

On near-optimality conditions for controlled Forward-Backward Stochastic Systems

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Outline

- 1 Introduction to Stochastic Control
- 2 Stochastic maximum principle
- 3 Near-optimal controls
- 4 FBSDE as state model



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W is a **standard Wiener process** on $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \in [0, T]}, \mathbb{P})$, with $(\mathcal{F}_t)_{t \in [0, T]}$ being his completed canonical filtration.



Cost function

Further, define for each admissible $u(\cdot)$ the functional

$$J(u(\cdot)) = \mathbf{E} \left[\int_0^T \ell(t, X_t, u_t) dt + h(X_T) \right], \quad (2)$$



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Usually, the goal is to find such a strategy $u^*(\cdot) \in \mathcal{U}_{ad}$ so that

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We call $u^*(\cdot)$ **optimal control** to control problem (1)-(3).



Hamiltonian function

Now, define the **Hamiltonian** of the problem by

$$H(t, x, u, y, z) = b'(t, x, u)y + \text{Tr}(\sigma'(t, x, u)z) - \ell(t, x, u).$$



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This will help to reduce the infinite dimensional optimization problem to finite dimensional one.



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In other words, u_t^* maximizes the function $H(t, X_t^*, \cdot, Y_t^*, Z_t^*)$ over U .



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Theorem (Sufficient Maximum principle)

Conversely, if the variational inequality

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holds for some admissible $\hat{u}(\cdot)$ where $(\hat{X}, \hat{Y}, \hat{Z})$ are the associated forward and backward processes, $H \left(t, \cdot, \cdot, \hat{Y}_t, \hat{Z}_t \right)$ is concave and $h(\cdot)$ is convex



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and send $\rho \rightarrow 0_+$. The variational inequality is obtained by expanding the difference on the r.h.s.



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- If $\mathcal{O}(\varepsilon) = C\varepsilon^\lambda$ for some $\lambda > 0$ independent of the constant C then $u^\varepsilon(\cdot)$ is called **near-optimal control of order λ** .



Necessary near-optimal maximum principle, Zhou 1998

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holds for all $u \in U$.



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holds for all $u \in U$.

In other words, **$u^\varepsilon(\cdot)$ near-maximizes the function $H(t, X_t^\varepsilon, \cdot, Y_t^\varepsilon, Z_t^\varepsilon)$** over U in an integral sense with order $C\varepsilon^\lambda$.



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Conversely, if the variational inequality

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*holds for any $\varepsilon > 0$ and some admissible family $(u^\varepsilon(\cdot))_{\varepsilon > 0}$,
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What is on the poster?

On the poster, a result by M.Hafayed, P.V. and S.Abbas is presented. We consider the state equation of the form

$$\left\{ \begin{array}{l} dx(t) = f(t, x(t), u(t)) dt + \sigma(t, x(t), u(t)) dW(t) \\ \quad + \int_{\Theta} c(t, x(t-), u(t), \theta) \tilde{N}(d\theta, dt), \\ -dy(t) = \int_{\Theta} g(t, x(t), y(t), z(t), r_t(\theta), u(t)) \mu(d\theta) dt - z(t) dW(t) \\ \quad - \int_{\Theta} r_t(\theta) \tilde{N}(d\theta, dt); \quad x(0) = \zeta, \quad y(T) = \phi(x(T)), \end{array} \right.$$

with the functional to be minimized

$$J(u(\cdot)) = \mathbb{E} \left[\int_0^T \int_{\Theta} \ell(t, x(t), y(t), z(t), r_t(\theta), u(t)) \mu(d\theta) dt \right. \\ \left. + h(x(T)) + \gamma(y(0)) \right].$$



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holds for all $u \in U$.

Here, H is the Hamiltonian of the problem,

$\Lambda_t^\varepsilon(\theta) = (x^\varepsilon(t), y^\varepsilon(t), z^\varepsilon(t), r_t^\varepsilon(\theta))$ and

$\Psi_t^\varepsilon(\theta) = (p_t^\varepsilon, q_t^\varepsilon, k_t^\varepsilon, R_t^\varepsilon(\theta))$ are the solutions to state and adjoint equations respectively, corresponding to $u^\varepsilon(\cdot)$.



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holds for any $\varepsilon > 0$ and some admissible family $(u^\varepsilon(\cdot))_{\varepsilon > 0}$, $H(t, \cdot, \cdot, \Psi_t^\varepsilon(\cdot))$ is concave and $h(\cdot), \gamma(\cdot)$ are convex then $(u^\varepsilon(\cdot))_{\varepsilon > 0}$ is near-optimal control of order λ .



That's the end, my friend...

Thank you for your attention.



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