

# Singular control of SPDEs and backward SPDEs with reflection

Bernt Øksendal<sup>1,2</sup>      Agnès Sulem<sup>3</sup>,      Tusheng Zhang<sup>4,1</sup>

23 June 2011

## Abstract

In the first part, we consider general singular control problems for random fields given by a stochastic partial differential equation (SPDE). We show that under some conditions the optimal singular control can be identified with the solution of a coupled system of SPDE and *a kind of reflected backward SPDE* (RBSPDE). In the second part, existence and uniqueness of solutions of RBSPDEs are established, which is of independent interest.

**Key Words:** Stochastic partial differential equations (SPDEs), singular control of SPDEs, maximum principles, comparison theorem for SPDEs, reflected SPDEs, optimal stopping of SPDEs.

*MSC(2010):* Primary 60H15 Secondary 93E20, 35R60.

## 1 Introduction

Let  $B_t, t \geq 0$  be an  $m$ -dimensional Brownian motion on a filtered probability space  $(\Omega, \mathcal{F}, \mathcal{F}_t, P)$ . Let  $D$  be a bounded smooth domain in  $\mathbb{R}^d$ . Fix  $T > 0$  and let  $\phi(\omega, x)$  be an  $\mathcal{F}_T$ -measurable  $H = L^2(D)$ -valued random variable. Let

$$k : [0, T] \times D \times \mathbb{R} \times \mathbb{R}^m \rightarrow \mathbb{R}$$

---

<sup>1</sup>Center of Mathematics for Applications (CMA), Dept. of Mathematics, University of Oslo, P.O. Box 1053 Blindern, N-0316 Oslo, Norway, email: [oksendal@math.uio.no](mailto:oksendal@math.uio.no). The research leading to these results has received funding from the European Research Council under the European Community's Seventh Framework Programme (FP7/2007-2013) / ERC grant agreement no [228087].

<sup>2</sup>Norwegian School of Economics and Business Administration, Helleveien 30, N-5045 Bergen, Norway.

<sup>3</sup>INRIA Paris-Rocquencourt, Domaine de Voluceau, Rocquencourt, BP 105, Le Chesnay Cedex, 78153, France, email: [agnes.sulem@inria.fr](mailto:agnes.sulem@inria.fr)

<sup>4</sup>School of Mathematics, University of Manchester, Oxford Road, Manchester M139PL, United Kingdom, email: [Tusheng.zhang@manchester.ac.uk](mailto:Tusheng.zhang@manchester.ac.uk)

be a given measurable mapping and  $L(t, x) : [0, T] \times D \rightarrow \mathbb{R}$  a given continuous function. Consider the problem to find  $\mathcal{F}_t$ -adapted random fields  $u(t, x) \in \mathbb{R}, Z(t, x) \in \mathbb{R}^m, \eta(t, x) \in \mathbb{R}^+$  left-continuous and increasing w.r.t.  $t$ , such that

$$\begin{aligned} du(t, x) &= -Au(t, x)dt - k(t, x, u(t, x), Z(t, x))dt + Z(t, x)dB_t, t \in (0, T) \\ &\quad -\eta(dt, x), t \in (0, T), \end{aligned} \tag{1.1}$$

$$\begin{aligned} u(t, x) &\geq L(t, x), \\ \int_0^T \int_D (u(t, x) - L(t, x))\eta(dt, x) &= 0, \\ u(T, x) &= \phi(x) \quad a.s, \end{aligned} \tag{1.2}$$

where  $A$  is a second order linear partial differential operator. This is a backward stochastic partial differential equation (BSPDE) with reflection.

The maximum principle method for solving a stochastic control problem for stochastic partial differential equations involves a BSPDE for the adjoint processes  $p(t, x), q(t, x)$ . See [ØPZ].

The purpose of this paper is twofold: (i) We study a class of singular control problems for SPDEs and prove a maximum principle for the solution of such problems. This maximum principle leads to a kind of reflected backward stochastic partial differential equations. (ii) We study backward stochastic *partial* differential equations (BSPDEs) with reflection. This means that we solve the BSPDE with the constraint that the solution must stay in a pre-described region.

## 2 Singular control of SPDEs

Suppose the state equation is an SPDE of the form

$$\begin{aligned} dY(t, x) &= \{AY(t, x) + b(t, x, Y(t, x))\}dt + \sigma(t, x, Y(t, x))dB(t) \\ &\quad + \lambda(t, x, Y(t, x))\xi(dt, x); (t, x) \in [0, T] \times D \end{aligned} \tag{2.1}$$

$$\begin{cases} Y(0, x) &= y_0(x); x \in D \\ Y(t, x) &= y_1(t, x); (t, x) \in (0, T) \times \partial D. \end{cases} \tag{2.2}$$

Here  $A$  is a given linear second order partial differential operator.

The *performance functional* is given by

$$\begin{aligned} J(\xi) &= E \left[ \int_D \int_0^T f(t, x, Y(t, x))dtdx + \int_D g(x, Y(T, x))dx \right. \\ &\quad \left. + \int_D \int_0^T h(t, x, Y(t, x))\xi(dt, x) \right], \end{aligned} \tag{2.3}$$

where  $f(t, x, y)$ ,  $g(x, y)$  and  $h(t, x, y)$  are bounded measurable functions which are differentiable in the argument  $y$  and continuous w.r.t.  $t$ .

We want to maximize  $J(\xi)$  over all  $\xi \in \mathcal{A}$ , where  $\mathcal{A}$  is a given family of adapted processes  $\xi(t, x)$ , which are non-decreasing and left-continuous w.r.t.  $t$  for all  $x$ ,  $\xi(0, x) = 0$ . We call  $\mathcal{A}$  the set of admissible singular controls. Thus we want to find  $\xi^* \in \mathcal{A}$  (called an optimal control) such that

$$\sup_{\xi \in \mathcal{A}} J(\xi) = J(\xi^*)$$

Define the *Hamiltonian*  $H$  by

$$\begin{aligned} H(t, x, y, p, q)(dt, \xi(dt, x)) &= \{f(t, x, y) + b(t, x, y)p + \sigma(t, x, y)q\}dt \\ &+ \{\lambda(t, x, y)p + h(t, x, y)\}\xi(dt, x). \end{aligned} \quad (2.4)$$

To this Hamiltonian we associate the following *backward* SPDE (BSPDE) in the unknown process  $(p(t, x), q(t, x))$ :

$$\begin{aligned} dp(t, x) &= - \left\{ A^*p(t, x)dt + \frac{\partial H}{\partial y}(t, x, Y(t, x), p(t, x), q(t, x))(dt, \xi(dt, x)) \right\} \\ &+ q(t, x)dB(t); \quad (t, x) \in (0, T) \times D \end{aligned} \quad (2.5)$$

with boundary/terminal values

$$p(T, x) = \frac{\partial g}{\partial y}(x, Y(T, x)); \quad x \in D \quad (2.6)$$

$$p(t, x) = 0; \quad (t, x) \in (0, T) \times \partial D. \quad (2.7)$$

Here  $A^*$  denotes the adjoint of the operator  $A$ .

**Theorem 2.1 (Sufficient maximum principle for singular control of SPDE)** *Let  $\hat{\xi} \in \mathcal{A}$  with corresponding solutions  $\hat{Y}(t, x)$ ,  $\hat{p}(t, x)$ ,  $\hat{q}(t, x)$ . Assume that*

$$y \rightarrow h(x, y) \text{ is concave} \quad (2.8)$$

and

$$\begin{aligned} (y, \xi) \rightarrow H(t, x, y, \hat{p}(t, x), \hat{q}(t, x))(dt, \xi(dt, x)) \\ \text{is concave.} \end{aligned} \quad (2.9)$$

Assume that

$$\begin{aligned} E\left[\int_D \left(\int_0^T \{(Y^\xi(t, x) - \hat{Y}(t, x))^2 \hat{q}^2(t, x) + \hat{p}^2(t, x)(\sigma(t, x, Y^\xi(t, x)) - \sigma(t, x, \hat{Y}(t, x)))^2\} \right. \right. \\ \left. \left. dt\right)dx\right] < \infty, \quad \text{for all } \xi \in \mathcal{A}. \end{aligned} \quad (2.10)$$

Moreover, assume that the following maximum condition holds:

$$\hat{\xi}(dt, x) \in \operatorname{argmax}_{\xi \in \mathcal{A}} H(t, x, \hat{Y}(t, x), \hat{p}(t, x), \hat{q}(t, x))(dt, \xi(dt, x)), \quad (2.11)$$

i.e.

$$\begin{aligned} & \{\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x))\}\xi(dt, x) \\ & \leq \{\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x))\}\hat{\xi}(dt, x) \text{ for all } \xi \in \mathcal{A}. \end{aligned} \quad (2.12)$$

Then  $\hat{\xi}$  is an optimal singular control.

**Proof of Theorem 2.1** Choose  $\xi \in \mathcal{A}$  and put  $Y = Y^\xi$ . Then by (2.3) we can write

$$J(\xi) - J(\hat{\xi}) = I_1 + I_2 + I_3, \quad (2.13)$$

where

$$I_1 = E \left[ \int_0^T \int_D \left\{ f(t, x, Y(t, x)) - f(t, x, \hat{Y}(t, x)) \right\} dx dt \right] \quad (2.14)$$

$$I_2 = E \left[ \int_D \left\{ g(x, Y(T, x)) - g(x, \hat{Y}(T, x)) \right\} dx \right] \quad (2.15)$$

$$I_3 = E \left[ \int_0^T \int_D \left\{ h(t, x, Y(t, x))\xi(dt, x) - h(t, x, \hat{Y}(t, x))\hat{\xi}(dt, x) \right\} \right]. \quad (2.16)$$

By our definition of  $H$  we have

$$\begin{aligned} I_1 &= E \left[ \int_0^T \int_D \left\{ H(t, x, Y(t, x), \hat{p}(t, x), \hat{q}(t, x))(dt, \xi(dt, x)) \right. \right. \\ & \quad \left. \left. - H(t, x, \hat{Y}(t, x), \hat{p}(t, x), \hat{q}(t, x))(dt, \hat{\xi}(dt, x)) \right\} \right. \\ & \quad - \int_0^T \int_D \left\{ b(t, x, Y(t, x)) - b(t, x, \hat{Y}(t, x)) \right\} \hat{p}(t, x) dx dt \\ & \quad - \int_0^T \int_D \left\{ \sigma(t, x, Y(t, x)) - \sigma(t, x, \hat{Y}(t, x)) \right\} \hat{q}(t, x) dx dt \\ & \quad - \int_0^T \int_D \hat{p}(t, x) \left\{ \lambda(t, x, Y(t, x))\xi(dt, x) - \lambda(t, x, \hat{Y}(t, x))\hat{\xi}(dt, x) \right\} dx \\ & \quad \left. - \int_0^T \int_D \left\{ h(t, x, Y(t, x))\xi(dt, x) - h(t, x, \hat{Y}(t, x))\hat{\xi}(dt, x) \right\} dx \right]. \end{aligned} \quad (2.17)$$

By (2.10) and concavity of  $g$  we have, with  $\tilde{Y} = Y - \hat{Y}$ ,

$$\begin{aligned}
I_2 &\leq E \left[ \int_D \frac{\partial g}{\partial y}(x, \hat{Y}(T, x))(Y(T, x) - \hat{Y}(T, x))dx \right] = E \left[ \int_D \hat{p}(T, x)\tilde{Y}(T, x)dx \right] \\
&= E \left[ \int_D \int_0^T \tilde{Y}(t, x)d\hat{p}(t, x)dx + \int_D \int_0^T \hat{p}(t, x)d\tilde{Y}(t, x)dx \right. \\
&\quad \left. + \int_D \int_0^T \{\sigma(t, x, Y(t, x)) - \sigma(t, x, \hat{Y}(t, x))\}\hat{q}(t, x)dt dx \right] \\
&= E \left[ \int_D \int_0^T \tilde{Y}(t, x) \left\{ -A^*\hat{p}(t, x)dt - \frac{\partial H}{\partial y}(t, x, \hat{Y}, \hat{p}, \hat{q})(dt, \hat{\xi}(dt, x)) \right\} dx \right. \\
&\quad + \int_D \int_0^T \hat{p}(t, x)\{A\tilde{Y}(t, x) + b(t, x, Y(t, x)) - b(t, x, \hat{Y}(t, x))\}dt dx \\
&\quad + \int_D \int_0^T \hat{p}(t, x)\{\lambda(t, x, Y(t, x))\xi(dt, x) - \lambda(t, x, \hat{Y}(t, x))\hat{\xi}(dt, x)\}dx \\
&\quad \left. + \int_D \int_0^T \{\sigma(t, x, Y(t, x)) - \sigma(t, x, \hat{Y}(t, x))\}\hat{q}(t, x)dt dx \right]. \tag{2.18}
\end{aligned}$$

Using integration by parts we get, since  $\tilde{Y}(t, x) = \hat{p}(t, x) = 0$  for all  $(t, x) \in (0, T) \times \partial D$ ,

$$\int_D \tilde{Y}(t, x)A^*\hat{p}(t, x)dx = \int_D \hat{p}(t, x)A\tilde{Y}(t, x)dx. \tag{2.19}$$

Hence, combining (2.13)-(2.19) and concavity of  $H$ ,

$$\begin{aligned}
J(\xi) - J(\hat{\xi}) &\leq E \left[ \int_D \int_0^T \{H(t, x, Y(t, x), \hat{p}(t, x), \hat{q}(t, x))(dt, \xi(dt, x)) \right. \\
&\quad \left. - H(t, x, \hat{Y}(t, x), \hat{p}(t, x), \hat{q}(t, x))(dt, \hat{\xi}(dt, x)) - \tilde{Y}(t, x)\frac{\partial H}{\partial y}(t, x, \hat{Y}, \hat{p}, \hat{q})(dt, \hat{\xi}(dt, x)) \right\} dx \Big] \\
&\leq \left[ \int_D \int_0^T \nabla_{\xi}H(t, x, \hat{Y}(t, x), \hat{p}(t, x), \hat{q}(t, x))(\xi(dt, x) - \hat{\xi}(dt, x))dx \right] \\
&= E \left[ \int_D \int_0^T \{\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x))\}(\xi(dt, x) - \hat{\xi}(dt, x))dx \right] \\
&\leq 0 \text{ by (2.12).}
\end{aligned}$$

This proves that  $\hat{\xi}$  is optimal.  $\square$

For  $\xi \in \mathcal{A}$  we let  $\mathcal{V}(\xi)$  denote the set of adapted processes  $\zeta(t, x)$  of finite variation w.r.t.  $t$  such that there exists  $\delta = \delta(\xi) > 0$  such that  $\xi + y\zeta \in \mathcal{A}$  for all  $y \in [0, \delta]$ .

Proceeding as in [OS] we prove the following useful result:

**Lemma 2.2** *The inequality (2.12) is equivalent to the following two variational inequalities:*

$$\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x)) \leq 0 \text{ for all } t, x \tag{2.20}$$

$$\{\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x))\}\hat{\xi}(dt, x) = 0 \text{ for all } t, x \tag{2.21}$$

Proof. (i). Suppose (2.12) holds. Choosing  $\xi = \hat{\xi} + y\zeta$  with  $\zeta \in \mathcal{V}(\hat{\xi})$  and  $y \in (0, \delta(\hat{\xi}))$  we deduce that

$$\{\lambda(s, x, \hat{Y}(s, x))\hat{p}(s, x) + h(s, x, \hat{Y}(s, x))\}\zeta(ds, x) \leq 0; (s, x) \in (0, T) \times D \quad (2.22)$$

for all  $\zeta \in \mathcal{V}(\hat{\xi})$ .

In particular, this holds if we fix  $t \in (0, T)$  and put

$$\zeta(ds, x) = a(\omega)\delta_t(ds)\phi(x); (s, x, \omega) \in (0, T) \times D \times \Omega,$$

where  $a(\omega) \geq 0$  is  $\mathcal{F}_t$ -measurable and bounded,  $\phi(x) \geq 0$  is bounded, deterministic and  $\delta_t(ds)$  denotes the Dirac measure at  $t$ . Then we get

$$\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x)) \leq 0 \text{ for all } t, x \quad (2.23)$$

which is (2.20).

On the other hand, clearly  $\zeta(dt, x) := \hat{\xi}(dt, x) \in \mathcal{V}(\hat{\xi})$  and this choice of  $\zeta$  in (2.22) gives

$$\{\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x))\}\hat{\xi}(dt, x) \leq 0; (t, x) \in (0, T) \times D \quad (2.24)$$

Similarly, we can choose  $\zeta(dt, x) = -\hat{\xi}(dt, x) \in \mathcal{V}(\hat{\xi})$  and this gives

$$\{\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x))\}\hat{\xi}(dt, x) \leq 0; (t, x) \in (0, T) \times D \quad (2.25)$$

combining (2.24) and (2.25) we get

$$\{\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x))\}\hat{\xi}(dt, x) = 0$$

which is (2.21). Together with (2.23) this proves (i).

(ii). Conversely, suppose (2.20) and (2.21) hold. Since  $\xi(dt, x) \geq 0$  for all  $\xi \in \mathcal{A}$  we see that (2.12) follows.  $\square$

We may formulate what we have proved as follows:

**Theorem 2.3** (*Sufficient maximum principle II*) *Suppose the conditions of Theorem 2.1 hold. Suppose  $\xi \in \mathcal{A}$ , and that  $\xi$  together with its corresponding processes  $Y^\xi(t, x), p^\xi(t, x), q^\xi(t, x)$  solve the coupled SPDE-RBSPDE system consisting of the SPDE (2.1)-(2.2) together with the reflected backward SPDE (RBSPDE) given by*

$$\begin{aligned} dp^\xi(t, x) = & - \left\{ A^* p^\xi(t, x) + \frac{\partial f}{\partial y}(t, x, Y^\xi(t, x)) + \frac{\partial b}{\partial y}(t, x, Y^\xi(t, x)) p^\xi(t, x) \right. \\ & \left. + \frac{\partial \sigma}{\partial y}(t, x, Y^\xi(t, x)) q^\xi(t, x) \right\} dt \\ & - \left\{ \frac{\partial \lambda}{\partial y}(t, x, Y^\xi(t, x)) p^\xi(t, x) + \frac{\partial h}{\partial y}(t, x, Y^\xi(t, x)) \right\} \xi(dt, x); (t, x) \in [0, T] \times D \end{aligned}$$

$$\lambda(t, x, Y^\xi(t, x)) p^\xi(t, x) + h(t, x, Y^\xi(t, x)) \leq 0; \text{ for all } t, x, \text{ a.s.}$$

$$\{\lambda(t, x, Y^\xi(t, x)) p^\xi(t, x) + h(t, x, Y^\xi(t, x))\} \xi(dt, x) = 0; \text{ for all } t, x, \text{ a.s.}$$

$$p(T, x) = \frac{\partial g}{\partial y}(x, Y^\xi(T, x)); x \in D$$

$$p(t, x) = 0; (t, x) \in (0, T) \times \partial D.$$

Then  $\xi$  maximizes the performance functional  $J(\xi)$ .

The concavity conditions of Theorem 2.1 are not always satisfied in applications, and it is of interest to have a maximum principle which does not need these assumptions. Moreover, it is useful to have a version which is of so called “necessary type”. To this end, we first prove some auxiliary results:

**Lemma 2.4** Let  $\xi(dt, x) \in \mathcal{A}$  and choose  $\zeta(dt, x) \in \mathcal{V}(\xi)$ . Define the derivative process

$$\mathcal{Y}(t, x) = \lim_{y \rightarrow 0^+} \frac{1}{y} (Y^{\xi+y\zeta}(t, x) - Y^\xi(t, x)). \quad (2.26)$$

Then  $\mathcal{Y}$  satisfies the SPDE

$$\begin{aligned} d\mathcal{Y}(t, x) &= A\mathcal{Y}(t, x)dt + \mathcal{Y}(t, x) \left[ \frac{\partial b}{\partial y}(t, x, Y(t, x))dt \right. \\ &\quad \left. + \frac{\partial \sigma}{\partial y}(t, x, Y(t, x))dB(t) + \frac{\partial \lambda}{\partial y}(t, x, Y(t, x))\xi(dt, x) \right] \\ &\quad + \lambda(t, x, Y(t, x))\zeta(dt, x); \quad (t, x) \in [0, T] \times D \\ \mathcal{Y}(t, x) &= 0; \quad (t, x) \in (0, T) \times \partial D \\ \mathcal{Y}(0, x) &= 0; \quad x \in D \end{aligned} \quad (2.27)$$

Proof. This follows from the equation (2.1)-(2.2) for  $Y(t, x)$ . We omit the details.  $\square$

**Lemma 2.5** Let  $\xi(dt, x) \in \mathcal{A}$  and  $\zeta(dt, x) \in \mathcal{V}(\xi)$ . Put  $\eta = \xi + y\zeta; y \in [0, \delta(\xi)]$ . Assume that

$$\begin{aligned} E \left[ \int_D \left( \int_0^T \{ (Y^\eta(t, x) - Y^\xi(t, x))^2 q^2(t, x) \right. \right. \\ \left. \left. + p^2(t, x) (\sigma(t, x, Y^\eta(t, x)) - \sigma(t, x, Y^\xi(t, x)))^2 \} dt \right) dx \right] < \infty \quad \text{for all } y \in [0, \delta(\xi)], \end{aligned} \quad (2.28)$$

where  $(p(t, x), q(t, x))$  is the solution of (2.5)-(2.7) corresponding to  $Y^\xi(t, x)$ . Then

$$\begin{aligned} &\lim_{y \rightarrow 0^+} \frac{1}{y} (J(\xi + y\zeta) - J(\xi)) \\ &= E \left[ \int_D \left( \int_0^T \{ \lambda(t, x, Y(t, x))p(t, x) + h(t, x, Y(t, x)) \} \zeta(dt, x) \right) dx \right]. \end{aligned} \quad (2.29)$$

Proof. By (2.3) and (2.26), we have

$$\begin{aligned} &\lim_{y \rightarrow 0^+} \frac{1}{y} (J(\xi + y\zeta) - J(\xi)) \\ &= E \left[ \int_D \left\{ \int_0^T \frac{\partial f}{\partial y}(t, x, Y(t, x)) \mathcal{Y}(t, x) dt + \frac{\partial g}{\partial y}(x, Y(T, x)) \mathcal{Y}(T, x) \right\} dx \right. \\ &\quad \left. + \int_D \int_0^T \frac{\partial h}{\partial y}(t, x, Y(t, x)) \mathcal{Y}(t, x) \xi(dt, x) dx + \int_D \int_0^T h(t, x, Y(t, x)) \zeta(dt, x) dx \right]. \end{aligned} \quad (2.30)$$

By (2.4) and (2.27) we obtain

$$\begin{aligned}
& E\left[\int_D \int_0^T \frac{\partial f}{\partial y}(t, x, Y(t, x))\mathcal{Y}(t, x)dt dx\right] \\
&= E\left[\int_D \left(\int_0^T \mathcal{Y}(t, x)\left\{\frac{\partial H}{\partial y}(dt, \xi(dt, x)) - p(t, x)\frac{\partial b}{\partial y}(t, x)dt\right.\right.\right. \\
&\quad \left.\left.\left.- q(t, x)\frac{\partial \sigma}{\partial y}(t, x)dt - (p(t, x)\frac{\partial \lambda}{\partial y}(t, x) + \frac{\partial h}{\partial y}(t, x))\xi(dt, x)\right\}\right)dx\right], \tag{2.31}
\end{aligned}$$

where we have used the abbreviated notation

$$\frac{\partial H}{\partial y}(dt, \xi(dt, x)) = \frac{\partial H}{\partial y}(t, x, Y(t, x), p(t, x), q(t, x))(dt, \xi(dt, x))$$

etc.

By the Itô formula and (2.5), (2.28) we see that

$$\begin{aligned}
& E\left[\int_D \frac{\partial g}{\partial y}(x)\mathcal{Y}(T, x)dx\right] \\
&= E\left[\int_D p(T, x)\mathcal{Y}(T, x)dx\right] \\
&= E\left[\int_D \left(\int_0^T \{p(t, x)d\mathcal{Y}(t, x) + \mathcal{Y}(t, x)dp(t, x)\} + [p(\cdot, x), \mathcal{Y}(\cdot, x)](T)\right)dx\right] \\
&= E\left[\int_D \left(\int_0^T [p(t, x)\{A\mathcal{Y}(t, x)dt + \mathcal{Y}(t, x)\frac{\partial b}{\partial y}(t, x)dt\right.\right. \\
&\quad \left.\left.+ \mathcal{Y}(t, x)\frac{\partial \lambda}{\partial y}(t, x)\xi(dt, x) + \lambda(t, x)\zeta(dt, x)\right\}\right. \\
&\quad \left.+ \mathcal{Y}(t, x)\{-A^*p(t, x)dt - \frac{\partial H}{\partial y}(dt, \xi(dt, x))\}\right. \\
&\quad \left.+ \mathcal{Y}(t, x)\frac{\partial \sigma}{\partial y}(t, x)q(t, x)]dt\right)dx], \tag{2.32}
\end{aligned}$$

where  $[p(\cdot, x), \mathcal{Y}(\cdot, x)](t)$  denotes the covariation process of  $p(\cdot, x)$  and  $\mathcal{Y}(\cdot, x)$ .

Since  $p(t, x) = \mathcal{Y}(t, x) = 0$  for  $x \in \partial D$ , we deduce that

$$\int_D p(t, x)A\mathcal{Y}(t, x)dx = \int_D A^*p(t, x)\mathcal{Y}(t, x)dx. \tag{2.33}$$

Therefore, substituting (2.31) and (2.32) into (2.30), we get

$$\begin{aligned}
& \lim_{y \rightarrow 0^+} \frac{1}{y}(J(\xi + y\zeta) - J(\xi)) \\
&= E\left[\int_D \left(\int_0^T \{\lambda(t, x)p(t, x) + h(t, s)\}\zeta(dt, x)\right)dx\right].
\end{aligned}$$

□

We can now state our necessary maximum principle:



**Theorem 2.6** [*Necessary maximum principle*]

(i) Suppose  $\xi^* \in \mathcal{A}$  is optimal, i.e.

$$\max_{\xi \in \mathcal{A}} J(\xi) = J(\xi^*). \quad (2.34)$$

Let  $Y^*, (p^*, q^*)$  be the corresponding solution of (2.1)-(2.2) and (2.5)-(2.7), respectively, and assume that (2.28) holds with  $\xi = \xi^*$ . Then

$$\lambda(t, x, Y^*(t, x))p^*(t, x) + h(t, x, Y^*(t, x)) \leq 0 \quad \text{for all } t, x \in [0, T] \times D, \text{ a.s.} \quad (2.35)$$

and

$$\{\lambda(t, x, Y^*(t, x))p^*(t, x) + h(t, x, Y^*(t, x))\}\xi^*(dt, x) = 0 \quad \text{for all } t, x \in [0, T] \times D, \text{ a.s.} \quad (2.36)$$

(ii) Conversely, suppose that there exists  $\hat{\xi} \in \mathcal{A}$  such that the corresponding solutions  $\hat{Y}(t, x), (\hat{p}(t, x), \hat{q}(t, x))$  of (2.1)-(2.2) and (2.5)-(2.7), respectively, satisfy

$$\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x)) \leq 0 \quad \text{for all } t, x \in [0, T] \times D, \text{ a.s.} \quad (2.37)$$

and

$$\{\lambda(t, x, \hat{Y}(t, x))\hat{p}(t, x) + h(t, x, \hat{Y}(t, x))\}\hat{\xi}(dt, x) = 0 \quad \text{for all } t, x \in [0, T] \times D, \text{ a.s.} \quad (2.38)$$

Then  $\hat{\xi}$  is a directional sub-stationary point for  $J(\cdot)$ , in the sense that

$$\lim_{y \rightarrow 0^+} \frac{1}{y} (J(\hat{\xi} + y\zeta) - J(\hat{\xi})) \leq 0 \quad \text{for all } \zeta \in \mathcal{V}(\hat{\xi}). \quad (2.39)$$

*Proof.* This is proved in a similar way as in Theorem 2.4 in [ØS]. For completeness we give the details:

(i) If  $\xi \in \mathcal{A}$  is optimal, we get by Lemma 2.5

$$\begin{aligned} 0 &\geq \lim_{y \rightarrow 0^+} \frac{1}{y} (J(\xi + y\zeta) - J(\xi)) \\ &= E\left[\int_D \int_0^T \{\lambda(t, x)p(t, x) + h(t, x)\}\zeta(dt, x)dx\right], \quad \text{for all } \zeta \in \mathcal{V}(\xi). \end{aligned} \quad (2.40)$$

In particular, this holds if we choose  $\zeta$  such that

$$\zeta(ds, x) = a(\omega)\delta_t(s)\phi(x) \quad (2.41)$$

for some fixed  $t \in [0, T]$  and some bounded  $\mathcal{F}_t$ -measurable random variable  $a(\omega) \geq 0$  and some bounded, deterministic  $\phi(x) \geq 0$ , where  $\delta_t(s)$  is Dirac measure at  $t$ . Then (2.40) gets the form

$$E\left[\int_D \{\lambda(t, x)p(t, x) + h(t, x)\}a(\omega)\phi(x)dx\right] \leq 0.$$

Since this holds for all such  $a(\omega), \phi(x)$  we deduce that

$$\lambda(t, x)p(t, x) + h(t, x) \leq 0 \quad \text{for all } t, x, a.s. \quad (2.42)$$

Next, if we choose  $\zeta(dt, x) = \xi(dt, x) \in \mathcal{V}(\xi)$ , we get from (2.40)

$$E\left[\int_D \int_0^T \{\lambda(t, x)p(t, x) + h(t, x)\}\xi(dt, x)dx\right] \leq 0. \quad (2.43)$$

On the other hand, we can also choose  $\zeta(dt, x) = -\xi(dt, x) \in \mathcal{V}(\xi)$ , and this gives

$$E\left[\int_D \int_0^T \{\lambda(t, x)p(t, x) + h(t, x)\}\xi(dt, x)dx\right] \geq 0. \quad (2.44)$$

Combining (2.43) and (2.44) we get

$$E\left[\int_D \int_0^T \{\lambda(t, x)p(t, x) + h(t, x)\}\xi(dt, x)dx\right] = 0. \quad (2.45)$$

Combining (2.42) and (2.45) we see that

$$\{\lambda(t, x)p(t, x) + h(t, x)\}q(dt, x) = 0 \quad \text{for all } t, x, a.s. \quad (2.46)$$

as claimed. This proves (i).

(ii) Conversely, suppose  $\hat{\xi} \in \mathcal{A}$  is as in (ii). Then (2.39) follows from Lemma 2.5. □

### 3 Existence and Uniqueness

In this section, we will prove the main existence and uniqueness result for reflected backward stochastic partial differential equations. For notational simplicity, we choose the operator  $A$  to be the Laplacian operator  $\Delta$ . However, our methods work equally well for general second order differential operators like

$$A = \frac{1}{2} \sum_{i,j=1}^d \frac{\partial}{\partial x_i} (a_{ij}(x) \frac{\partial}{\partial x_j}),$$

where  $a = (a_{ij}(x)) : D \rightarrow \mathbb{R}^{d \times d}$  ( $d > 2$ ) is a measurable, symmetric matrix-valued function which satisfies the uniform elliptic condition

$$\lambda|z|^2 \leq \sum_{i,j=1}^d a_{ij}(x)z_i z_j \leq \Lambda|z|^2, \quad \forall z \in \mathbb{R}^d \text{ and } x \in D$$

for some constant  $\lambda, \Lambda > 0$

First we will establish a comparison theorem for BSPDEs, which is of independent interest. Consider two backward SPDEs:

$$\begin{aligned} du_1(t, x) &= -\Delta u_1(t)dt - b_1(t, u_1(t, x), Z_1(t, x))dt + Z_1(t, x)dB_t, t \in (0, T) \\ u_1(T, x) &= \phi_1(x) \quad a.s. \end{aligned} \quad (3.1)$$

$$\begin{aligned} du_2(t, x) &= -\Delta u_2(t)dt - b_2(t, u_2(t, x), Z_2(t, x))dt + Z_2(t, x)dB_t, t \in (0, T) \\ u_2(T, x) &= \phi_2(x) \quad a.s. \end{aligned} \quad (3.2)$$

From now on, if  $u(t, x)$  is a function of  $(t, x)$ , we write  $u(t)$  for the function  $u(t, \cdot)$ .

The following result is a comparison theorem for backward stochastic partial differential equations.

**Theorem 3.1** (*Comparison theorem for BSPDEs*) Suppose  $\phi_1(x) \leq \phi_2(x)$  and  $b_1(t, u, z) \leq b_2(t, u, z)$ . Then we have  $u_1(t, x) \leq u_2(t, x), x \in D$ , a.e. for every  $t \in [0, T]$ .

**Proof.** For  $n \geq 1$ , define functions  $\psi_n(z), f_n(x)$  as follows (see [DP1]).

$$\psi_n(z) = \begin{cases} 0 & \text{if } z \leq 0, \\ 2nz & \text{if } 0 \leq z \leq \frac{1}{n}, \\ 2 & \text{if } z > \frac{1}{n}. \end{cases} \quad (3.3)$$

$$f_n(x) = \begin{cases} 0 & \text{if } x \leq 0, \\ \int_0^x dy \int_0^y \psi_n(z)dz & \text{if } x > 0. \end{cases} \quad (3.4)$$

We have

$$f'_n(x) = \begin{cases} 0 & \text{if } x \leq 0, \\ nx^2 & \text{if } x \leq \frac{1}{n}, \\ 2x - \frac{1}{n} & \text{if } x > \frac{1}{n}. \end{cases} \quad (3.5)$$

Also  $f_n(x) \uparrow (x^+)^2$  as  $n \rightarrow \infty$ . For  $h \in K := L^2(D)$ , set

$$F_n(h) = \int_D f_n(h(x))dx.$$

$F_n$  has the following derivatives for  $h_1, h_2 \in K$ ,

$$F'_n(h)(h_1) = \int_D f'_n(h(x))h_1(x)dx, \quad (3.6)$$

$$F''_n(h)(h_1, h_2) = \int_D f''_n(h(x))h_1(x)h_2(x)dx. \quad (3.7)$$

Applying Ito's formula we get

$$\begin{aligned}
& F_n(u_1(t) - u_2(t)) \\
= & F_n(\phi_1 - \phi_2) + \int_t^T F'_n(u_1(s) - u_2(s))(\Delta(u_1(s) - u_2(s)))ds \\
& + \int_t^T F'_n(u_1(s) - u_2(s))(b_1(s, u_1(s), Z_1(s)) - b_2(s, u_2(s), Z_2(s)))ds \\
& - \int_t^T F'_n(u_1(s) - u_2(s))(Z_1(s) - Z_2(s))dB_s \\
& - \frac{1}{2} \int_t^T F''_n(u_1(s) - u_2(s))(Z_1(s) - Z_2(s), Z_1(s) - Z_2(s))ds \\
= &: I_n^1 + I_n^2 + I_n^3 + I_n^4 + I_n^5, \tag{3.8}
\end{aligned}$$

where,

$$\begin{aligned}
I_n^2 &= \int_t^T F'_n(u_1(s) - u_2(s))(\Delta(u_1(s) - u_2(s)))ds \\
&= \int_t^T \int_D f'_n(u_1(s, x) - u_2(s, x))(\Delta(u_1(s, x) - u_2(s, x)))dxds \\
&= - \int_t^T \int_D f''_n(u_1(s, x) - u_2(s, x))|\nabla(u_1(s, x) - u_2(s, x))|^2 dxds \leq 0, \tag{3.9}
\end{aligned}$$

$$\begin{aligned}
I_n^5 &= -n \int_t^T \int_D \chi_{\{0 \leq u_1(s, x) - u_2(s, x) \leq \frac{1}{n}\}} (u_1(s, x) - u_2(s, x)) |Z_1(s, x) - Z_2(s, x)|^2 dxds \\
&\quad - \int_t^T \int_D \chi_{\{u_1(s, x) - u_2(s, x) > \frac{1}{n}\}} |Z_1(s, x) - Z_2(s, x)|^2 dxds. \tag{3.10}
\end{aligned}$$

For  $I_n^3$ , we have

$$\begin{aligned}
I_n^3 &= \int_t^T \int_D f'_n(u_1(s, x) - u_2(s, x))(b_1(s, u_1(s, x), Z_1(s, x)) - b_2(s, u_2(s, x), Z_2(s, x)))dxds \\
&= \int_t^T \int_D f'_n(u_1(s, x) - u_2(s, x))(b_1(s, u_1(s, x), Z_1(s, x)) - b_2(s, u_1(s, x), Z_1(s, x)))dxds \\
&\quad + \int_t^T \int_D f'_n(u_1(s, x) - u_2(s, x))(b_2(s, u_1(s, x), Z_1(s, x)) - b_2(s, u_2(s, x), Z_1(s, x)))dxds \\
&\quad + \int_t^T \int_D f'_n(u_1(s, x) - u_2(s, x))(b_2(s, u_2(s, x), Z_1(s, x)) - b_2(s, u_2(s, x), Z_2(s, x)))dxds \\
&\leq \int_t^T \int_D f'_n(u_1(s, x) - u_2(s, x))(b_2(s, u_2(s, x), Z_1(s, x)) - b_2(s, u_2(s, x), Z_2(s, x)))dxds \\
&\quad + C \int_t^T \int_D ((u_1(s, x) - u_2(s, x))^+)^2 dxds := I_{n,1}^3 + I_{n,2}^3, \tag{3.11}
\end{aligned}$$

where the Lipschitz condition of  $b$  and the assumption  $b_1 \leq b_2$  have been used.  $I_{n,1}^3$  can be estimated as follows:

$$\begin{aligned}
I_{n,1}^3 &\leq C \int_t^T \int_D f'_n(u_1(s,x) - u_2(s,x)) |Z_1(s,x) - Z_2(s,x)| dx ds \\
&= C \int_t^T \int_D \chi_{\{0 \leq u_1(s,x) - u_2(s,x) \leq \frac{1}{n}\}} n (u_1(s,x) - u_2(s,x))^2 |Z_1(s,x) - Z_2(s,x)| dx ds \\
&\quad + C \int_t^T \int_D \chi_{\{u_1(s,x) - u_2(s,x) > \frac{1}{n}\}} [2(u_1(s,x) - u_2(s,x)) - \frac{1}{n}] |Z_1(s,x) - Z_2(s,x)| dx ds \\
&\leq C \int_t^T \int_D \chi_{\{u_1(s,x) - u_2(s,x) > \frac{1}{n}\}} (2(u_1(s,x) - u_2(s,x)) - \frac{1}{n})^2 dx ds \\
&\quad + \int_t^T \int_D \chi_{\{u_1(s,x) - u_2(s,x) > \frac{1}{n}\}} |Z_1(s,x) - Z_2(s,x)|^2 dx ds \\
&\quad + \frac{1}{4} C^2 \int_t^T \int_D \chi_{\{0 \leq u_1(s,x) - u_2(s,x) \leq \frac{1}{n}\}} n (u_1(s,x) - u_2(s,x))^3 dx ds \\
&\quad + \int_t^T \int_D \chi_{\{0 \leq u_1(s,x) - u_2(s,x) \leq \frac{1}{n}\}} n (u_1(s,x) - u_2(s,x))^2 |Z_1(s,x) - Z_2(s,x)|^2 dx ds \\
&\leq C' \int_t^T \int_D ((u_1(s,x) - u_2(s,x))^+)^2 dx ds \\
&\quad + \int_t^T \int_D \chi_{\{u_1(s,x) - u_2(s,x) > \frac{1}{n}\}} |Z_1(s,x) - Z_2(s,x)|^2 dx ds \\
&\quad + \int_t^T \int_D \chi_{\{0 \leq u_1(s,x) - u_2(s,x) \leq \frac{1}{n}\}} n (u_1(s,x) - u_2(s,x))^2 |Z_1(s,x) - Z_2(s,x)|^2 dx ds
\end{aligned} \tag{3.12}$$

(3.10), (3.11) and (3.12) imply that

$$I_n^3 + I_n^5 \leq C \int_t^T \int_D ((u_1(s,x) - u_2(s,x))^+)^2 dx ds \tag{3.13}$$

Thus it follows from (3.8), (3.9) and (3.13) that

$$\begin{aligned}
&F_n(u_1(t) - u_2(t)) \\
&\leq F_n(\phi_1 - \phi_2) + C \int_t^T \int_D ((u_1(s,x) - u_2(s,x))^+)^2 dx ds \\
&\quad - \int_t^T F'_n(u_1(s) - u_2(s)) (Z_1(s) - Z_2(s)) dB_s
\end{aligned} \tag{3.14}$$

Take expectation and let  $n \rightarrow \infty$  to get

$$E\left[\int_D ((u_1(t,x) - u_2(t,x))^+)^2 dx\right] \leq \int_t^T ds E\left[\int_D ((u_1(s,x) - u_2(s,x))^+)^2 dx\right] \tag{3.15}$$

Gronwall's inequality yields that

$$E\left[\int_D ((u_1(t, x) - u_2(t, x))^+)^2 dx\right] = 0, \quad (3.16)$$

which completes the proof of the theorem.  $\blacksquare$

**Remark.** After this paper was written we became aware of the paper [MYZ], where a similar comparison theorem is proved. However, the theorems are not identical and the proofs are quite different.

We now proceed to prove existence and uniqueness of the reflected BSPDEs. Let  $V = W_0^{1,2}(D)$  be the Sobolev space of order one with the usual norm  $\|\cdot\|$ . Consider the reflected backward stochastic partial differential equation:

$$du(t) = -\Delta u(t)dt - b(t, u(t, x), Z(t, x))dt + Z(t, x)dB_t, t \in (0, T) \quad (3.17)$$

$$-\eta(dt, x), t \in (0, T), \quad (3.18)$$

$$u(t, x) \geq L(t, x),$$

$$\int_0^T \int_D (u(t, x) - L(t, x))\eta(dt, x)dx = 0,$$

$$u(T, x) = \phi(x) \quad a.s. \quad (3.19)$$

**Theorem 3.2** Assume that  $E[\|\phi\|_K^2] < \infty$ . and that

$$|b(s, u_1, z_1) - b(s, u_2, z_2)| \leq C(|u_1 - u_2| + |z_1 - z_2|).$$

Let  $L(t, x)$  be a measurable function which is differentiable in  $t$  and twice differentiable in  $x$  such that

$$\int_0^T \int_D L'(t, x)^2 dx dt < \infty, \quad \int_0^T \int_D |\Delta L(t, x)|^2 dx dt < \infty.$$

Then there exists a unique  $K \times L^2(D, \mathbb{R}^m) \times K$ -valued progressively measurable process  $(u(t, x), Z(t, x), \eta(t, x))$  such that

$$(i) \quad E\left[\int_0^T \|u(t)\|_V^2 dt\right] < \infty, \quad E\left[\int_0^T |Z(t)|_{L^2(D, \mathbb{R}^m)}^2 dt\right] < \infty.$$

$$(ii) \quad \eta \text{ is a } K\text{-valued continuous process, non-negative and nondecreasing in } t \text{ and } \eta(0, x) = 0.$$

$$(iii) \quad u(t, x) = \phi(x) + \int_t^T \Delta u(t, x) ds + \int_t^T b(s, u(s, x), Z(s, x)) ds - \int_t^T Z(s, x) dB_s + \eta(T, x) - \eta(t, x); \quad 0 \leq t \leq T, \quad (3.20)$$

$$(iv) \quad u(t, x) \geq L(t, x) \quad a.e. \quad x \in D, \forall t \in [0, T].$$

$$(v) \quad \int_0^T \int_D (u(t, x) - L(t, x))\eta(dt, x)dx = 0$$

where  $u(t)$  stands for the  $K$ -valued continuous process  $u(t, \cdot)$  and (iii) is understood as an equation in the dual space  $V^*$  of  $V$ .

For the proof of the theorem, we introduce the penalized BSPDEs:

$$\begin{aligned} du^n(t) &= -\Delta u^n(t)dt - b(t, u^n(t, x), Z^n(t, x))dt + Z^n(t, x)dB_t \\ &\quad -n(u^n(t, x) - L(t, x))^- dt, \quad t \in (0, T) \end{aligned} \quad (3.21)$$

$$u^n(T, x) = \phi(x) \quad a.s. \quad (3.22)$$

According to [ØPZ], the solution  $(u^n, Z^n)$  of the above equation exists and is unique. We are going to show that the sequence  $(u^n, Z^n)$  has a limit, which will be a solution of the equation (3.20). First we need some a priori estimates.

**Lemma 3.3** *Let  $(u^n, Z^n)$  be the solution of equation (3.21). We have*

$$\sup_n E[\sup_t |u^n(t)|_K^2] < \infty, \quad (3.23)$$

$$\sup_n E[\int_0^T \|u^n(t)\|_V^2] < \infty, \quad (3.24)$$

$$\sup_n E[\int_0^T |Z^n(t)|_{L^2(D, \mathbb{R}^m)}^2] < \infty. \quad (3.25)$$

**Proof.** Take a function  $f(t, x) \in C_0^{2,2}([-1, T+1] \times D)$  satisfying  $f(t, x) \geq L(t, x)$ . Applying Itô's formula, it follows that

$$\begin{aligned} |u^n(t) - f(t)|_K^2 &= |\phi - f(T)|_K^2 + 2 \int_t^T \langle u^n(s) - f(s), \Delta u^n(s) \rangle ds \\ &\quad + 2 \int_t^T \langle u^n(s) - f(s), b(s, u^n(s), Z^n(s)) \rangle ds \\ &\quad - 2 \int_t^T \langle u^n(s) - f(s), Z^n(s) \rangle dB_s \\ &\quad + 2n \int_t^T \langle u^n(s) - f(s), (u^n(s) - L(s))^- \rangle ds - \int_t^T |Z^n(s)|_{L^2(D, \mathbb{R}^m)}^2 ds \\ &\quad + 2 \int_t^T \langle u^n(s) - f(s), f'(s) \rangle ds, \quad a.s. \end{aligned} \quad (3.26)$$

where  $\langle, \rangle$  denotes the inner product in  $K$ . Now we estimate each of the terms on the right hand side.

$$\begin{aligned} &2 \int_t^T \langle u^n(s) - f(s), \Delta u^n(s) \rangle ds \\ &= -2 \int_t^T \|u^n(s)\|_V^2 ds + 2 \int_t^T \left\langle \frac{\partial f(s)}{\partial x}, \frac{\partial u^n(s)}{\partial x} \right\rangle ds \\ &\leq - \int_t^T \|u^n(s)\|_V^2 ds + \int_t^T \|f(s)\|_V^2 ds \end{aligned} \quad (3.27)$$

$$\begin{aligned}
& 2 \int_t^T \langle u^n(s) - f(s), b(s, u^n(s), Z^n(s)) \rangle ds \\
= & 2 \int_t^T \langle u^n(s) - f(s), b(s, u^n(s), Z^n(s)) - b(s, f(s), Z^n(s)) \rangle ds \\
& + 2 \int_t^T \langle u^n(s) - f(s), b(s, f(s), Z^n(s)) - b(s, f(s), 0) \rangle ds \\
& + 2 \int_t^T \langle u^n(s) - f(s), b(s, f(s), 0) \rangle ds \\
\leq & C \int_t^T |u^n(s) - f(s)|_H^2 ds + \frac{1}{2} \int_t^T |Z^n(s)|_{L^2(D, \mathbb{R}^m)}^2 ds \\
& + C \int_t^T |b(s, f(s), 0)|_H^2 ds \tag{3.28}
\end{aligned}$$

$$\begin{aligned}
& 2n \int_t^T \langle u^n(s) - f(s), (u^n(s) - L(s))^- \rangle ds \\
= & 2n \int_t^T \int_D (u^n(s, x) - f(s, x)) \chi_{\{u^n(s, x) \leq L(s, x)\}} (L(s, x) - u^n(s, x)) ds dx \leq 0 \tag{3.29}
\end{aligned}$$

Substituting (3.27), (3.28) and (3.29) into (3.26) we obtain

$$\begin{aligned}
& |u^n(t) - f(t)|_K^2 + \int_t^T \|u^n(s)\|_V^2 ds + \frac{1}{2} \int_t^T |Z^n(s)|_{L^2(D, \mathbb{R}^m)}^2 ds \\
\leq & |\phi - f(T)|_K^2 + C \int_t^T |u^n(s) - f(s)|_K^2 ds + C \int_t^T |b(s, f(s), 0)|_K^2 ds \\
& + \int_t^T \|f(s)\|_V^2 ds - 2 \int_t^T \langle u^n(s) - f(s), Z^n(s) \rangle dB_s \tag{3.30}
\end{aligned}$$

Take expectation and use the Gronwall inequality to obtain

$$\sup_n \sup_t E[|u^n(t)|_K^2] < \infty \tag{3.31}$$

$$\sup_n E\left[\int_0^T \|u^n(t)\|_V^2 dt\right] < \infty \tag{3.32}$$

$$\sup_n E\left[\int_0^T |Z^n(t)|_{L^2(D, \mathbb{R}^m)}^2 dt\right] < \infty \tag{3.33}$$

By virtue of (3.33), (3.31) can be further strengthened to (3.23). Indeed, by Burkholder



inequality,

$$\begin{aligned}
& E \left[ 2 \sup_{v \leq t \leq T} \left| \int_t^T \langle u^n(s) - f(s), Z^n(s) \rangle dB_s \right| \right] \\
& \leq CE \left[ \left( \int_v^T |u^n(s) - f(s)|_K^2 |Z^n(s)|_{L^2(D, \mathbb{R}^m)}^2 ds \right)^{\frac{1}{2}} \right] \\
& \leq CE \left[ \sup_{v \leq s \leq T} (|u^n(s) - f(s)|_K) \left( \int_v^T |Z^n(s)|_{L^2(D, \mathbb{R}^m)}^2 ds \right)^{\frac{1}{2}} \right] \\
& \leq \frac{1}{2} E \left[ \sup_{v \leq s \leq T} (|u^n(s) - f(s)|_K^2) \right] + CE \left[ \int_v^T |Z^n(s)|_{L^2(D, \mathbb{R}^m)}^2 ds \right] \tag{3.34}
\end{aligned}$$

With (3.34), taking superum over  $t \in [v, T]$  on both sides of (3.26) we obtain (3.23).  $\blacksquare$

We need the following estimates.

**Lemma 3.4** *Suppose the conditions in Theorem 3.2 hold. Then there is a constant  $C$  such that*

$$E \left[ \int_0^T \int_D ((u^n(t, x) - L(t, x))^-)^2 dx dt \right] \leq \frac{C}{n^2}. \tag{3.35}$$

**Proof.** Let  $f_m$  be defined as in the proof of Theorem 3.1. Then  $f_m(x) \uparrow (x^+)^2$  and  $f'_m(x) \uparrow 2x^+$  as  $m \rightarrow \infty$ . For  $h \in K$ , set

$$G_m(h) = \int_D f_m(-h(x)) dx.$$

It is easy to see that for  $h_1, h_2 \in K$ ,

$$G'_m(h)(h_1) = - \int_D f'_m(-h(x)) h_1(x) dx, \tag{3.36}$$

$$G''_m(h)(h_1, h_2) = \int_D f''_m(-h(x)) h_1(x) h_2(x) dx. \tag{3.37}$$

Applying Itô's formula we get

$$\begin{aligned}
& G_m(u^n(t) - L(t)) \\
= & G_m(\phi - L(T)) + \int_t^T G'_m(u^n(s) - L(s))(\Delta u^n(s))ds \\
& + \int_t^T G'_m(u^n(s) - L(s))(b(s, u^n(s), Z^n(s)))ds \\
& + n \int_t^T G'_m(u^n(s) - L(s))((u^n(s) - L(s))^-)ds \\
& + \int_t^T G'_m(u^n(s) - L(s))(L'(s))ds \\
& - \int_t^T G'_m(u^n(s) - L(s))(Z^n(s))dB_s \\
& - \frac{1}{2} \int_t^T G''_m(Z^n(s), Z^n(s))ds \\
=: & I_m^1 + I_m^2 + I_m^3 + I_m^4 + I_m^5 + I_m^6 + I_m^7. \tag{3.38}
\end{aligned}$$

Now,

$$\begin{aligned}
I_m^2 &= \int_t^T G'_m(u^n(s) - L(s))(\Delta u^n(s))ds \\
= & - \int_t^T \int_D f'_m(L(s, x) - u^n(s, x))(\Delta(u^n(s, x) - L(s, x)))dxds \\
& - \int_t^T \int_D f'_m(L(s, x) - u^n(s, x))(\Delta L(s, x))dxds \\
\leq & - \int_t^T \int_D f''_m(L(s, x) - u^n(s, x))|\nabla(u^n(s, x) - L(s, x))|^2dxds \\
& + \frac{1}{4}n \int_t^T \int_D f'_m(L(s, x) - u^n(s, x))^2dxds \\
& + \frac{C}{n} \int_t^T \int_D (\Delta L(s, x))^2dxds, \tag{3.39}
\end{aligned}$$

$$\begin{aligned}
I_m^3 &= - \int_t^T \int_D f'_m(L(s, x) - u^n(s, x))b(s, u^n(s, x), Z^n(s, x))dxds \\
\leq & \frac{1}{4}n \int_t^T \int_D f'_m(L(s, x) - u^n(s, x))^2ds \\
& + \frac{C}{n} \int_t^T \int_D (b(s, u^n(s, x), Z^n(s, x)))^2dxds, \tag{3.40}
\end{aligned}$$

$$\begin{aligned}
I_m^5 &= - \int_t^T \int_D f'_m(L(s, x) - u^n(s, x))(L'(s, x)) dx ds \\
&\leq \frac{1}{4}n \int_t^T \int_D f'_m(L(s, x) - u^n(s, x))^2 ds \\
&\quad + \frac{C}{n} \int_t^T \int_D (L'(s, x))^2 dx ds.
\end{aligned} \tag{3.41}$$

Combining (3.38)–(3.41) and taking expectation we obtain

$$\begin{aligned}
&E[G_m(u^n(t) - L(t))] \\
\leq &E[G_m(\phi - L(T))] + \frac{3}{4}n \int_t^T \int_D f'_m(L(s, x) - u^n(s, x))^2 ds \\
&+ \frac{C}{n}E[\int_t^T \int_D (L'(s, x))^2 dx ds] + \frac{C}{n}E[\int_t^T \int_D (\Delta L(s, x))^2 dx ds] \\
&+ \frac{C}{n}E[\int_t^T \int_D (b(s, u^n(s, x), Z^n(s, x)))^2 dx ds] \\
&- nE[\int_t^T \int_D f'_m(L(s, x) - u^n(s, x))((u^n(s, x) - L(s, x))^-) ds].
\end{aligned} \tag{3.42}$$

Letting  $m \rightarrow \infty$  we conclude that

$$\begin{aligned}
&E[\int_D ((u^n(t, x) - L(t, x))^-)^2 dx] \\
\leq &\frac{3}{4}nE[\int_t^T \int_D ((u^n(s, x) - L(s, x))^-)^2 dx ds] \\
&- nE[\int_t^T \int_D ((u^n(s, x) - L(s, x))^-)^2 dx ds] + \frac{C'}{n},
\end{aligned} \tag{3.43}$$

where the Lipschitz condition of  $b$  and Lemma 3.3 have been used. In particular we have

$$E[\int_t^T \int_D ((u^n(s, x) - L(s, x))^-)^2 dx ds] \leq \frac{C'}{n^2}. \tag{3.44}$$

■

**Lemma 3.5** *Let  $(u^n, Z^n)$  be the solution of equation (3.21). We have*

$$\lim_{n, m \rightarrow \infty} E[\sup_{0 \leq t \leq T} |u^n(t) - u^m(t)|_K^2] = 0, \tag{3.45}$$

$$\lim_{n, m \rightarrow \infty} E[\int_0^T \|u^n(t) - u^m(t)\|_V^2 dt] = 0. \tag{3.46}$$

$$\lim_{n, m \rightarrow \infty} E[\int_0^T |Z^n(t) - Z^m(t)|_{L^2(D, \mathbb{R}^m)}^2 dt] = 0. \tag{3.47}$$

**Proof.** Applying Itô's formula, it follows that

$$\begin{aligned}
& |u^n(t) - u^m(t)|_K^2 \\
= & 2 \int_t^T \langle u^n(s) - u^m(s), \Delta(u^n(s) - u^m(s)) \rangle ds \\
& + 2 \int_t^T \langle u^n(s) - u^m(s), b(s, u^n(s), Z^n(s)) - b(s, u^m(s), Z^m(s)) \rangle ds \\
& - 2 \int_t^T \langle u^n(s) - u^m(s), Z^n(s) - Z^m(s) \rangle dB_s \\
& + 2 \int_t^T \langle u^n(s) - u^m(s), n(u^n(s) - L(s))^- - m(u^m(s) - L(s))^- \rangle ds \\
& - \int_t^T |Z^n(s) - Z^m(s)|_{L^2(D, \mathbb{R}^m)}^2 ds
\end{aligned} \tag{3.48}$$

Now we estimate each of the terms on the right side.

$$\begin{aligned}
& 2 \int_t^T \langle u^n(s) - u^m(s), \Delta(u^n(s) - u^m(s)) \rangle ds \\
= & -2 \int_t^T \|u^n(s) - u^m(s)\|_V^2 ds.
\end{aligned} \tag{3.49}$$

By the Lipschitz continuity of  $b$  and the inequality  $ab \leq \varepsilon a^2 + C_\varepsilon b^2$ , one has

$$\begin{aligned}
& 2 \int_t^T \langle u^n(s) - u^m(s), b(s, u^n(s), Z^n(s)) - b(s, u^m(s), Z^m(s)) \rangle ds \\
\leq & C \int_t^T |u^n(s) - u^m(s)|_K^2 ds + \frac{1}{2} \int_t^T |Z^n(s) - Z^m(s)|_{L^2(D, \mathbb{R}^m)}^2 ds.
\end{aligned} \tag{3.50}$$

In view of (3.44),

$$\begin{aligned}
& 2E\left[\int_t^T \langle u^n(s) - u^m(s), n(u^n(s) - L(s))^- - m(u^m(s) - L(s))^- \rangle ds\right] \\
= & 2nE\left[\int_t^T \langle u^n(s) - L(s), (u^n(s) - L(s))^- \rangle ds\right] \\
& + 2mE\left[\int_t^T \langle L(s) - u^n(s), (u^m(s) - L(s))^- \rangle ds\right] \\
& + 2mE\left[\int_t^T \langle u^m(s) - L(s), (u^m(s) - L(s))^- \rangle ds\right] \\
& + 2nE\left[\int_t^T \langle L(s) - u^m(s), (u^n(s) - L(s))^- \rangle ds\right] \\
\leq & 2mE\left[\int_t^T \langle L(s) - u^n(s), (u^m(s) - L(s))^- \rangle ds\right] \\
& + 2nE\left[\int_t^T \langle L(s) - u^m(s), (u^n(s) - L(s))^- \rangle ds\right] \\
\leq & 2mE\left[\int_t^T \int_D (u^n(s, x) - L(s, x))^- (u^m(s, x) - L(s, x))^- dx ds\right] \\
& + 2nE\left[\int_t^T \int_D (u^m(s, x) - L(s, x))^- (u^n(s, x) - L(s, x))^- dx ds\right] \\
\leq & 2m(E\left[\int_t^T \int_D ((u^n(s, x) - L(s, x))^-)^2 dx ds\right])^{\frac{1}{2}} (E\left[\int_t^T \int_D ((u^m(s, x) - L(s, x))^-)^2 dx ds\right])^{\frac{1}{2}} \\
& + 2n(E\left[\int_t^T \int_D ((u^n(s, x) - L(s, x))^-)^2 dx ds\right])^{\frac{1}{2}} (E\left[\int_t^T \int_D ((u^m(s, x) - L(s, x))^-)^2 dx ds\right])^{\frac{1}{2}} \\
\leq & C'\left(\frac{1}{n} + \frac{1}{m}\right). \tag{3.51}
\end{aligned}$$

It follows from (3.48) and (3.49) that

$$\begin{aligned}
& E[|u^n(t) - u^m(t)|_K^2] + \frac{1}{2}E\left[\int_t^T |Z^n(s) - Z^m(s)|_{L^2(D, \mathbb{R}^m)}^2 ds\right] \\
& + E\left[\int_t^T \|u^n(s) - u^m(s)\|_V^2 ds\right] \\
\leq & C \int_t^T E[|u^n(s) - u^m(s)|_K^2] ds + C'\left(\frac{1}{n} + \frac{1}{m}\right). \tag{3.52}
\end{aligned}$$

Application of the Gronwall inequality yields

$$\lim_{n, m \rightarrow \infty} \left\{ E[|u^n(t) - u^m(t)|_K^2] + \frac{1}{2}E\left[\int_t^T |Z^n(s) - Z^m(s)|_{L^2(D, \mathbb{R}^m)}^2 ds\right] \right\} = 0, \tag{3.53}$$

$$\lim_{n,m \rightarrow \infty} E\left[\int_t^T \|u^n(s) - u^m(s)\|_V^2 ds\right] = 0. \quad (3.54)$$

By (3.53) and the Burkholder inequality we can further show that

$$\lim_{n,m \rightarrow \infty} E\left[\sup_{0 \leq t \leq T} |u^n(t) - u^m(t)|_K^2\right] = 0. \quad (3.55)$$

The proof is complete.  $\blacksquare$

**Proof of Theorem 3.2.** From Lemma 3.5 we know that  $(u^n, Z^n), n \geq 1$ , forms a Cauchy sequence. Denote by  $u(t, x), Z(t, x)$  the limit of  $u^n$  and  $Z^n$ . Put

$$\bar{\eta}^n(t, x) = n(u^n(t, x) - L(t, x))^-$$

Lemma 3.4 implies that  $\bar{\eta}^n(t, x)$  admits a non-negative weak limit, denoted by  $\bar{\eta}(t, x)$ , in the following Hilbert space:

$$\bar{K} = \{h; \quad h \text{ is a } K\text{-valued adapted process such that } E\left[\int_0^T |h(s)|_K^2 ds\right] < \infty\}$$

with inner product

$$\langle h_1, h_2 \rangle_{\bar{K}} = E\left[\int_0^T \int_D h_1(t, x) h_2(t, x) dt dx\right].$$

Set  $\eta(t, x) = \int_0^t \bar{\eta}(s, x) ds$ . Then  $\eta$  is a continuous  $K$ -valued process which is increasing in  $t$ . Keeping Lemma 3.5 in mind and letting  $n \rightarrow \infty$  in (3.21) we obtain

$$\begin{aligned} & u(t, x) \\ &= \phi(x) + \int_t^T \Delta u(s, x) ds + \int_t^T b(s, u(s, x), Z(s, x)) ds - \int_t^T Z(s, x) dB_s \\ & \quad + \eta(T, x) - \eta(t, x); \quad 0 \leq t \leq T. \end{aligned} \quad (3.56)$$

Recall from Lemma 3.4 that

$$E\left[\int_t^T \int_D ((u^n(s, x) - L(s, x))^-)^2 dx ds\right] \leq C' \frac{1}{n^2}$$

By the Fatou Lemma, this implies that  $E\left[\int_t^T \int_D ((u(s, x) - L(s, x))^-)^2 dx ds\right] = 0$ . In view of the continuity of  $u$  in  $t$ , we conclude  $u(t, x) \geq L(t, x)$  a.e. in  $x$ , for every  $t \geq 0$ . Combining the strong convergence of  $u^n$  and the weak convergence of  $\bar{\eta}^n$ , we also have

$$\begin{aligned} & E\left[\int_0^T \int_D (u(s, x) - L(s, x)) \eta(dt, x) dx\right] \\ &= E\left[\int_0^T \int_D (u(s, x) - L(s, x)) \bar{\eta}(t, x) dt dx\right] \\ &\leq \lim_{n \rightarrow \infty} E\left[\int_0^T \int_D (u^n(s, x) - L(s, x)) \bar{\eta}^n(t, x) dt dx\right] \leq 0 \end{aligned} \quad (3.57)$$

Hence,

$$\int_0^T \int_D (u(s, x) - L(s, x)) \eta(dt, x) dx = 0, \quad a.s.$$

We have shown that  $(u, Z, \eta)$  is a solution to the reflected BSPDE (3.17).

**Uniqueness.** Let  $(u_1, Z_1, \eta_1)$ ,  $(u_2, Z_2, \eta_2)$  be two such solutions to equation (3.20). By Itô's formula, we have

$$\begin{aligned} & |u_1(t) - u_2(t)|_K^2 \\ = & 2 \int_t^T \langle u_1(s) - u_2(s), \Delta(u_1(s) - u_2(s)) \rangle ds \\ & + 2 \int_t^T \langle u_1(s) - u_2(s), b(s, u_1(s), Z_1(s)) - b(s, u_2(s), Z_2(s)) \rangle ds \\ & - 2 \int_t^T \langle u_1(s) - u_2(s), Z_1(s) - Z_2(s) \rangle dB_s \\ & + 2 \int_t^T \langle u_1(s) - u_2(s), \eta_1(ds) - \eta_2(ds) \rangle \\ & - \int_t^T |Z_1(s) - Z_2(s)|_{L^2(D, \mathbb{R}^m)}^2 ds \end{aligned} \quad (3.58)$$

Similar to the proof of Lemma 3.5, we have

$$2 \int_t^T \langle u_1(s) - u_2(s), \Delta(u_1(s) - u_2(s)) \rangle ds \leq 0, \quad (3.59)$$

and

$$\begin{aligned} & 2 \int_t^T \langle u_1(s) - u_2(s), b(s, u_1(s), Z_1(s)) - b(s, u_2(s), Z_2(s)) \rangle ds \\ \leq & C \int_t^T |u_1(s) - u_2(s)|_K^2 ds + \frac{1}{2} \int_t^T |Z_1(s) - Z_2(s)|_{L^2(D, \mathbb{R}^m)}^2 ds \end{aligned} \quad (3.60)$$

On the other hand,

$$\begin{aligned}
& 2E\left[\int_t^T \langle u_1(s) - u_2(s), \eta_1(ds) - \eta_2(ds) \rangle\right] \\
&= 2E\left[\int_t^T \int_D (u_1(s, x) - L(s, x))\eta_1(ds, x)dx\right] \\
&\quad - 2E\left[\int_t^T \int_D (u_1(s, x) - L(s, x))\eta_2(ds, x)dx\right] \\
&\quad + 2E\left[\int_t^T \int_D (u_2(s, x) - L(s, x))\eta_2(ds, x)dx\right] \\
&\quad - 2E\left[\int_t^T \int_D (u_2(s, x) - L(s, x))\eta_1(ds, x)dx\right] \\
&\leq 0
\end{aligned} \tag{3.61}$$

Combining (3.58)—(3.61) we arrive at

$$\begin{aligned}
& E[|u_1(t) - u_2(t)|_K^2] + \frac{1}{2}E\left[\int_t^T |Z_1(s) - Z_2(s)|_{L^2(D, \mathbb{R}^m)}^2 ds\right] \\
&\leq C \int_t^T E[|u_1(s) - u_2(s)|_K^2] ds.
\end{aligned} \tag{3.62}$$

Appealing to Gronwall inequality, this implies

$$u_1 = u_2, \quad Z_1 = Z_2$$

which further gives  $\eta_1 = \eta_2$  from the equation they satisfy.  $\square$

## 4 Link to optimal stopping

In this section, we provide a link between the solution of a reflected backward stochastic partial differential equation and an optimal stopping problem. Let  $u(t, x)$  be the solution of the following reflected BSPDE.

$$\begin{aligned}
& u(t, x) \\
&= \phi(x) + \int_t^T \frac{1}{2} \Delta u(t, x) ds + \int_t^T k(s, x, u(s, x), Z(s, x)) ds - \int_t^T Z(s, x) dB_s \\
&\quad + \eta(T, x) - \eta(t, x); \quad 0 \leq t \leq T, \\
& u(t, x) \geq L(t, x), \\
& \int_0^T \int_D (u(s, x) - L(s, x)) \eta(dt, x) dx = 0 \quad a.s.
\end{aligned} \tag{4.1}$$



Let  $\mathcal{S}_{t,T}$  be the set of all stopping times  $\tau$  satisfying  $t \leq \tau \leq T$ . For  $\tau \in \mathcal{S}_{t,T}$ , define

$$R_t(\tau, x) = \int_t^\tau P_{s-t}k(s, x)ds + P_{\tau-t}L(\tau, x)\chi_{\{\tau < T\}} + P_{\tau-t}\phi(x)\chi_{\{\tau = T\}},$$

where  $k(s, \cdot) = k(s, \cdot, u(s, \cdot), Z(s, \cdot))$  and  $P_t$  denotes the semigroup generated by the Laplacian operator  $\frac{1}{2}\Delta$ , i.e.

$$P_t f(x) = (2\pi t)^{-d/2} \int_{\mathbb{R}^d} f(y) \exp\left(-\frac{|y-x|^2}{2t}\right) dy; f \in L^1(\mathbb{R}^d).$$

Here, and in the following we will use the simplified notation  $P_t k(s, x) = (P_t k(s, \cdot))(x)$  etc.

**Theorem 4.1**  $u(t, x)$  is the value function of the the optimal stopping problem associated with  $R_t(\tau, x)$ , i.e.,

$$u(t, x) = \text{esssup}_{\tau \in \mathcal{S}_{t,T}} E[R_t(\tau, x) | \mathcal{F}_t] \quad (4.2)$$

**Proof.** Observe that  $u$  admits the following mild representation:

$$\begin{aligned} & u(t, x) \\ = & P_{T-t}\phi(x) + \int_t^T P_{s-t}(k(s, u(s, x), Z(s, x)))ds - \int_t^T P_{s-t}(Z(s, x))dB_s \\ & + \int_t^T P_{s-t}\eta(ds, x); \quad 0 \leq t \leq T. \end{aligned} \quad (4.3)$$

This implies that for any stopping time  $\tau$  with  $t \leq \tau \leq T$ , we have

$$\begin{aligned} & u(t, x) \\ = & P_{\tau-t}(u(\tau, x)) + \int_t^\tau P_{s-t}(k(s, x))ds - \int_t^\tau P_{s-t}(Z(s, x))dB_s \\ & + \int_t^\tau P_{s-t}\eta(ds, x); \quad 0 \leq t \leq \tau. \end{aligned} \quad (4.4)$$

Since  $\eta(s, x)$  is increasing in  $s$  and  $u(s, x) \geq L(s, x)$  for  $s < T$ , it follows that

$$u(t, x) \geq R_t(\tau, x) - \int_t^\tau P_{s-t}(Z(s, x))dB_s \quad (4.5)$$

Take conditional expectation with respect to  $\mathcal{F}_t$  on both sides to get

$$\begin{aligned} & u(t, x) \\ \geq & E[R_t(\tau, x) | \mathcal{F}_t] - E\left[\int_t^\tau P_{s-t}(Z(s, x))dB_s | \mathcal{F}_t\right] \\ = & E[R_t(\tau, x) | \mathcal{F}_t]. \end{aligned} \quad (4.6)$$

As  $\tau$  is arbitrary, we obtain

$$u(t, x) \geq \text{ess sup}_{\tau \in \mathcal{S}_{t,T}} E[R_t(\tau, x) | \mathcal{F}_t] \quad (4.7)$$

Now, define

$$\hat{\tau}_t = \inf\{s \in [t, T) | u(s) = L(s)\} \wedge T$$

From the property of  $\eta$ , it is not increasing on the interval  $[t, \hat{\tau}_t]$ . Therefore,  $\int_t^{\hat{\tau}_t} P_{s-t} \eta(ds, x) = 0$ . Thus we have from (4.4) that

$$\begin{aligned} & u(t, x) \\ &= P_{\hat{\tau}_t-t}(u(\hat{\tau}_t), x) + \int_t^{\hat{\tau}_t} P_{s-t}(k(s, x))ds - \int_t^{\hat{\tau}_t} P_{s-t}(Z(s, x))dB_s \\ &= R_t(\hat{\tau}_t, x) - \int_t^{\hat{\tau}_t} P_{s-t}(Z(s, x))dB_s. \end{aligned} \quad (4.8)$$

Taking conditional expectation yields that

$$u(t, x) = E[R_t(\hat{\tau}_t, x) | \mathcal{F}_t]$$

Combining this with (4.7) we obtain the theorem. ■

## References

- [DP1] C. Donai-Martin, E. Pardoux: White noise driven SPDEs with reflection. Probab. Theory Rel. Fields 95, 1-24(1993).
- [DP2] C. Donai-Martin, E. Pardoux: EDPS réfléchies et calcul de Malliavin. (French)[SPDEs with reflection and Malliavin Calculus]. Bull. Sci. Math. 121(5)(1997), 405-422.
- [GP] A. Gegout-Petit, E. Pardoux: Equations Différentielles Stochastiques Rétrogrades Réfléchies Dans Un Convexe. Stochastics and Stochastics Reports 57 (1996) 111-128.
- [HP] U. G. Haussmann, E. Pardoux: Stochastic variational inequalities of parabolic type. Appl. Math. Optim. 20(1989), 163-192.
- [MYZ] J. Ma, H. Yin and J. Zhang: On non-Markovian forward-backward SDEs and backward stochastic PDEs. Manuscript June 16, 2011 (USC, Los Angeles).
- [NP] D. Nualart, E. Pardoux: White noise driven by quasilinear SPDEs with reflection. Probab. Theory Rel. Fields 93,77-89(1992).
- [ØS] B. Øksendal, A. Sulem: Singular stochastic control and optimal stopping with partial information of jump diffusions. Preprint 2010, Oslo.

- [ØPZ] B. Øksendal, F. Proske and T. Zhang: Backward stochastic partial differential equations with jumps and application to optimal control of random jump fields. *Stochastics* 77:5 (2005) 381-399.
- [PP1] E. Pardoux and S. Peng: Adapted solutions of backward stochastic differential equations. *System and Control Letters* 14 (1990) 55-61.
- [PP2] E. Pardoux and S. Peng: Backward doubly stochastic differential equations and systems of quasilinear stochastic partial differential equations. *Probab. Theory and Rel. Fields* 98 (1994) 209-227.
- [Z] T.Zhang : White noise driven SPDEs with reflection: strong Feller properties and Harnack inequalities. *Potential Analysis* 33:2 (2010) 137-151.