \times M^i_1(z_i(t)) \times M^i_2(z_i(t)) \\
\mu_4(z(t)) &= M^i_2(z_i(t)) \times M^i_1(z_i(t)) \times M^i_2(z_i(t)) \\
\mu_5(z(t)) &= M^i_2(z_i(t)) \times M^i_1(z_i(t)) \times M^i_2(z_i(t)) \\
\mu_6(z(t)) &= M^i_2(z_i(t)) \times M^i_1(z_i(t)) \times M^i_2(z_i(t)) \\
\mu_7(z(t)) &= M^i_2(z_i(t)) \times M^i_1(z_i(t)) \times M^i_2(z_i(t)) \\
\mu_8(z(t)) &= M^i_2(z_i(t)) \times M^i_1(z_i(t)) \times M^i_2(z_i(t))
\end{align*}
\]

Simulation results and discussion

To demonstrate the effectiveness of the proposed observer and controller, we consider a numerical example obtained from the stimulation of a fishery characterized by the parameter values given in Table 1 which are retained from the literature [4, 14, 15]. Here we have employed for the simulation a constant fishing effort \( E(t) = \bar{E} \) and arbitrary initial states: \( x(0) = (0, 9, 3, 1.5) \) and \( \dot{x}(0) = (1.5, 3, 5, 4.7) \).
It is clear that the parameters satisfy assumptions (1), (2), (3). Using an LMI solver, and from conditions of theorem 1 we first obtain the observer parameters. With the circle region $D(30,30)$, the minimum attenuation value is $\gamma = 1.6080$:

\[
\begin{align*}
L_1 &= 10\begin{bmatrix} 7.17 & 0.83 & -0.53 \end{bmatrix}, \\
L_2 &= 10\begin{bmatrix} 7.91 & 0.96 & -0.67 \end{bmatrix}, \\
L_3 &= 10\begin{bmatrix} 8.25 & 0.61 & -0.33 \end{bmatrix}, \\
L_4 &= 10\begin{bmatrix} 1.17 & 0.05 & -0.02 \end{bmatrix}, \\
L_5 &= 10\begin{bmatrix} 6.76 & 0.76 & -0.56 \end{bmatrix}, \\
L_6 &= 10\begin{bmatrix} 0.07 & 0.18 & -0.16 \end{bmatrix}, \\
L_7 &= 10\begin{bmatrix} 1.26 & -0.12 & 0.13 \end{bmatrix}, \\
L_8 &= 10\begin{bmatrix} 1.15 & 0.05 & -0.05 \end{bmatrix}, \\
\end{align*}
\]

\[
\begin{align*}
F_1 &= -9.9848, & F_2 &= 0.2534, & F_3 &= 0.2532, & F_4 &= 10.5709, \\
F_5 &= -9.9824, & F_6 &= 0.3071, & F_7 &= 0.3560, & F_8 &= 10.5444.
\end{align*}
\]

Next, we design the controller. By solving the conditions in Theorem 2 with the circle region $D(30,30)$, one obtains the minimum attenuation value $\gamma = 1.8234$. Numerical matrixes of $\hat{A}_{ii}, \hat{B}_{Ki}, \hat{C}_{Ki}$ and $\hat{D}_{Ki}$ are not given here to limit the length of this paper.

It is supposed that $\omega(t)$ is band-limited white noise (Fig 5). Fig. 2 illustrates fault-estimation simulation results. Simulation results for the system output response are shown in Fig. 3. The states estimation error is given in Fig. 4.

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**Conclusion**

In this paper, an observer-based robust fault estimation and FTC is developed for a harvested fish population system, using the T-S approach. The proposed design guarantees given stability requirements, while limiting the influence of disturbances, in the presence of actuator faults. Simulation results showed the effectiveness of the proposed design. The present paper shows that the control and estimation problems in fisheries management can also be investigated from the point of view of engineers, by combining modern control theory, computer science and mathematics.

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