Stochastic differential equations harvesting models: simulation and numerical solution

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Outline

- 1 Introduction
- 2 Problem Definition
- 3 Solution
- 4 Application

1. Introduction

1.1. Stochastic Gompertz model with harvesting

$$dX_t = rX_t \ln \left(\frac{K}{X_t} \right) dt - qE_tX_t dt + \sigma_1X_t dW_t^X, \quad X(0) = x > 0.$$

X_t stock size at time t r intrinsic growth rate K carrying capacity q catchability parameter		
K carrying capacity	X_t	stock size at time t
	r	intrinsic growth rate
q catchability parameter	K	carrying capacity
	q	catchability parameter
E_t fishing effort at time t	E_t	fishing effort at time t
σ_1 noise intensity	σ_1	noise intensity
W_t^X standard Wiener process	W_t^X	standard Wiener process
x initial population size (known)	X	initial population size (known)
$Y_t := qE_tX_t$ yield	$Y_t := qE_tX_t$	yield

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2.1. Variables

• Fish price, P_t , follows a Geometric Brownian Motion:

$$dP_t = \mu P_t dt + \sigma_2 P_t dW_t^P, \quad P(0) = p > 0.$$

Costs are defined as:

$$C_t = c_1 E_t + c_2 E_t^2.$$

Profit is the difference between revenues and costs:

$$\Pi_t = P_t \cdot Y_t - C_t
= (P_t q X_t - c_1 - c_2 E_t) E_t.$$

• The total expected discounted profit over the interval (t, T) is given by the functional:

$$J = \mathbb{E}\left[\int\limits_t^T e^{-\delta au} \Pi(au) d au \Bigg| X(t) = x_t, P(t) = p_t
ight] := \mathbb{E}_{x_t,p_t}\left[\int\limits_t^T e^{-\delta au} \Pi(au) d au
ight].$$

2.2. Problem Formalization

Goal: Using E(t) as control, solve the Stochastic Optimal Control Problem (SOCP):

$$J^* := \max_{\substack{E(\tau) \\ 0 \le \tau \le T}} J = \max_{\substack{E(\tau) \\ 0 \le \tau \le T}} \mathbb{E}_{x,p} \left[\int_0^T e^{-\delta \tau} \Pi(\tau) d\tau \right]$$

s.t.

growth equation:
$$dX_t = rX_t \ln \left(\frac{K}{X_t}\right) dt - qE_tX_t dt + \sigma_1X_t dW_t^X$$
,

price dynamics:
$$dP_t = \mu P_t dt + \sigma_2 P_t dW_t^P$$
,

effort restrictions:
$$0 \le E_{min} \le E(t) \le E_{max} < \infty, \forall t \in [0, T],$$

terminal condition:
$$J(X_T, P_T, T) = 0$$
,

initial conditions:
$$X(0) = x$$
, $P(0) = p$.

2.3. HJB and Control Function

Using dynamic programming, the solution to the SOCP is obtained via the HJB equation:

$$-\frac{\partial J^*(X_t, P_t, t)}{\partial t} = (P_t q X_t - c_1 - c_2 E_t^*) E_t^* - \delta J^*(X_t, P_t, t)$$

$$+ \frac{\partial J^*(X_t, P_t, t)}{\partial X_t} \left(r X_t \ln \left(\frac{K}{X_t} \right) - q E_t^* X_t \right) + \frac{\partial J^*(X_t, P_t, t)}{\partial P_t} \mu P_t$$

$$+ \frac{1}{2} \frac{\partial^2 J^*(X_t, P_t, t)}{\partial X_t^2} \sigma_1^2 X_t^2 + \frac{1}{2} \frac{\partial^2 J^*(X_t, P_t, t)}{\partial P_t^2} \sigma_2^2 P_t^2$$

$$+ \frac{\partial^2 J^*(X_t, P_t, t)}{\partial X_t \partial P_t} \rho \sigma_1 X_t \sigma_2 P_t,$$

The unconstrained effort is: $E_{free}^*(t) = \frac{qX_t}{2c_2} \left(P_t - \frac{\partial J^*(X_t, P_t, t)}{\partial X_t} \right) - \frac{c_1}{2c_2}$, which turns to be the optimal variable effort if boundaries are satisfied.

$$E^*(t) = \begin{cases} E_{min}, & \text{if} \quad E_{free}^*(t) < E_{min} \\ E_{free}^*(t), & \text{if} \quad E_{min} \le E_{free}^*(t) \le E_{max}, \\ E_{max}, & \text{if} \quad E_{free}^*(t) > E_{max} \end{cases}$$

2.4. Discretization

The time derivative is approximated by a forward difference quotient.

$$\frac{\partial J_{i,l,j}^*}{\partial t} \approx \frac{J_{i,l,j+1}^* - J_{i,l,j}^*}{\Delta t}, \quad 0 \le i \le m, \quad 0 \le p \le k, \quad 0 \le j \le n-1.$$

Population derivatives are approximated by the following schemes.

$$\begin{array}{lcl} \frac{\partial J_{i,l,j}^*}{\partial x} & \approx & \frac{J_{i+1,l,j}^* - J_{i-1,l,j}^*}{2\Delta x}, & 1 \leq i \leq m-1, \\ \frac{\partial^2 J_{i,l,j}^*}{\partial x^2} & \approx & \frac{J_{i+1,l,j}^* - 2J_{i,l,j}^* + J_{i-1,l,j}^*}{\Delta x^2}, & 1 \leq i \leq m-1, \\ \frac{\partial J_{m,l,j}^*}{\partial x} & \approx & \frac{J_{m,l,j}^* - J_{m-1,l,j}^*}{\Delta x}, & i = m, \\ \frac{\partial^2 J_{m,l,j}^*}{\partial x^2} & \approx & \frac{J_{m,l,j}^* - 2J_{m-1,l,j}^* + J_{m-2,l,j}^*}{\Delta x^2} & i = m. \end{array}$$

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2.4. Discretization

• Partial derivatives w.r.t. price follow the same reasoning as population ones.

$$\begin{array}{lll} \frac{\partial J_{i,l,j}^*}{\partial p} & \approx & \frac{J_{i,l+1,j}^* - J_{i,l-1,j}^*}{2\Delta p}, & 1 \leq l \leq k-1, \\ \\ \frac{\partial^2 J_{i,l,j}^*}{\partial p^2} & \approx & \frac{J_{i,l+1,j}^* - 2J_{i,l,j}^* + J_{i,l-1,j}^*}{\Delta p^2}, & 1 \leq l \leq k-1, \\ \\ \frac{\partial J_{i,k,j}^*}{\partial p} & \approx & \frac{J_{i,k,j}^* - J_{i,k-1,j}^*}{\Delta p}, & l = k, \\ \\ \frac{\partial^2 J_{i,k,j}^*}{\partial p^2} & \approx & \frac{J_{i,k,j}^* - 2J_{i,k-1,j}^* + J_{i,k-2,j}^*}{\Delta p^2} & l = k, \\ \\ \frac{\partial J_{i,0,j}^*}{\partial p} & \approx & \frac{J_{i,1,j}^* - J_{i,0,j}^*}{\Delta p}, & l = 0, \\ \\ \frac{\partial^2 J_{i,0,j}^*}{\partial p^2} & \approx & \frac{J_{i,2,j}^* - 2J_{i,1,j}^* + J_{i,0,j}^*}{\Delta p^2} & l = 0. \end{array}$$

2.4. Discretization

• The cross partial derivatives w.r.t. population and price schemes are presented below.

$$\begin{array}{lll} \frac{\partial J_{i,l,j}^*}{\partial x \partial \rho} & \approx & \frac{J_{i+1,l+1,j}^* - J_{i-1,l+1,j}^* - J_{i+1,l-1,j}^* + J_{i-1,l-1,j}^*}{4\Delta x \Delta \rho}, & 1 \leq l \leq k-1, & 1 \leq i \leq m-1 \\ \frac{\partial J_{m,l,j}^*}{\partial x \partial \rho} & \approx & \frac{J_{m,l+1,j}^* - J_{m-1,l+1,j}^* - J_{m,l-1,j}^* + J_{m-1,l-1,j}^*}{2\Delta x \Delta \rho}, & 1 \leq l \leq k-1, & i = m \\ \frac{\partial J_{i,k,j}^*}{\partial x \partial \rho} & \approx & \frac{J_{i+1,k,j}^* - J_{i-1,k,j}^* - J_{i+1,k-1,j}^* + J_{i-1,k-1,j}^*}{2\Delta x \Delta \rho}, & l = k, & 1 \leq i \leq m-1 \\ \frac{\partial J_{m,k,j}^*}{\partial x \partial \rho} & \approx & \frac{J_{m,k,j}^* - J_{m-1,k,j}^* - J_{m,k-1,j}^* + J_{m-1,k-1,j}^*}{\Delta x \Delta \rho}, & l = k, & i = m \\ \frac{\partial J_{i,0,j}^*}{\partial x \partial \rho} & \approx & \frac{J_{i+1,1,j}^* - J_{i-1,1,j}^* - J_{i+1,0,j}^* + J_{i-1,0,j}^*}{2\Delta x \Delta \rho}, & l = 0, & 1 \leq i \leq m-1 \\ \frac{\partial J_{m,0,j}^*}{\partial x \partial \rho} & \approx & \frac{J_{m,1,j}^* - J_{m-1,1,j}^* - J_{m,0,j}^* + J_{m-1,0,j}^*}{\Delta x \Delta \rho}, & l = 0, & i = m \end{array}$$

3. Solution

 When discretizations are applied and some simplifications performed, it is possible to write the system with matrices A, B and C such that

$$A\mathbf{J}_{-}^{*}=B\;\mathbf{J}_{+}^{*}+C,$$

with

$$J_-^* = \begin{bmatrix} J_0^* & \mid & J_1^* & \mid & \cdots & \mid & J_{n-1}^* \end{bmatrix}, \quad J_+^* = \begin{bmatrix} J_1^* & \mid & J_2^* & \mid & \cdots & \mid & J_n^* \end{bmatrix},$$

and

$$J_{i}^{*} = \begin{bmatrix} J_{0,0,j}^{*} & \cdots & J_{i,l,j}^{*} & \cdots & J_{m,k,j}^{*} \end{bmatrix}', \quad 0 \leq i \leq m, \quad 0 \leq l \leq k, \quad 0 \leq j \leq n.$$

' denotes the transpose operator.

4.1. Scenarios

We will present and compare 3 scenarios:

S1 Profit based on stochastic prices: P_t is described by the SDE $dP_t = \mu P_t dt + \sigma_2 P_t dW_t^P$, and the profit is given by

$$\Pi_t = P_t Y_t - C_t = (P_t q X_t - c_1 - c_2 E_t) E_t.$$

S2 Profit based on deterministic Prices: P_t is defined as $P_t = p_1 - p_2 Y_t$, and the profit is given by

$$\Pi_t = P_t Y_t - C_t = (p_1 q X_t - c_1) E_t - (p_2 q^2 X_t^2 + c_2) E_t^2.$$

S3 Profit based on a penalised effort:

$$\Pi_t = P_t Y_t - (C_t + C_t^{pen}(\varepsilon)) = (p_1 q X_t - c_1) E_t - (p_2 q^2 X_t^2 + c_2) E_t^2 - \varepsilon (E_t - E_{ref})^2,$$

- where the artificial cost component penalizes profit values when the effort takes abrupt changes from a reference effort value, say E_{ref} .
- The higher (lower) the value of ε , the higher (lower) the impact on effort and, consequently, the lower (higher) the profit.

4.2. Data

Parameter	Value	Units
Population growth rate: r	1.331	year $^{-1}$
Population carrying capacity: K	11400	tonnes
Initial population size: x	0.5 <i>K</i>	tonnes
Maximum population size: x_{max}	2 <i>K</i>	tonnes
Population volatility: σ_1	0.2	${\sf year}^{-1/2}$
Catchability: q	$9.77 \cdot 10^{-5}$	$SFU^{-1} \cdot year^{-1}$
Maximum allowed effort: E_{max}	r/q	SFU
Minimum allowed effort: E_{min}	0	SFU
Linear cost coefficient: c_1	1156.8	$BDT \cdot SFU^{-1} \cdot year^{-1}$
Quadratic cost coefficient: c_2	0.01	$BDT \cdot SFU^{-2} \cdot year^{-1}$
Discount factor: δ	0.05	${\sf year}^{-1}$
Time horizon: T	50	year

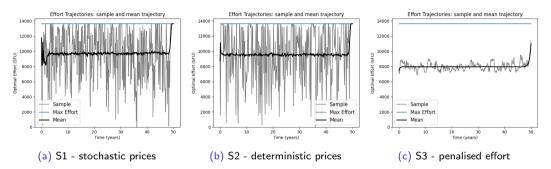
 $\ensuremath{\mathsf{BDT}}$ is an abbreviation for Bangladesh Taka.

4.2. Data

Parameters	Value	Units
Constant coefficient: p_1	8362.3	$BDT\cdottonnes^{-1}$
Linear coefficient: p_2	0	
Reference Effort: E_{ref}	$0.5 \cdot r/q$	SFU
Magnitude of Penalisation: $arepsilon$	0.4	
Price growth rate: μ	0.001	${\sf year}^{-1}$
Price volatility: σ_2	0.01	${\sf year}^{-1/2}$
Initial price value: p_0	8362.3	$BDT\cdotyear^{-1}$
Wiener processes correlation: ρ	0	

4.3. Effort

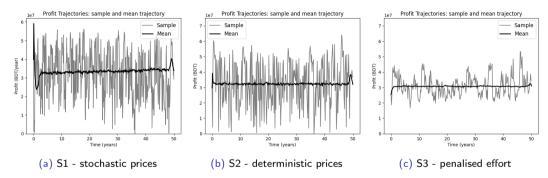
Effort trajectories: mean and sample trajectory for each scenario



- Besides being optimal, effort strategies (a) and (b) cannot be implemented due to social and logistic issues arising from the frequent and significant adjustments on effort.
- Regarding (c), the penalization parameter reduces the amplitude of oscillations, benefiting social issues, but logistical problems remain, albeit to a lesser extent.

4.4. Profit

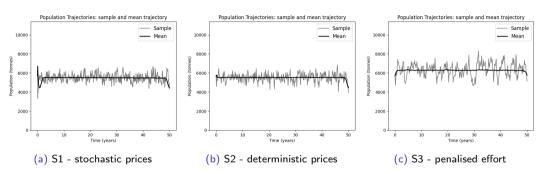
Profit trajectories: mean and sample trajectory for each scenario



- Effort influences profit by affecting both revenues and costs. More aggressive policies raise costs and reduce profit.
- In case (c), profit never reaches zero because there are no inactive periods; in (a), profit shows a slight upward trend due to the drift in price dynamics.

4.5. Population

Population trajectories: mean and sample trajectory for each scenario



- Due to softer effort strategy, (c) presents a higher population value.
- In general, population decreases whenever effort increases to maximum allowed levels.
- All trajectories present a stable population size, guaranteeing the sustainability of the activity in the long run.

4.6. Comparison between models

Model	J^* (x 10^6 BDT)	Δ (%)
S1 - stochastic prices	605.813	+2.19
S2 - deterministic prices	592.840	(reference)
S3 - penalised effort	561.756	-5.24

Main bibliography

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Thank you! Moitas grazas!

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