

*2023 - March, 2nd*

# OPEN-LOOP NASH EQUILIBRIUM (OLNE)

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# Differential game Example: OPEN-LOOP NASH EQ.

(Dockner p.87)

$$\begin{aligned} \max_{u \geq 0} J^1(u(\cdot)) &= \int_0^T e^{-rt} \left[ v(t) - x(t) - \frac{\alpha}{2} u^2(t) \right] dt \\ \max_{v \in [0,1]} J^2(v(\cdot)) &= \int_0^T e^{-rt} [v(t) - x(t)] dt \\ \text{s.t. } \dot{x}(t) &= 1 + v(t) - u(t)\sqrt{x(t)}, \\ x(0) &= x^0 \end{aligned}$$

Assume  $v(t) = \psi(t)$  for P2, find best response strategy for P1

$$H^{C1}(x, u, \lambda, t) = p_0 \left( \psi - x - \frac{\alpha}{2} u^2 \right) + \lambda (1 + \psi - u \sqrt{x})$$

(P<sub>0</sub>=1)

Assume  $u(t) = \Phi(t)$  for P1, find best response strategy for P2

$$H^{C2}(x, v, \lambda, t) = p_0 (v - x) + \lambda (1 + v - \Phi \sqrt{x})$$

(P<sub>0</sub>=1)

# Player 1

$$H^c(x, u, \lambda, t) = 0 - x - \frac{d}{2} u^2 + \lambda (1 + \delta - u \sqrt{x})$$

$$u^* = \underset{u \geq 0}{\text{argmax}} H^c(x)$$

$$\frac{\partial H^c}{\partial u} = -d u - \lambda \sqrt{x} = 0$$

$$\frac{\partial^2 H^c}{\partial u^2} = -d < 0 \quad \text{concave}$$

$$u^*(t) = - \frac{\lambda(t) \sqrt{x(t)}}{d}$$

$$\dot{\lambda}(t) = - \frac{\partial H^c}{\partial x} + \lambda \lambda(t) = 1 + \frac{\lambda(t) u}{2 \sqrt{x}} + \lambda \lambda(t)$$

CO-STATE SYSTEM PDE backward

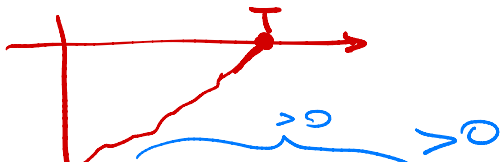
$$\begin{cases} \dot{\lambda}(t) = 1 - \frac{\lambda^2(t) \sqrt{x}}{2 \sqrt{x} d} + \lambda \lambda(t) & \text{Riccati eq} \\ \lambda(T) = 0 \end{cases}$$

$$\begin{cases} S(x(T)) = 0 \\ x(T) \in \mathbb{R} \end{cases} \Rightarrow \delta = 0$$

# Player 1

$$\dot{\lambda}(T) = 1$$

$$\dot{\lambda} > 0$$



$$\exists! \lambda(t) = \frac{e \left( 1 - e^{-\sqrt{x^2 + 2/d} (T-t)} \right)}{\left( x - \sqrt{x^2 + 2/d} \right) e^{-c(T-t)} - \left( x + \sqrt{x^2 + 2/d} \right)}$$

$< (x - \sqrt{\quad}) < (x + \sqrt{\quad})$

$$\phi(t) = \dot{u}^* = - \frac{\lambda \sqrt{x}}{d} \geq 0$$

best response

$\lambda(t) = 0 \Leftrightarrow t = T$

$$\begin{cases} \dot{x}(t) = 1 + \psi(t) + \frac{\lambda(t)x(t)}{d} & \text{Linear ODE} \\ x(0) = x_0 \end{cases}$$

$x(t) = \dots$  ?  $\rightarrow$  strategy of P2 ?!

Such a  $\phi$  is only a candidate

Apply ARROW'S sufficiency Theorem

$$(H^{c1})^* = H^{c2}(x, u^*, \lambda, t) = \sigma - x - \frac{d}{2} \left( \frac{-\lambda \sqrt{x}}{d} \right)^2 + \lambda \left( 1 + \sigma + \frac{\lambda \sqrt{x}}{d} \sqrt{x} \right)$$

$$= \sigma - x - \frac{\lambda^2 x}{2d} + \lambda + \lambda \sigma + \frac{\lambda^2 x}{d}$$

$\Rightarrow$  linear in  $x$   
 $\Rightarrow$  concave in  $x$

$\Rightarrow \phi$  is optimal strategy.  $\Rightarrow$  ARROW ✓

# Player 2

$$u(t) = \phi(t) \text{ player 1}$$

$$H^{c2}(x, \sigma, \mu, t) = \sigma - x + \mu (1 + \sigma - \phi \sqrt{x}) \text{ linear in } \sigma$$

$$\bullet \text{ argmax}_{\sigma \in [0, 1]} H^{c2} = (1 + \mu) \sigma - x + \mu (1 - \phi \sqrt{x})$$

$$\phi^* = \sigma^* = \begin{cases} 0, & \mu < -1 \\ 1, & \mu > -1 \end{cases}$$

bang-bang  
sol

$$\bullet \dot{\mu}(t) = - \frac{\partial H^{c2}}{\partial x} + \lambda \mu(t) = 1 + \frac{\mu \phi}{2\sqrt{x}} + \lambda \mu(t)$$

$\phi = -\frac{\lambda \sqrt{x}}{a}$

$$= 1 + \lambda \mu(t) - \frac{\mu \lambda}{2a}$$

$$\bullet \mu(\tau) = 0$$

# Player 2

$$\begin{cases} \dot{\lambda} = 1 + \kappa \lambda - \frac{1}{2a} \lambda^2 & \lambda(T) = 0 \\ \dot{\mu} = 1 + \kappa \mu - \frac{1}{2a} \mu^2 & \mu(T) = 0 \end{cases}$$

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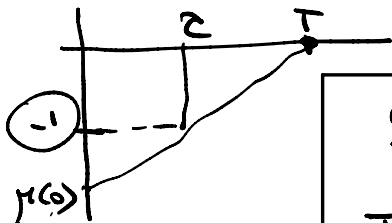

$$\dot{\lambda} - \dot{\mu} = \frac{1}{2a} \lambda (\mu - \lambda) + \kappa (\lambda - \mu)$$

$$y(t) = \lambda - \mu$$

$$\begin{cases} \dot{y}(t) = \frac{\lambda y}{2a} + \kappa y = \left( \frac{\lambda}{2a} + \kappa \right) y \Rightarrow y(t) = 0 \\ y(T) = 0 \end{cases}$$

$\Downarrow$   
 $\lambda(t) = \mu(t)$

# Player 2



$$\mu(0) < -1$$

$$\Leftrightarrow T > \frac{1}{c} \ln \left( \frac{2 - (x - \sqrt{x^2 + 2/d})}{2 - (x + \sqrt{x^2 + 2/d})} \right) = z$$

$$\mu(0) > -1 \Rightarrow z = 0$$

$$\underline{u(t) = \psi(t) = \begin{cases} 0, & t \in [0, z) \\ 1, & t \in [z, T] \end{cases}}$$

degenerate  
strategies  
not depending  
on the current  
state



Check optimality

$$H^{c2}(x, \sigma^*, \mu, t) = \underbrace{\sigma^*}_{0 \leq \sigma^* \leq 1} x + \mu \left( x + \underbrace{\sigma^*}_{0 \leq \sigma^* \leq 1} - \underbrace{\phi(\sqrt{x})}_{-\frac{\lambda \sqrt{x}}{\alpha}} \right)$$

Linear in  $x \Rightarrow$  Arrow's Theorem holds

Open-Loop Nash EQ

$$(\phi^*, \psi^*) \quad \underline{\phi^*(t)} = -\frac{\lambda(t) \sqrt{x(t)}}{\alpha}$$

$$\underline{\psi^*(t)} = \begin{cases} 0 & t \in [0, \tau) \\ 1 & t \in [\tau, T] \end{cases}$$

$\tau, \tau$  see above

$x^*(t)$  state function

$$\begin{cases} \dot{x}(t) = 1 + \sigma^*(t) - a(t)\sqrt{x(t)} \\ x(0) = x_0 \end{cases}$$

$$u^* = -\frac{\lambda \sqrt{x}}{a}$$

In  $[0, \tau)$   $\sigma^* = 0 = \psi^*$

$$\dot{x}(t) = 1 + \frac{\lambda}{a} \sqrt{x(t)}$$

$$x(t) = e^{\int_0^t \frac{\lambda}{a} ds} \left\{ x_0 + \int_0^t (1 + \psi) e^{-\int_0^s \frac{\lambda}{a} ds} ds \right\}$$



## Player 2

$$\text{Im } [\tau, \tau] \quad \sigma^* = 1 = \psi^*$$

$$\begin{cases} \dot{x}(t) = 2 + \frac{\lambda(t)x(t)}{d} \\ x(\tau) = x_2 \end{cases}$$

$$x(t) = e^{\int_{\tau}^t \frac{\lambda(s)}{d} ds} \left[ x_2 + \int_{\tau}^t e^{-\int_{\tau}^s \frac{\lambda(s)}{d} ds} ds \right]$$

# MARKOVIAN NASH EQUILIBRIUM (MNE)

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# Nash equilibrium for a differential game

Finding a **Nash equilibrium** in a differential game with  $N$  players is equivalent to **solve  $N$  Optimal Control problems.**

- OPEN-LOOP NASH EQUILIBRIUM (OLNE)  
Pontryagin's Maximum Principle (1962) **PMP**

$$(\Phi^1(t), \Phi^2(t), \dots, \Phi^i(t), \dots, \Phi^N(t))$$

- MARKOVIAN NASH EQUILIBRIUM (MNE)  
Hamilton Jacobi Bellman ('50s) **HJB**

$$(\Phi^1(t, x(t)), \Phi^2(t, x(t)), \dots, \Phi^i(t, x(t)), \dots, \Phi^N(t, x(t)))$$

# MARKOVIAN NASH EQUILIBRIUM (MNE)

**Definition 4.1** The  $N$ -tuple  $(\phi^1, \phi^2, \dots, \phi^N)$  of functions  $\phi^i : X \times [0, T] \mapsto \mathbb{R}^m$ ,  $i \in \{1, 2, \dots, N\}$ , is called a Markovian Nash equilibrium if, for each  $i \in \{1, 2, \dots, N\}$ , an optimal control path  $u^i(\cdot)$  of the problem (4.1) exists and is given by the Markovian strategy  $u^i(t) = \phi^i(x(t), t)$ .

## MARKOVIAN NASH EQ. (MNE)

Hamilton Jacobi Bellman Equation approach

Assume the existence and differentiability of Value function

$$V^i(x, t) = \max J^i$$

# Hamilton Jacobi Bellman Equation approach

$$\text{maximize } \int_{t_0}^T e^{-r(t-t_0)} F_0(x(t), u(t), t) dt + e^{-r(T-t_0)} S(x(T))$$

$$\begin{aligned} \text{subject to } \dot{x}(t) &= f(x(t), u(t), t) \\ \underline{x(t_0)} &= x \\ \underline{u(t)} &\in \mathcal{U}(x(t), t) \end{aligned}$$

Looking for feedback strategies  $\Phi(x(t), t)$

Value function  $V(x, t)$

# Hamilton Jacobi Bellman Equation approach: Value function

## Definition

If  $P_{x,t}$  has an optimal solution, then let  $V(x, t)$  be the optimal value

$$V(x, t) = \max_{u(\cdot)} \left\{ \int_t^T e^{-r(s-t)} F_0(x(s; u), u(s), s) ds + e^{-r(T-t)} S(X(T; u)) \right\}$$

$\downarrow$   
 $V(x, T) = \max_{u(\cdot)} \int_T^T$

where  $x(s; u)$  is the unique solution to

$$\begin{cases} \dot{x}(s) = f(x(s), u(s), s) \\ x(t) = x \end{cases}$$

associated with the control  $u(\cdot)$

~~$S(x(T))$~~

$$V(x, T) = S(x)$$

We assume the existence of the Value Function  $V(x, t)$



# Not differentiable Value Function

The differentiability of the Value Function is not assured, even if  $F_0, f \in C^\infty$

$$\text{maximize } \int_t^T x(s)u(s)ds$$

$$\text{subject to } \begin{aligned} \dot{x}(s) &= u(s) \\ x(t) &= x \\ u(s) &\in [-1, 1] \end{aligned}$$

$$J = \max \int_t^T x(s)\dot{x}(s)ds = \dots = \underbrace{x(T)^2}_{\text{max}} - \underbrace{x(t)^2}_{\text{min}}$$

$$u^*(t) = \begin{cases} 1 \\ -1 \end{cases}$$

$$\dot{x}(t) = \begin{cases} 1 \\ -1 \end{cases}$$


$$x^*(T) =$$

# Not differentiable Value Function

$$x^*(t) = \begin{cases} x - (T-t) \\ x + (T-t) \end{cases}$$

$$x > 0$$

$$x < 0$$


$$V(x, t) = \frac{(T-t)^2}{2} + (T-t)|x|$$

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NOT differentiable in  $x = 0$  for all  $t < T$ .

In the HJB approach (suff. cond) differentiability is assumed.

# Sufficiency conditions: Hamilton Jacobi Bellman Equation

## Theorem (HJB equation)

Let  $V : X \times [0, T] \mapsto \mathcal{R}$  be a continuously differentiable function which satisfies the HJB equation **PDE**

$$rV(x, t) - \frac{\partial V(x, t)}{\partial t} = \max_{u \in \mathcal{U}(x, t)} \left\{ F_0(x, u, t) + \frac{\partial V(x, t)}{\partial x} f(x, u, t) \right\} \quad (1)$$

and the terminal condition

$$V(x, T) = S(x)$$

for all  $(x, t) \in X \times [0, T]$ . Let  $\Phi(x, t)$  denote the set of controls  $u \in \mathcal{U}(x, t)$  maximizing the RHS of 1. If  $u(\cdot)$  is a feasible control path with corresponding state trajectory  $x(\cdot)$  and if  $u(t) \in \Phi(x(t), t)$  holds for almost all  $t \in [0, T]$  then  $u(\cdot)$  is an optimal control path. Moreover  $V(x, t)$  is the optimal value (function) of problem  $P_{x,t}$ .

# Hamilton Jacobi Bellman approach

- a) Write HJB Eq assuming  $V(x, t)$  differentiable

$$rV(x, t) - \frac{\partial V(x, t)}{\partial t} = \max_{u \in \mathcal{U}} \left\{ F_0(x, u, t) + \frac{\partial V(x, t)}{\partial x} f(x, u, t) \right\}$$

*Handwritten notes: A green bracket above the right-hand side is labeled  $g(u)$ . A green arrow points from the  $u$  in the bracket to the  $u$  in the  $f(x, u, t)$  term.*

- b) Find from RHS  $\max_{u \in \mathcal{U}} \{ \} \Rightarrow \underline{u^*(x, t, V_x)} \forall t, \forall x$

- c) Insert  $u^*$  in HJB eq.  $\Rightarrow$  PDE

$$\begin{cases} rV(x, t) - V_t(x, t) = F_0(x, \underline{u^*}, t) + V_x(x, t) f(x, \underline{u^*}, t) \\ V(x, T) = S(x(T)) = S(x) \end{cases}$$

*Handwritten notes: Red brackets and underlines highlight  $u^*$  in the equations.*

- d) From c) try to guess a form for  $V(x, t)$  (generally a polynomial with degree equal to the maximum degree between HJB and Boundary condition (see example))

# Differential game Example: MARKOVIAN NASH EQ.

(Dockner p.87)

$$\begin{aligned}\max_{u \geq 0} J^1(u(\cdot)) &= \int_0^T e^{-rt} \left[ v(t) - x(t) - \frac{\alpha}{2} u^2(t) \right] dt \\ \max_{v \in [0,1]} J^2(u(\cdot)) &= \int_0^T e^{-rt} [v(t) - x(t)] dt \\ \text{s.t. } \dot{x}(t) &= 1 + v(t) - u(t)\sqrt{x(t)}, \\ x(0) &= x^0\end{aligned}$$

Assume  $v(t) = \psi(x, t)$  for P2, find best response  $\Phi(x, t)$  strategy for P1

Assume  $u(t) = \Phi(x, t)$  for P1, find best response strategy  $\psi(x, t)$  for P2

## Player 2

$$rV - V_t = \max_{\sigma \in [0,1]} \left\{ \sigma - x + V_x \left( x + \sigma - \underbrace{u(V_x)}_{\phi} \right) \right\}$$

$$\sigma = \begin{cases} 0 & x + V_x < 0 \\ 1 & x + V_x > 0 \end{cases}$$

⋮

⇒ equivalent to OLN E

⇒ degenerate Markovian  
Nash equilibrium

# Differential game Example: MARKOVIAN NASH EQ.

**Player 1:** Look for  $u \in \Phi(x, t)$ , associated HJB equation

$$rV(x, t) - \frac{\partial V(x, t)}{\partial t} = \max_{u \in \mathcal{U}} \left\{ F_0(x, u, t) + \frac{\partial V(x, t)}{\partial x} f(x, u, t) \right\}$$

$$rV(x, t) - \frac{\partial V(x, t)}{\partial t} = \max_{u \geq 0} \left\{ \underbrace{v - x - \frac{\alpha}{2} u^2 + V_x(1 + v - u\sqrt{x})}_{g(u)} \right\}$$

b)  $g'(u) = -\alpha u - V_x \sqrt{x} = 0$   
 $g''(u) = -\alpha < 0$

$$u^* = \phi(x, t) = -\frac{V_x \sqrt{x}}{\alpha}$$

(assume  $V_x < 0$   
 $\Rightarrow u^*$  optimal)

c) Substitute

$$\begin{cases} rV - V_t = v - x - \frac{\alpha}{2} \left( \frac{V_x^2 x}{\alpha^2} \right) + V_x \left( 1 + v + \frac{V_x^2 x}{\alpha} \right) \\ V(x, T) = 0 \end{cases}$$

# Player 1

$$\begin{cases} xV - V_t = \sigma - x + \frac{V_x^2}{2d} + V_x(1+\theta) \\ V(x, T) = 0 \end{cases}$$

degree  $x$ : 1  
degree  $t$ : 0

degree  $(V) = k \quad \partial \omega \geq T x \Rightarrow \text{degree } V_x = k - 1$

degree  $(V_t) = k$

degree  $(V_x^2) = 2(k-1)$

$$k = 1 + 2(k-1) = 2k - 1 \Rightarrow k = 1$$

$\Rightarrow$  Look for  $V(x, t) = a(t)x + b(t) \Rightarrow$

$$V_x = a(t)$$

$$V_t = a'(t)x + b'(t)$$

HJB

$$\begin{cases} x(a(t)x + b(t)) - (a'(t)x + b'(t)) = \sigma - x + \frac{(a(t)x + b(t))^2}{2d} + a(t)(1+\theta) \\ a(T) = 0, b(T) = 0 \end{cases}$$



...

$$\begin{cases} a'(t) = r + \alpha a(t) - (a(t))^2 / \alpha \\ a(\tau) = 0 \end{cases}$$

$$\begin{cases} b'(t) = \alpha b(t) - (r + \theta) a(t) \\ b(\tau) = 0 \end{cases}$$

ODE's

$a(t)$   
 $\frac{1}{\alpha} a(t)$

Feedback Strategy

$$\phi(x, t) = -\frac{\sqrt{x} \sqrt{x}}{\alpha} = -\frac{a(t) \sqrt{x}}{\alpha}$$

The observed state of system at time  $t$

Player 2

$$\max \int_0^T e^{-\alpha t} [\sigma(t) - x(t)] dt$$

$$\begin{cases} \dot{x}(t) = 1 + \sigma(t) + \lambda(t)x(t)/\alpha \\ x(0) = x_0 \\ \sigma(t) \in [0, 1] \end{cases}$$

$$H^{2c} = \sigma - x + \tilde{\mu} (1 + \sigma + \lambda x / \alpha)$$

$$\frac{\partial H}{\partial \sigma} = 1 + \tilde{\mu} \quad \sigma(t) = \begin{cases} 0 & \tilde{\mu} < -1 \\ 1 & \tilde{\mu} > -1 \end{cases}$$

$$\dot{\tilde{\mu}} = -\frac{\partial H^{2c}}{\partial x} + \mu \tilde{\mu}(t) = 1 - \frac{\lambda}{\alpha} \tilde{\mu} + x \tilde{\mu} \Rightarrow \tilde{\mu} = \frac{\mu}{\alpha - \lambda}$$

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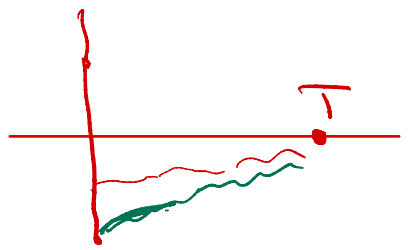
Thesis  $MNE \neq OLNE$

$$\tilde{\sigma} = \begin{cases} 0 & \tilde{\mu} < -1 \\ 1 & \tilde{\mu} > -1 \end{cases} \quad \sigma = \begin{cases} 0 & \mu < -1 \\ 1 & \underline{\mu} > -1 \end{cases}$$

To prove that  $MNE \neq OLNE$  we need to prove that  $\tilde{\mu}(t) \neq \mu(t)$

$$\dot{\tilde{\mu}} = 1 - \frac{\lambda}{2} \tilde{\mu}(t) + \lambda \tilde{f}(t) < 1 - \frac{\lambda}{2} \mu(t) + \lambda \mu(t) = \dot{\mu} \Big|_{OLNE}$$

$$\forall t \in [0, T] \quad \begin{cases} \dot{\tilde{\mu}}_{MNE} < \dot{\mu}_{OLNE} \\ \tilde{\mu}(T) = \mu(T) = 0 \end{cases}$$



$$\Rightarrow \tilde{\mu}(t) > \mu(t) \neq 0$$

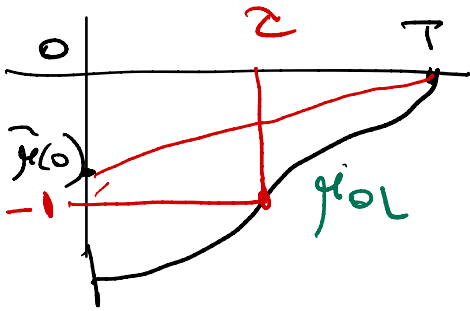

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MNE

$$(\Phi_{MNE}^N, \Psi_{MNE}^N) \neq (\Phi_{OL}^N, \Psi_{OL}^N)$$

$$\tilde{f}(t) > f(t)_{OL}$$

$$\sigma(t) = \varphi(t) =$$



$$a) \tilde{f}(0) > -1 \Rightarrow \forall t \tilde{f}(t) > -1$$

$$\Downarrow$$

$$\varphi(t) = 1$$

$$b) \tilde{f}(0) > -1$$

$$\exists \tau > 0 : \tilde{f}(\tau) = -1 \quad \tau < \tau$$

$$c) \tilde{f}(0) > 0 > -1$$

$$\exists \tau > 0 : \tilde{f}(\tau) = -1$$

$$\varphi = \begin{cases} 1 & t \in [0, \delta_1] \\ 0 & t \in (\delta_1, \delta_2) \\ 1 & t \in [\delta_2, T] \end{cases}$$

