

# Optimal switching problems with an infinite set of modes: an approach by randomization

M.-A. Morlais (LMM - IRA, Le Mans Université - France)

j.w.w. M. Fuhrman (University Degli Studi di Milano, Milano, Italy)

A Backward stochastic excursion with Ying Hu  
in honor of his 60th birthday

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## Outline of the talk

### I- Preliminaries & motivations

- The Optimal Switching problem (OSP): primal formulation.
- Motivation for the "randomization" (dual) approach.
- The dual formulation.

### II- The two main results

- (i) equality between the two value functions;
- (ii) new BSDE characterization.
- (iii) Comments & ideas of proof.

### III- Conclusion & perspectives

## I.1 Primal optimal switching problem and value function

On a standard prob. space  $(\Omega, \mathbb{F}, \mathbb{P})$ , let

- ▶  $W$ : standard  $d$ -dim. Brownian Motion,  $W$   $\mathbb{F}$ -adapted.  
usually:  $\mathbb{F} = \mathcal{F}^W \vee \mathcal{N}$ .
- ▶  $T$  fixed finite horizon;  $A$  set of modes (possibly **infinite**).
- ▶  $\forall (x_0, e) \in \mathbb{R}^n \times A$ , let  $X^e$  (path dependent) proc. s.t.

$$\forall t \in [0, T], \quad X_t^e = x_0 + \int_0^t (b^e(s, X^e) ds + \sigma^e(s, X^e) dW_s),$$

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Let  $(f^e)_e$ ,  $(g^e)_e$  and  $(c_{e,e'})_{(e,e')}$ : 3 families of (possib. **random**) real-valued data

- (i)  $f^e(s, X)$ : instant. profit (when system in mode  $e$ )
- (ii)  $g^e(X)$ : payoff at time  $T$  when syst. in mode  $e$ ,
- (iii)  $c_{e,e'}(s, X)$ : *nonnegative* penalty costs at time  $s$ .

## I.1 Primal optimal switching problem and value function

1. Let  $\alpha = (\tau^n, \xi^n)_{n \geq 1}$  a *management* strategy s.t.
  - (i)  $\tau^n$  increas. seq. of  $\mathbb{R}^+$  valued  $\mathbb{F}$ -stopping times;
  - (ii) for each  $n$ ,  $\xi^n$  both  $A$ -valued and  $\mathcal{F}_{\tau_n}^W$ -meas.

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  - (ii) for each  $n$ ,  $\xi^n$  both  $A$ -valued and  $\mathcal{F}_{\tau_n}^W$ -meas.
2. To  $\alpha$ , we associate the state proc.  $a$  as follows

$$a_s = \xi^1 \mathbf{1}_{s < \tau_1} + \sum_{n \geq 1} \xi^{n+1} \mathbf{1}_{\tau^n \leq s < \tau_{n+1}} \mathbf{1}_{\tau^n < T}$$

$a$ : piecewise constant proc.  $A$ -valued

By abuse, one may replace  $\alpha$  by  $a$ .

## I.1 Primal value function: Admissible set $\mathcal{A}$

$a = (\tau^n, \xi^n)$  is said *admissible* i.e.  $a$  in  $\mathcal{A}_t$  if

- H<sub>1</sub>**  $(\tau^n(\cdot), \xi^n(\cdot))_{n \in \mathbb{R}^+} \times A$ -valued  $\mathbb{F}$ -adapt. s. t.  
 $\tau_n(\omega) \rightarrow +\infty$  and  $\tau^n < \tau^{n+1}$ ,  $\mathbb{P}$ -a.s and  $\tau_0 = t$ .  
 $a$  is in  $\mathcal{A}_t^e \subset \mathcal{A}_t$  if  $\xi_0 = e$  (at  $t = \tau_0$ ).

**simultaneous switchings prohibited**, i.e.

$$\forall (a_1, a_2, a_3) \in A^3, \quad c_{a_1, a_2}(t, x) + c_{a_2, a_3}(t, x) > c_{a_1, a_3}(t, x)$$

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- H<sub>2</sub>** **H<sub>1</sub>** implies:  $N_T^a(\omega) = \text{Card}\{\tau^n(\omega), \tau^n < T\} < +\infty$ ,  $\mathbb{P}$ -a.s

- H<sub>3</sub>** Impose  $\tau^n \neq T$ : **no switching at terminal time.**

In finite case, equivalent to:

$$\forall (i, j) \in A \times A, \quad g^i(x) > g^j(x) - c_{i,j}(T, x).$$



## I.1. Primal optimal switching problem (OSP) and value function

1. For  $a$  in  $\mathcal{A}$ ,  $X^\alpha$  (or  $X^a$ ) the controlled proc. s.t.

$$dX^a = b^a(s, X^a)ds + \sigma^a(s, X^a)dW_s$$

$$\text{with } b^a(s, x) = b^{\xi_0}(s, x)\mathbf{1}_{s < \tau^1} + \sum_{n \geq 1} b^{\xi_n}(s, x)\mathbf{1}_{\tau^n \leq s < \tau^{n+1}}.$$

Similar definition for  $\sigma^a(s, x)$ .

**Remark:**  $b$  and  $\sigma$  path-dependent  $\Rightarrow X^a$  no more Markovian (PDE approach not available).

## I.1. Primal OSP: Technical assumptions (1)

► Mathematical assumptions:

- $A$ : Borel set (example: any subspace of  $\mathbb{R}^d$ );
- Both  $(b^e, \sigma^e)_e, (f^e, g^e), (c_{e,e'})_{e,e'}$  may be path-dependent;
- Let  $\mathbb{C}^n$ : set of continuous paths  $(s \mapsto x(s))_{s \in [0, T]}$

Topology on  $\mathbb{C}^n$ :  $|x|_* = \sup_{s \in [0, T]} |x(s)|$

- Measurability

$(t, \omega, e) \mapsto b^e(t, x(\omega), \omega), \sigma^e(t, \omega, x(\omega), e)$  are  
 $\text{Prog}(\mathbb{C}^n) \otimes \mathcal{B}(A)$  meas.; (similar for  $f^e, g^e, c_{e,e'}$ )

$\text{Prog}(\mathbb{C}^n)$ :  $\sigma$ -algebra of prog. measurable maps on  
 $[0, T] \times \Omega$ .

## I.1. Primal OSP: Technical assumptions (2)

(i) ) Continuity of data w.r.t  $(x, e)$

• For every  $t$  in  $[0, T]$ ,

$(x, e) \mapsto b_t(x, e), \sigma_t(x, e), f_t(x, e), g(x, e)$  are continuous on  $\mathbb{C}^n \times A$   
 $(x, e, e') \mapsto c_t(x, e, e')$  is continuous on  $\mathbb{C}^n \times A \times A$ .

• Regularity & growth assumpt (wrt  $x$ ):

$\exists K > 0$  s.t.  $\forall (t, x, x', e, e') \in [0, T] \times \mathbb{C}^n \times \mathbb{C}^n \times A \times A$ ,

(ii)  $|b_t(x, e) - b_t(x', e)| + |\sigma_t(x, e) - \sigma_t(x', e)| \leq K|x - x'|_{t^*}$   
Similar for other data.

(iii)  $|b(t, 0, e)| + |\sigma(t, 0, e)| \leq K;$

## I.1. Primal OSP: Technical assumptions (3)

- Growth assumpt wrt  $x$  (cont')

$\exists r, K > 0$  s.t.  $\forall (t, x, x', e, e') \in [0, T] \times \mathbb{C}^n \times \mathbb{C}^n \times \mathbf{A} \times \mathbf{A}$ ,

(iii)  $|f(t, x, e) + |g(x, e)| + |c(t, x, e, e')| \leq K(1 + |x|_{t*}^r).$

**Comment:** Thanks to those assumptions, one gets

(a) Strong estim. of the moments of proc.  $X^e$

(Cosso-Confortola-Fuhrman '18 );

(b) Estimate for the value functional

## I.1 Primal control problem: the value function

1. Fixing  $e$  in  $A$ , let  $\mathcal{V}^e$  be the primal value function s.t.

$$\mathcal{V}^e = \sup_{\alpha \in \mathcal{A}^e} (J(\alpha)), \text{ where}$$

$$J(\alpha) = \mathbb{E} \left( g^{a_T}(X) + \int_0^T f^{a_s}(s, X^a) ds - \sum_{\substack{n \geq 1, \\ \tau_n < T}} c_{\xi_{n-1}, \xi_n}(\tau^n, X_{\tau^n}^a) \right)$$

## I.1 OSP with finite set of modes- BSDE characterization

Under *appropriate* assumptions on data  $(f^e, g^e, (c_{e,e'}))$  with  $e, e' \in \mathcal{J} = \{1, \dots, m\}$

there exists a solution  $(Y^e, Z^e, K^e)_{e \in \mathcal{J}}$  to the BSDE system

$$\left\{ \begin{array}{l} Y_t^e = g^e(X_T) + \int_t^T f_s^e(X_s) ds + K_T^e - K_t^e \\ \quad - \int_t^T Z_s^e dW_s, \\ Y_s^e \geq \max_{\{e' \in \mathcal{J} \setminus \{e\}\}} \left( Y_s^{e'} - c_{e,e'}(s, X_s) \right) \text{ and} \\ \int_0^T (Y_s^e - \max_{\{e' \in \mathcal{J} \setminus \{e\}\}} \left( Y_s^{e'} - c_{e,e'}(s, X_s) \right)) dK_s^e = 0 \end{array} \right.$$

s.t.  $Y_0^e = \mathcal{V}^e$ .

## A (non exhaustive) review of the literature

### (1) **OSP with finite set of modes:**

- (i) Using PDE approaches: Ishii-Koike '91, Yong-Zhou '99, Ludkowski '05, Carmona-Ludkovski '07-08, ...
- (ii) Using BSDE and analyt. tools: Hamadène-Jeanblanc '02, Djehiche-Hamadene-Popier '08, Hamadène Zhang '10, Hu-Tang '10, Chassagneux-Elie -Kharroubi '11; Elie-Kharroubi '10, '14 ...
- (iii) Standard OSP with refinements: infinite horizon, Levy driven case (forward diff), partial information, non positive costs (Lundstrom-Olofsson, R. Martyr, B. El Asri) ..

## A (non exhaustive) review of the literature

### (1) **OSP with finite set of modes:**

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- (iii) Standard OSP with refinements: infinite horizon, Levy driven case (forward diff), partial information, non positive costs (Lundstrom-Olofsson, R. Martyr, B. El Asri) ..

### (2) **Connection between "finite" OSP & constrained BSDE:**

- (a) Ma-Pham-Kharroubi '10 (Markovian setting)
- (b) Elie-Kharroubi ('14) (Non Markovian case)



## I.3. Why choosing the "randomization" method ?

1. when  $A$  infinite, the (*a priori infinite*) system of RBSDEs does not seem well posed (at least to us...)
2. BSDE charact. of primal OSP: many ingredients use the finiteness of  $A$ .

## I.3. Why choosing the "randomization" method ?

1. when  $A$  infinite, the (*a priori infinite*) system of RBSDEs does not seem well posed (at least to us...)
2. BSDE charact. of primal OSP: many ingredients use the finiteness of  $A$ .
3. Randomization allows to tackle general cases: path-dependency, degenerate diffusions, case of an infinite set of modes.
4. Another motivation: in the case of finite OSP, connection already proved by Elie & Kharroubi.

## I.2 Randomized set-up & dual formulation

1. On  $(\Omega', \mathbb{F}', \mathbb{P}')$   $\mu = (\sigma^m, \zeta^m)_m$ : Poisson random meas. s.t.
  - (i) the marks  $(\sigma^m, \zeta^m)_m$  are  $\mathbb{R}^+ \times A$ -valued;
  - (ii)  $\mu$  **indep.** of  $W$  with  $\bar{\mu}(de, ds) = \lambda(de)ds$  and  $\lambda$  intensity meas. with **full support** on  $A$  and  $\lambda(\mathbf{A}) < +\infty$ .

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2. The *randomized* dual set up  $:= (\hat{\Omega}, \hat{\mathbb{P}}, \hat{\mathcal{F}}, \hat{W}, \hat{\mu})$ :
  - (2.i) Let  $\hat{\Omega} := \Omega \times \Omega'$ ,  $\hat{\mathbb{P}} = \mathbb{P} \otimes \mathbb{P}'$  and  $\hat{\mathcal{F}} = \mathbb{F}^{W, \mu}$ , with

$$\mathbb{F}^{W, \mu} := (\mathbb{F}^W \vee \mathbb{F}^\mu) \vee \mathcal{N}$$

- (2.ii)  $\hat{W}(\omega, \omega') = W(\omega)$  remains a  $\mathbb{F}^{W, \mu}$ -Brownian motion;  
 $\hat{\mu} := (\hat{\sigma}^m, \hat{\zeta}^m)_m$  Poisson r.m. with  $\mathbb{F}^{W, \mu}$ -prog. meas random marks and **same determ. compensator**  $\hat{\mu}$ .

## I.2. The randomized set-up and dual formulation

1. Let  $I$  (resp.  $\hat{I}$ ) the Poisson point proc. assoc. with  $\mu$  (resp.  $\hat{\mu}$ ) as follows

$$\forall t \in [0, T], \quad I_t = \zeta^0 \mathbf{1}_{t < \sigma^1} + \sum_{m \geq 1} \zeta^m \mathbf{1}_{\sigma^m \leq t < \sigma^{m+1}}.$$

Note that  $N_T^I := \text{Card}\{m \geq 1, \sigma_m(\omega') < T\} < \infty, \mathbb{P}'\text{-a.s.}$

2. On *randomized* prob. space,  $(\hat{I}, X^{\hat{I}})$  is a **forward uncontrolled proc.** with

$$X_t^{\hat{I}} = x_0 + \int_0^t (b^{\hat{I}s}(s, X^{\hat{I}}) ds + \sigma^{\hat{I}s}(s, X^{\hat{I}}) dW_s)$$

## I.2. The randomized set-up and dual formulation

1. To any proc.  $\hat{\nu} \mathbb{F}^{W, \mu}$ -meas., let  $\kappa^{\hat{\nu}}$  the Doleans-Dade proc.

$$\kappa_T^{\hat{\nu}} = \mathcal{E}_T((\hat{\nu} - 1) \star \tilde{\mu}) = e^{-\int_0^T \int_A (\hat{\nu}_s(e) - 1) \lambda(de) ds} \prod_{\substack{m \geq 1 \\ \zeta_m < T}} \hat{\nu}_{\sigma^m}(\zeta^m)$$

2. Let  $\hat{\mathbb{P}}^{\hat{\nu}}$  with density  $\kappa^{\hat{\nu}}$ , i.e.  $\frac{d\hat{\mathbb{P}}^{\hat{\nu}}}{d\hat{\mathbb{P}}} = \kappa^{\hat{\nu}}$

then, under  $\hat{\mathbb{P}}^{\hat{\nu}}$ ,

(a)  $\hat{I}$  remains Poisson point proc.;

(b) its new compensated meas.  $\hat{\nu}_s(e) \lambda(de) ds$

3. Set of dual controls

$$\mathcal{A}^R := \{ \hat{\nu} : \hat{\Omega} \times [0, T] \times A \mapsto ]0, \infty[ \text{ meas. and essentially bounded} \}$$

## I.2 The randomized set-up: dual formulation

1. Let  $\mathcal{V}_0^R = \sup_{\hat{\nu} \in \mathcal{A}^R} J^R(\hat{\nu})$  be the dual value function with

$$J^R(\hat{\nu}) = \underbrace{\hat{\mathbb{E}}^{\hat{\nu}} \left( g(X^I, I_T) + \int_t^T f(s, X^I, I_s) ds \right)}_{=J_1^R(\hat{\nu})} - \underbrace{\hat{\mathbb{E}}^{\hat{\nu}} \left( \sum_{m \geq 1} c_{\zeta_{m-1}, \zeta_m}(\sigma^m, X_{\sigma^m}) \right)}_{=J_2^R(\hat{\nu})}$$

$\hat{\mathbb{E}}^{\hat{\nu}}$  stands for expectation under meas.  $\hat{\mathbb{P}}^{\hat{\nu}}$ .

## II. Theorem 1

Under all previous assumptions on the primal & dual version of the OSP, one obtains

$$v_0 = v_0^{\mathcal{R}} = v_0(x, e).$$

This common value function only depends on  $X_0 = x$  and initial mode  $e$  and not of the choice of the randomized set up: (i.e. **neither on the construction of the extended dual set-up nor on the choice of intensity measure  $\lambda$** ).



## II. Theorem 2: BSDE characterization

The following BSDE (with constrained jumps)

$$\left\{ \begin{array}{l} Y_t^{\mathcal{R}} = g(X, I_T) + \int_t^T f_s(X, I_s) ds + K_T - K_t \\ \quad - \int_t^T Z_s dW_s - \int_{(t, T]} \int_A U_s(e) \mu(ds de), \\ U_t(e) \leq c_t(X, I_{t-}, e), \quad (\text{non-linear jump constraint}) \end{array} \right. \quad (1)$$

admits a *minimal* solution  $Y^{\mathcal{R}}$  such that

$$Y_0^{\mathcal{R}} = \mathcal{V}_0^{\mathcal{R}}.$$

**Remark:** (??) is a BSDE with constrained jumps.

(i)  $K$  non decreas. predic. proc s.t.  $K$  **only càdlàg** in general.

(ii)  $Y_t^{\mathcal{R}}$  is  $\mathcal{F}_t^{W, \mu}$ -adapted.

## Connection with BSDE in the case of finite set of modes (Elie-Kharroubi '14)

Let  $\mathcal{J}$  set of modes and let  $(Y^e)_{e \in \mathcal{J}}$  solving

$$\left\{ \begin{array}{l} Y_t^e = g(e, X_T) + \int_t^T f_s^e(X_s) ds + K_T^e - K_t^e \\ \quad - \int_t^T Z_s^e dW_s, \\ Y_s^e \geq \max_{\{j \in \mathcal{J} \setminus \{i\}\}} (Y_s^j - c_{e,j}(s, X_s)) \text{ and} \\ \int_0^T (Y_s^e - \max_{\{j \in \mathcal{J} \setminus \{e\}\}} (Y_s^j - c_{e,j}(s, X_s))) dK_s^e = 0 \end{array} \right. \quad (2)$$

If both the dual BSDE (??) and BSDE system (??) have a solution then

$$Y_t^{\mathcal{R}} = Y_t^{l_t} \text{ and } U_t(e) = Y_t^e - Y_t^{l_t^-}.$$

## The new BSDE representation

Let  $Y^{\mathcal{R}}$  be the *minimal* solution of following BSDE

$$\left\{ \begin{array}{l} Y_t = g(X, I_T) + \int_t^T f_s(X, I_s) ds + K_T - K_t \\ \quad - \int_t^T Z_s dW_s - \int_{(t, T]} \int_A U_s(e) \mu(ds de), \\ U_t(e) \leq c_t(X, I_{t-}, e), \lambda(de) ds d\mathbb{P} - \text{a.e.} \end{array} \right. \quad (3)$$

Since one has

$$Y_0^{\mathcal{R}} = \mathcal{V}_0^{\mathcal{R}} = \sup_{\nu \in \mathcal{A}^{\mathcal{R}}} J^{\mathcal{R}}(\nu),$$

then, combining with first main result

$$Y_0^{\mathcal{R}} = \mathcal{V}_0^{\mathcal{R}} = \mathcal{V}_0 = \sup_{\alpha \in \mathcal{A}} \mathcal{J}(\alpha).$$

## Theorem 2: sketch of proof (1/3)

1. Existence by penalization: let  $(Y^n, Z^n, U^n)$  solve

$$Y_t^n = g(X, I_T) + \int_t^T f_s(X, I_s) ds + K_T^n - K_t^n \\ - \int_t^T Z_s^n dW_s - \int_t^T \int_A U_s^n(a) \mu(ds da),$$

where  $K_t^n = n \int_0^t \int_A (U_s^n(e) - c_s(X, I_{s-}, e))^+ \lambda(de) ds$ .

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where  $K_t^n = n \int_0^t \int_A (U_s^n(e) - c_s(X, I_{s-}, e))^+ \lambda(de) ds$ .

2.a Probab representation of  $Y^n$

$$Y_t^n = \text{ess sup}_{\nu \in \mathcal{V}_n} \mathbb{E}^\nu \left( g(X, I_T) + \int_t^T f_s(X, I_s) ds \right. \\ \left. - \sum_{l \geq 1} \mathbf{1}_{t < \sigma_l < T} c_{\sigma_l}(X, \eta_{l-1}, \eta_l) \mid \mathcal{F}_t^{W, \mu} \right),$$

where  $\mathcal{V}_n = \{\nu \in \mathcal{V}, \text{ s.t. } \nu \in ]0; n]\}$ .

## Theorem 2: sketch of proof (2/3)

2.b For all  $\nu$  in  $\mathcal{V}_n$ , & taking  $\mathbb{E}^\nu(|\mathcal{F}_t^{W,\mu})$

$$Y_t^n = \mathbb{E}^\nu \left( g(X, I_T) + \int_t^T f_s(X, I_s) ds - \sum_{\substack{l \geq 1 \\ t \leq \sigma_l < T}} c_{\sigma_l}(X, \eta_{l-1}, \eta_l) | \mathcal{F}_t^{W,\mu} \right) \\ + \underbrace{\mathbb{E}^\nu \left( \int_t^T \int_A \{ n(\hat{U}_s^n(a))^+ - \hat{U}_s^n(a) \nu_s(a) \} \lambda(da) ds | \mathcal{F}_t^{W,\mu} \right)}_{\geq 0}$$

with  $\hat{U}_s^n(a) = U_s^n(a) - c_s(X, I_{s-}, a)$  & using  $nx^+ - \nu x \geq 0$

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with  $\hat{U}_s^n(a) = U_s^n(a) - c_s(X, I_{s-}, a)$  & using  $nx^+ - \nu x \geq 0$

2.c Setting  $\nu^{\epsilon,n}(a) =$

$$n \mathbf{1}_{\{\hat{U}_s^n(a) \geq 0\}} + \epsilon \mathbf{1}_{\{-1 < \hat{U}_s^n(a) < 0\}} - \epsilon (\hat{U}_s^n(a))^{-1} \mathbf{1}_{\{\hat{U}_s^n(a) \leq -1\}}$$

then

$$\nu^{\epsilon,n} \in ]0, n] \text{ and } \nu^{\epsilon,n} \leq \epsilon \text{ on } \{\hat{U}_s^n(a) < 0\}$$

## Theorem 2: sketch of proof (3/3)

$$2.c \quad Y_t^n \leq \varepsilon(T-t)\lambda(A) +$$

$$\mathbb{E}^{\nu^{\varepsilon,n}} \left[ \int_t^T f_s(X, I_s) ds + g(X, I_T) - \sum_{\substack{n \geq 1 \\ t \leq \sigma_l < T}} c_{\sigma_n}(X, \eta_{n-1}, \eta_n) \middle| \mathcal{F}_t^{W, \mu} \right]$$



## Theorem 2: sketch of proof (3/3)

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$$\mathbb{E}^{\nu^{\varepsilon,n}} \left[ \int_t^T f_s(X, I_s) ds + g(X, I_T) - \sum_{\substack{n \geq 1 \\ t \leq \sigma_l < T}} c_{\sigma_n}(X, \eta_{n-1}, \eta_n) \middle| \mathcal{F}_t^{W, \mu} \right]$$

3. By comparison (Royer '05),  $Y^n$  non decreasing, we set

$$Y = \lim \nearrow Y_t^n.$$

4. (2.a) gives  $\sup_n \mathbb{E}(\sup_t |Y_t^n|^2) < \infty$  & standard BSDE estimates

$$\exists C > 0, \quad \forall n \quad |Y^n|_{S^2} + |Z^n|_{L^2} + |U^n|_{L^2} + |K^n|_{S^2} \leq C.$$

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5. An (extended) Peng's monotonic limit theorem

$$\forall 1 \leq p < 2, \quad |Y^n - Y|_{L^p} + |Z^n - Z|_{L^p} + |U^n - U|_{L^p} \rightarrow 0, \text{ and}$$

$$K^n - K \xrightarrow{w} 0 \text{ yielding existence.}$$

# Conclusion & perspectives

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Thanks for your attention & happy birthday Ying.