

## OPTIMAL CONTROL WITH STATE-SPACE CONSTRAINT II\*

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**Abstract.** Optimal control of piecewise deterministic processes with state space constraint is studied. Under appropriate assumptions, it is shown that the optimal value function is the only viscosity solution on the open domain which is also a supersolution on the closed domain. Finally, the uniform continuity of the value function is obtained under a condition on the deterministic drift.

**Key words.** viscosity solutions, stochastic control, state-space constraint, piecewise deterministic processes

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**Introduction.** We are interested in the optimal control of jump processes with a state-space constraint. By that we mean the trajectories of the controlled process have to stay within a given subset  $\theta$  of  $\mathbb{R}^n$ . These kinds of processes arise naturally in some applications [5], [9], [10]. The deterministic counterpart of this problem is studied in [11] and the optimal value function is characterized as the viscosity solution of the corresponding Hamilton–Jacobi–Bellman (HJB) equation. Also the concept of viscosity solutions, introduced by M. G. Crandall and P.-L. Lions [2], was used to identify the boundary conditions satisfied by the optimal value function. For more information about viscosity solutions see [1], [3], [7], [8] and references therein.

In this paper we generalize the results mentioned above to a certain class of jump processes, namely piecewise deterministic processes. These kinds of processes are introduced by M. Davis [4] and used by D. Vermes in [12]. Let us summarize the construction of the piecewise deterministic processes.

Let  $u$  be a Borel measurable map of  $\bar{\theta} = [0, \infty)$  into a compact, separable metric space  $U$  and  $y_0(x, s; t, u)$  be the solution of

$$(0.1) \quad \frac{d}{dt} y_0(x, s, t, u) = b(y_0(x, s, t, u), u(x, t - s)) \quad \text{for } t \geq s$$

with initial data  $y(x, s, s, u) = x$ . Pick the first jump time  $T_1$  so that the jump rate is  $\lambda(y_0(x, 0, t, u))$ . Then construct the post-jump location  $Y_1$  such that  $Q(y_0(x, 0, \tau, u), u(x, \tau), \cdot)$  is its conditional distribution given  $T_1 = \tau$ . Starting from  $Y_1$  at time  $T_1$  select the inter-jump time  $T_2 - T_1$  and the second post-jump location  $Y_2$  similarly. Set  $T_0 = 0$ ,  $Y_0 = x$  and iterate the procedure above to obtain  $\{(T_n, Y_n) : n = 0, 1, \dots\}$ . Between the jumps  $T_n$  and  $T_{n+1}$  the process  $y(x, t, u)$  follows the deterministic trajectory passing through  $(Y_n, T_n)$ , i.e.

$$(0.2) \quad y(x, t, u) = y_0(Y_n, T_n, t, u) \quad \text{if } t \in [T_n, T_{n+1}).$$

Moreover,  $\{(Y_n, T_n)\}$  satisfies

$$(0.3) \quad \begin{aligned} &P(T_{n+1} - T_n \geq t | T_1, Y_1, \dots, T_n, Y_n) \\ &= \exp \left\{ - \int_{T_n}^{t+T_n} \lambda(y(x, s, u), u(Y_n, s - T_n)) ds \right\}, \end{aligned}$$

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$$(0.4) \quad \begin{aligned} P(Y_{n+1} \in A | T_1, Y_1, \dots, Y_n, T_{n+1}) \\ = Q(y_0(Y_n, T_n, T_{n+1}, u), u(Y_n, T_{n+1} - T_n), A) \quad \text{for all } A \subset \bar{\theta}. \end{aligned}$$

The process  $y(x, \cdot, u)$  is a strong Markov process and the following version of Ito's lemma is proved in [4]. Set  $y(t) = y(x, t, u)$  and  $u_n(t) = u(Y_n, t - T_n)$ . Then for any  $\psi \in C^1(\bar{\theta} \times [0, T])$  we have

$$(0.5) \quad \begin{aligned} E\psi(y(T), T) \\ = \psi(x, 0) + E \left\{ \sum_{n=0}^{\infty} \int_{T_n \wedge T}^{T_{n+1} \wedge T} \left[ b(y(t), u_n(t)) \nabla \psi(y(t), t) \right. \right. \\ \left. \left. + \frac{\partial}{\partial t} \psi(y(t), t) + \lambda(y(t), u_n(t)) \right. \right. \\ \left. \left. \cdot \int_{\bar{\theta}} [\psi(z, t) - \psi(y(t), t)] Q(y(t), u_n(t), dz) \right] dt \right\}. \end{aligned}$$

We assume that the post-jump locations are in  $\bar{\theta}$ . Then one can define the set of admissible strategies  $\mathcal{A}_{ad}$  as:

$$(0.6) \quad \mathcal{A}_{ad} := \left\{ u: \bar{\theta} \times [0, \infty) \rightarrow U, \text{ Borel measurable and } \left. \begin{aligned} P(y(x, t, u) \in \bar{\theta} \text{ for all } t \geq 0) = 1, \text{ for all } x \in \bar{\theta}. \end{aligned} \right\}.$$

The optimal value is given by

$$(0.7) \quad v(x) := \inf_{u \in \mathcal{A}_{ad}} E \left\{ \sum_{n=0}^{\infty} \int_{T_n}^{T_{n+1}} e^{-t} f(y(x, t, u), u(Y_n, t - T_n)) dt \right\}.$$

It is shown, in § 2, that  $v$  is the only viscosity solution of the corresponding HJB equation, satisfying the same boundary condition as in the deterministic case [11]. This result holds if the optimal value is in  $BUC(\bar{\theta})$  and the dynamic programming relation (0.8) is satisfied.

$$(0.8) \quad \begin{aligned} v(x) = \inf_{u \in \mathcal{A}_{ad}} E \left\{ \int_0^{T \wedge T_1} e^{-t} f(y(x, t, u), u(x, t)) dt + e^{-T \wedge T_1} v(y(x, T \wedge T_1, u)) \right\} \\ \text{for all } T \geq 0 \text{ and } x \in \bar{\theta}. \end{aligned}$$

Finally, in § 3 we show that under assumptions (A2)–(A4)  $v$  is in  $BUC(\bar{\theta})$  and satisfies the dynamic programming relation (0.8). Note that these assumptions yield that the optimal value of the corresponding deterministic problem is in  $BUC(\bar{\theta})$ . By an induction argument one can extend this result to piecewise deterministic processes with finitely many jumps. We eventually pass to the limit to conclude.

**1. Main result.** Let  $\theta$  be an open subset of  $\mathbb{R}^n$  with connected boundary satisfying:

(A.1) There are positive constants  $h, r$  and  $\mathbb{R}^n$ -valued bounded-uniformly continuous map  $\eta$  of  $\bar{\theta}$  such that

$$B(x + t\eta(x), tr) \subset \bar{\theta} \quad \text{for all } x \in \bar{\theta} \text{ and } t \in (0, h].$$

Here  $B(x, R)$  denotes the ball with center  $x$  and radius  $R$ .

*Remark 1.1.* If  $\theta$  is bounded and  $\partial\theta$  is  $C^1$ , then (A.1) is satisfied. Also boundaries with corners may satisfy (A.1), for example,  $\theta = \{(x, y) \in \mathbb{R}^2: x > 0, y > 0\}$ .

The strategies take values in  $U$  which is a compact, separable metric space. Also, we assume the following throughout the paper. Let  $x$  and  $y$  be in  $\bar{\theta}$ .

$$(1.1) \quad \sup_{\alpha \in U} |\gamma(x, \alpha) - \gamma(y, \alpha)| \leq L(\gamma)|x - y|, \quad \gamma = b, f \text{ or } \lambda,$$

$$(1.2) \quad \sup_{\substack{\alpha \in U \\ x \in \bar{\theta}}} |\gamma(x, \alpha)| \leq K(\gamma), \quad \gamma = b, f \text{ or } \lambda.$$

For each bounded, continuous function  $h$  on  $\bar{\theta}$ , there is a continuous function  $W_h$  with  $W_h(0) = 0$  such that

$$(1.3) \quad \sup_{\alpha \in U} \left| \int_{\bar{\theta}} h(z)Q(x, \alpha, dz) - \int_{\bar{\theta}} h(z)Q(y, \alpha, dz) \right| \leq W_h(|x - y|).$$

$$(1.4) \quad Q(x, \alpha, \bar{\theta}) = 1 \quad \text{for all } x \in \bar{\theta} \text{ and } \alpha \in U.$$

$$(1.5) \quad \lambda(x, \alpha) \geq 0 \quad \text{for all } x \in \bar{\theta} \text{ and } \alpha \in U.$$

The corresponding Hamiltonian  $H$  is a continuous map of  $\bar{\theta} \times \mathbb{R}^n \times BUC(\bar{\theta})$  given as:

$$(1.6) \quad H(x, p, \psi) = \sup_{\alpha \in U} \left\{ -b(x, \alpha) \cdot p - f(x, \alpha) - \lambda(x, \alpha) \int_{\bar{\theta}} [\psi(z) - \psi(x)]Q(x, \alpha, dy) \right\}.$$

This Hamiltonian is a nonlocal operator but still one can define a notion of viscosity solutions.

DEFINITION. Let  $K$  be a subset of  $\mathbb{R}^n$  and  $v \in BUC(\bar{K})$ .

(i) We say  $v$  is a *viscosity subsolution* of  $v(x) + H(x, Dv(x), v) = 0$  on  $K$  if  $v(x_0) + H(x_0, \nabla\psi(x_0), v) \leq 0$  whenever  $\psi \in C^1(N_{x_0})$  and  $(v - \psi)$  has a global maximum, relative to  $K$ , at  $x_0 \in K$ , where  $N_{x_0}$  is a neighborhood of  $x_0$ .

(ii) We say  $v$  is a *viscosity supersolution* of  $v(x) + H(x, Dv(x), v) = 0$  on  $K$  if  $v(x_0) + H(x_0, \nabla\psi(x_0), v) \geq 0$  whenever  $\psi \in C^1(N_{x_0})$  and  $(v - \psi)$  has a global minimum, relative to  $K$ , at  $x_0 \in K$ , where  $N_{x_0}$  is a neighborhood of  $x_0$ .

Remark 1.2. This is an obvious generalization of the original notion introduced by M. G. Crandall and P.-L. Lions [2]. The definition we used above is analogous to one of the definitions introduced in [1].

We are interested in the following notion of viscosity solutions.

DEFINITION.  $v \in BUC(\bar{\theta})$  is said to be a *constrained viscosity solution* of  $v(x) + H(x, Dv(x), v) = 0$  on  $\bar{\theta}$  if it is a subsolution on  $\theta$  and supersolution on  $\bar{\theta}$ .

Remark 1.3. The fact that  $v$  is a supersolution on the closed domain imposes a certain boundary condition. Suppose that  $v$  is smooth and a constrained viscosity solution. Then  $H(x, \nabla v(x) + \alpha v(x), v) \geq H(x, \nabla v(x), v)$  for all  $x \in \partial\theta$  and  $\alpha \geq 0$  ( $v(x)$  is the exterior normal vector). This effect is discussed in [11].

THEOREM 1.1. Suppose (A.1), (1.1)-(1.5) hold. Then there is at most one constrained viscosity solution of  $v(x) + H(x, Dv(x), v) = 0$  on  $\theta$ . Moreover if  $v \in BUC(\bar{\theta})$  and dynamic programming relation (0.8) holds, then the optimal value function  $v$  is a constrained viscosity solution.

**2. Proof of the main theorem.** We need the following lemma:

LEMMA 2.1.  $v \in BUC(\bar{\theta})$  is a viscosity subsolution of  $v(x) + H(x, Dv(x), v) = 0$  on  $\theta$  (or supersolution on  $\bar{\theta}$ ) if and only if

$$v(x_0) + H(x_0, \nabla\psi(x_0), \psi) \leq 0$$

(or  $\geq 0$ ) whenever  $\psi \in C^1(N_{x_0})$  and  $v - \psi$  has a global maximum relative to  $\bar{\theta}$  at  $x_0 \in \theta$  (or minimum at  $x_0 \in \bar{\theta}$  respectively), where  $N_{x_0}$  is a neighborhood of  $x_0$ .

*Proof.* We will prove the statement for subsolutions only, the other statement is proved exactly the same way.

*Necessity.* Suppose  $v \in BUC(\bar{\theta})$  is a viscosity subsolution and  $\psi, x_0$  are as above, i.e.

$$v(x_0) - \psi(x_0) = \max_{x \in \bar{\theta}} v(x) - \psi(x).$$

Then we have  $v(x_0) - v(z) \geq \psi(x_0) - \psi(z)$  for all  $z \in \bar{\theta}$ . Then (1.5) yields:

$$H(x_0, \nabla \psi(x_0), \psi) \leq H(x_0, \nabla \psi(x_0), v).$$

Hence the viscosity property of  $v$  gives the result.

*Sufficiency.* Let  $\psi \in C^1(N_{x_0})$  and  $(v - \psi)(x_0) = \max_{x \in \bar{\theta}} \{(v - \psi)(x)\} = 0$ . For each  $\varepsilon > 0$  we define  $\Phi^\varepsilon$  as follows:

$$(2.1) \quad \Phi^\varepsilon(x) = \psi(x)\chi^\varepsilon(x) + v(x)(1 - \chi^\varepsilon(x)) \quad \text{for } x \in \bar{\theta}$$

where  $\chi^\varepsilon$  is a smooth function satisfying

$$(2.2) \quad \begin{aligned} 0 &\leq \chi^\varepsilon \leq 1, \\ \chi^\varepsilon(x) &= 1 \quad \text{if } x \in B(x_0, \varepsilon), \\ \chi^\varepsilon(x) &= 0 \quad \text{if } x \in \mathbb{R}^n \setminus B(x_0, 2\varepsilon). \end{aligned}$$

Observe  $v(x_0) - \Phi^\varepsilon(x_0) = 0$  and  $v(x) - \Phi^\varepsilon(x) = (v(x) - \psi(x))\chi^\varepsilon(x) \leq 0$ . Hence

$$(2.3) \quad v(x_0) - \Phi^\varepsilon(x_0) = \max_{x \in \bar{\theta}} \{v(x) - \Phi^\varepsilon(x)\}.$$

Thus the hypothesis of the lemma and  $\nabla \Phi^\varepsilon(x_0) = \nabla \psi(x_0)$  yields

$$(2.4) \quad v(x_0) + H(x_0, \nabla \psi(x_0), \Phi^\varepsilon) \leq 0.$$

The following estimate follows (1.5):

$$(2.5) \quad \begin{aligned} &|H(x_0, \nabla \psi(x_0), \Phi^\varepsilon) - H(x_0, \nabla \psi(x_0), v)| \\ &\leq \sup_{\alpha \in U} \left\{ \lambda(x_0, \alpha) \int |\Phi^\varepsilon(x_0) - \Phi^\varepsilon(y) - v(x_0) + v(y)| Q(x_0, \alpha, dy) \right\}. \end{aligned}$$

Observe that  $\Phi^\varepsilon(x_0) = v(x_0)$  and  $\Phi^\varepsilon(x_0 + y) = v(x_0 + y)$  for  $y \notin B(0, 2\varepsilon)$ . Also for  $y \in B(0, 2\varepsilon)$

$$(2.6) \quad \begin{aligned} |\Phi^\varepsilon(x_0 + y) - v(x_0 + y)| &= |\psi(x_0 + y) - v(x_0 + y)|\chi^\varepsilon(x_0 + y) \\ &\leq |\psi(x_0 + y) - \psi(x_0)| + |v(x_0) - v(x_0 + y)| \\ &\leq \|\nabla \psi\|_\infty |y| + \omega_v(|y|) \\ &\leq 2\|\nabla \psi\|_\infty \varepsilon + \omega_v(2\varepsilon). \end{aligned}$$

Here  $\omega_v$  is the modulus of continuity of  $v$  and we used  $\psi(x_0) = v(x_0)$  in the second inequality. Combine (2.4)-(2.6) to conclude that  $v$  is a viscosity subsolution.  $\square$

*Remark 2.1.* It is easy to prove that in Lemma 2.1 we may replace  $\psi \in C^1(N_{x_0})$  by  $\psi \in C^1(\bar{\theta})$  (see [1]).

*Proof of Theorem 1.1.* Suppose  $v_1$  and  $v_2$  are two solutions in  $BUC(\bar{\theta})$ . For  $i = 1, 2$  define  $f_i$  and  $\bar{H}_i$  as follows

$$(2.7) \quad f_i(x, \alpha) = f(x, \alpha) + \lambda(x, \alpha) \int_{\bar{\theta}} (v_i(y) - v_i(x)) Q(x, \alpha, dy) \quad \text{for } x \in \bar{\theta}, \alpha \in U,$$

$$(2.8) \quad \bar{H}_i(x, p) = \sup_{\alpha \in U} \{-b(x, \alpha) \cdot p - f_i(x, \alpha)\} \quad \text{for } x \in \bar{\theta}, p \in \mathbb{R}^n.$$

Notice that  $\bar{H}_i$  is the Hamiltonian of the corresponding deterministic problem with running cost  $f_i$ . Using (1.1)-(1.4), one can show that the  $f_i$ 's are uniformly continuous in  $x$  uniformly with respect to  $\alpha$ . Pick  $z_\delta \in \bar{\theta}$  such that

$$v_1(x) - v_2(x) \leq v_1(z_\delta) - v_2(z_\delta) + \delta \quad \text{for all } x \in \bar{\theta}.$$

Then Corollary 2.3 in [11] yields

$$(2.9) \quad v_1(z_\delta) - v_2(z_\delta) \leq c\delta + \omega_{f_1}(c\delta) + \omega_{f_2}(c\delta) + \sup_{\alpha \in U} \{f_1(z_\delta, \alpha) - f_2(z_\delta, \alpha)\}.$$

But  $f_1(z_\delta, \alpha) - f_2(z_\delta, \alpha) \leq \delta\lambda(z_\delta, \alpha) \leq \delta K(\lambda)$  for every  $\alpha$ . Substitute this into (2.9) and send  $\delta$  to zero, to prove the uniqueness.

Let  $\psi \in C^1(\bar{\theta})$  and  $x_0 \in \theta$  such that  $(v - \psi)(x_0) = \max \{(v - \psi)(x); x \in \bar{\theta}\} = 0$ , where  $v$  is the optimal value. For any  $u \in \mathcal{A}_{ad}$  the dynamic programming relation (0.8) yields

$$\psi(x_0) = v(x_0) \leq E \left\{ \int_0^{t \wedge T_1} e^{-s} f(y(x_0, s, u), u(x_0, s)) ds + e^{-t \wedge T_1} v(y(x_0, t \wedge T_1, u)) \right\}.$$

Set  $y(s) = y(x_0, s, u)$  and  $u(s) = u(x_0, s)$ . Use  $v \leq \psi$  to obtain:

$$(2.10) \quad \psi(x_0) \leq E \left\{ \int_0^{t \wedge T_1} e^{-s} f(y(s), u(s)) ds + e^{-t \wedge T_1} \psi(y(t \wedge T_1)) \right\}.$$

Ito's formula (0.5) on  $e^{-s\psi(y(s))}$  yields

$$(2.11) \quad E \int_0^{t \wedge T_1} e^{-s} [\psi(y(s)) - b(y(s), u(s)) \cdot \nabla \psi(y(s)) - \bar{f}(y(s), u(s))] ds \leq 0$$

where

$$\bar{f}(x, \alpha) = f(x, \alpha) + \lambda(x, \alpha) \int_{\bar{\theta}} (\psi(z) - \psi(x)) Q(x, \alpha, dz).$$

Observe that on  $[0, t \wedge T_1]$   $y(\cdot)$  is a deterministic trajectory. Thus standard estimates on  $y(\cdot)$  and (1.1)-(1.4) yield

$$(2.12) \quad \frac{1}{t} E \int_0^{t \wedge T_1} [\psi(x_0) - b(x_0, u(s)) \cdot \nabla \psi(x_0) - \bar{f}(x_0, u(s))] ds \leq h(t)$$

where  $h$  is a continuous function with  $h(0) = 0$ . Since  $x_0 \in \theta$ , for any  $\alpha \in U$  there is a strategy  $u \in \mathcal{A}_{ad}$  such that  $u(x_0, t) = \alpha$  for all  $t \leq \text{dist}(x_0, \partial\theta)/K(b)$ . Use this strategy in (2.12) to obtain

$$[\psi(x_0) - b(x_0, \alpha) \cdot \nabla \psi(x_0) - \bar{f}(x_0, \alpha)] E[(t \wedge T_1)/t] \leq h(t).$$

Hence  $\psi(x_0) + H(x_0, \nabla \psi(x_0), \psi) \leq 0$ . So Lemma 2.1 and Remark 2.1 imply that  $v$  is a subsolution on  $\theta$ .

Now let  $\psi \in C^1(\bar{\theta})$  and  $(v - \psi)(x_0) = \min \{(v - \psi)(x); x \in \bar{\theta}\} = 0$  for some  $x_0 \in \bar{\theta}$ . The dynamic programming relation and  $v \geq \psi$  yield

$$(2.13) \quad v(x_0) = \psi(x_0) \geq \inf_{u \in \mathcal{A}_{ad}} E \left[ \int_0^{t \wedge T_1} e^{-s} f(y(s), u(s)) ds + e^{-t \wedge T_1} \psi(y(t \wedge T_1)) \right].$$

For  $t = 1/m$  one can pick  $u_m \in \mathcal{A}_{ad}$  such that

$$\psi(x_0) + \left(\frac{1}{m}\right)^2 \geq E \left[ \int_0^{1/m \wedge T_1} e^{-s} f(y(s), u_m(s)) ds + e^{-T_1 \wedge 1/m} \psi\left(y\left(T_1 \wedge \frac{1}{m}\right)\right) \right].$$

First, use Ito's lemma (0.5) on  $e^{-s}\psi(y(s))$  then (1.1)-(1.4), as in (2.10)-(2.12) above to obtain

$$(2.14) \quad mE \int_0^{T_1 \wedge 1/m} [\psi(x_0) - b(x_0, u_m(s)) \cdot \nabla \psi(x_0) - \bar{f}(x_0, u_m(s))] ds \geq K(m)$$

where  $K(m)$  is converging to zero as  $m$  tends to infinity. Rewrite (2.14) as

$$(2.15) \quad [\psi(x_0) - B(m) \cdot \nabla \psi(x_0) - F(m)]E(mT_1 \wedge 1) \geq K(m)$$

where

$$B(m) = \left( E \left( T_1 \wedge \frac{1}{m} \right) \right)^{-1} E \int_0^{T_1 \wedge 1/m} b(x_0, u_m(s)) ds,$$

$$F(m) = \left( E \left( T_1 \wedge \frac{1}{m} \right) \right)^{-1} E \int_0^{T_1 \wedge 1/m} \bar{f}(x_0, u_m(s)) ds.$$

Observe that  $(B(m), F(m)) \in \overline{\text{co}}\{(b(x_0, \alpha), \bar{f}(x_0, \alpha)): \alpha \in U\} := \overline{\text{co}}[BF(x_0)]$ . Hence there is  $(B, F) \in \overline{\text{co}}[BF(x_0)]$  such that  $(B(m), F(m))$  converges to  $(B, F)$  on a subsequence, denoted by  $m$  again. Pass to the limit in (2.15) to obtain

$$\psi(x_0) + \sup \{-B \cdot \nabla \psi(x_0) - F: (B, F) \in \overline{\text{co}}[BF(x_0)]\} \geq 0.$$

Also

$$\sup \{-B \cdot \nabla \psi(x_0) - F: (B, F) \in \overline{\text{co}}[BF(x_0)]\} = H(x_0, \nabla \psi(x_0), \psi).$$

Thus, Lemma 2.1 and Remark 2.1 imply that  $v$  is a viscosity supersolution on  $\bar{\theta}$ .  $\square$

**3. Uniform continuity and dynamic programming.** We assume the following.

(A.2) There is a Borel measurable map  $\alpha$  of  $\partial\theta$  into  $U$  and  $\beta$  positive satisfying  $b(x, \alpha(x)) \cdot \nu(x) \leq -\beta < 0$ , where  $\nu$  is the exterior normal vector.

(A.3) The boundary of  $\theta$  is of class  $C^2$ .

(A.4) If  $\partial\theta$  is not compact, there are constants  $\rho$  and  $l$  such that for any  $x \in \partial\theta$  there is a  $C^2(B(x, \rho))$  function  $T$  with  $C^1(B(x, \rho))$  inverse  $T^{-1}$  satisfying

$$(3.1) \quad \begin{aligned} & \text{(i)} \quad T(B(x, \rho) \cap \theta) \subset \{y \in R^n: y_n > 0\}, \\ & \text{(ii)} \quad T(B(x, \rho) \cap \partial\theta) \subset \{y \in R^n: y_n = 0\}, \\ & \text{(iii)} \quad \|T\|_{C^2(B(x, \rho))} + \|T^{-1}\|_{C^1(B(x, \rho))} \leq l. \end{aligned}$$

The subscript  $n$  denotes the  $n$ th component.

*Remark 3.1.* The assumption (A.2) holds with some  $\beta > 0$  if

$$\sup_{x \in \partial\theta} \min_{\alpha \in U} b(x, \alpha) \cdot \nu(x) < 0.$$

Note that we do not assume that  $b(x, \alpha)$  points inwards the domain  $\theta$  for all  $\alpha$  and  $x \in \partial\theta$ . Thus there may be controls that allow the deterministic process to reach the boundary.

*Remark 3.2.* The assumptions (A.2)-(A.4) are used to obtain the uniform continuity of the corresponding deterministic problem [11]. In particular see [11, Lemma 3.2].

Let  $v_0$  be the optimal value of the deterministic problem and define  $v^N$  as follows

$$v^N(x) = \inf_{u \in \mathcal{A}_d} J^N(x, u)$$

where

$$(3.2) \quad J^N(x, u) = E \left[ \int_0^{T_1} e^{-t} f(y(x, t, u), u(x, t)) dt + e^{-T_1} v^{N-1}(Y_1) \right].$$

LEMMA 3.1. Let  $v^{N-1} \in BUC(\bar{\theta})$ , then the dynamic programming relation holds for  $v^N$ , i.e., for all  $T > 0$

$$(3.3) \quad v^N(x) = \inf_{u \in \mathcal{A}_{ad}} E \left\{ \int_0^{T \wedge T_1} e^{-Tf}(y(x, t, u), u(x, t)) dt + e^{-T_1} v^{N-1}(Y_1) \chi_{[0, T_1]}(T_1) + e^{-T} v^N(y(x, T, u)) \chi_{(T, \infty)}(T_1) \right\}$$

where  $\chi_A$  is the indicator function of set  $A$ .

*Proof.* Fix  $x \in \bar{\theta}$  and  $T$  positive. Let  $I^N(x, u)$  be the right-hand side of (3.3) before taking the infimum. To simplify the notation, put  $y(t) = y_0(x, 0; t, u)$ ,  $u(t) = u(x, t)$ ,  $\lambda(t) = \lambda(y(t), u(t))$  and  $\Lambda(t) = \exp \{-\int_0^t \lambda(s) ds\}$ . Recall that  $y_0$  is the corresponding deterministic trajectory given by (0.1). In terms of these quantities  $I^N(x, u)$  is given by

$$(3.4) \quad \begin{aligned} I^N(x, u) &= \int_0^\infty \lambda(t) \Lambda(t) \left[ \int_0^{T \wedge t} e^{-sf}(y(s), u(s)) ds + e^{-t} \int_{\bar{\theta}} v^{N-1}(z) Q(y(t), u(t), dz) \chi_{[0, T]}(t) + e^{-T} v^N(y(T)) \chi_{(T, \infty)}(t) \right] dt \\ &+ \Lambda(\infty) \left[ \int_0^T e^{-t} f(y(t), u(t)) dt + e^{-T} v^N(y(T)) \right] \\ &= \int_0^T \lambda(t) \Lambda(t) \left[ \int_0^t e^{-sf}(y(s), u(s)) ds + e^{-t} \int_{\bar{\theta}} v^{N-1}(z) Q(y(t), u(t), dz) \right] dt \\ &+ \Lambda(T) \int_0^T e^{-sf}(y(s), u(s)) ds + \Lambda(T) e^{-T} v^N(y(T)). \end{aligned}$$

Since  $y(T)$  is a deterministic quantity determined by  $x, T$  and  $u$ , one can pick  $u^* \in \mathcal{A}_{ad}$  such that  $v^N(y(T)) \cong J^N(y(T), u^*) - \delta$ . Now we define  $\bar{u}$  as follows:

$$(3.5) \quad \bar{u}(z, t) = u(z, t) \chi_{[0, T]}(t) + u^*(y_0(z, 0, T, u), t - T) \chi_{[T, \infty)}(t).$$

Define  $\bar{y}(t) = \bar{y}(x, 0; t, \bar{u})$  and  $\bar{\lambda}, \bar{\Lambda}$  similarly. Then we have

$$(3.6) \quad \begin{aligned} J^N(y(T), u^*) &= (\Lambda(T))^{-1} \left\{ \int_0^\infty \bar{\lambda}(t+T) \bar{\Lambda}(t+T) \cdot \left[ \int_0^t e^{-sf}(\bar{y}(s+T), \bar{u}(x, s+T)) ds + e^{-t} \int_{\bar{\theta}} v^{N-1}(z) Q(\bar{y}(t+T), \bar{u}(x, t+T), dz) \right] dt + \bar{\Lambda}(\infty) \int_0^\infty e^{-sf}(\bar{y}(s+T), \bar{u}(x, s+T)) ds \right\}. \end{aligned}$$

Change variables in (3.6) and use  $v^N(y(T)) \cong J^N(y(T), u^*) - \delta$  to obtain

$$\begin{aligned} e^{-T} \Lambda(T) v^N(y(T)) \cong & \int_T^\infty \bar{\lambda}(t) \bar{\Lambda}(t) \left[ \int_T^t e^{-s} f(\bar{y}(s), \bar{u}(x, s)) dx \right. \\ & \left. + e^{-t} \int_{\bar{\theta}} v^{N-1}(z) Q(\bar{y}(t), \bar{u}(x, t), dz) \right] dt \\ & + \bar{\Lambda}(\infty) \int_T^\infty e^{-s} f(\bar{y}(s), \bar{u}(x, s)) ds - e^{-T} \Lambda(T) \delta. \end{aligned}$$

The fact that  $\int_T^\infty \bar{\lambda}(t) \bar{\Lambda}(t) dt = \Lambda(T) - \bar{\Lambda}(\infty)$  and the above inequality yield

$$\begin{aligned} \Lambda(T) \int_0^T e^{-s} f(y(s), u(s)) ds + \Lambda(T) e^{-T} v^N(y(T)) \\ \cong \int_T^\infty \bar{\lambda}(t) \bar{\Lambda}(t) \left[ \int_0^t e^{-s} f(\bar{y}(s), \bar{u}(x, s)) ds + e^{-t} \int_{\bar{\theta}} v^{N-1}(z) Q(\bar{y}(t), \bar{u}(x, t), dz) \right] dt \\ + \bar{\Lambda}(\infty) \int_0^\infty e^{-s} f(\bar{y}(s), \bar{u}(x, s)) ds - \delta. \end{aligned}$$

Substitute the above inequality into (3.4) and use the fact  $\lambda(t) = \bar{\lambda}(t)$ ,  $\Lambda(t) = \bar{\Lambda}(t)$  for  $t \in [0, T]$  to obtain

$$\begin{aligned} (3.7) \quad J^N(x, u) \cong & \int_0^\infty \bar{\lambda}(t) \bar{\Lambda}(t) \left[ \int_0^t e^{-s} f(\bar{y}(s), \bar{u}(x, s)) ds \right. \\ & \left. + e^{-t} \int_{\bar{\theta}} v^{N-1}(z) Q(\bar{y}(t), \bar{u}(x, t), dz) \right] dt \\ & + \bar{\Lambda}(\infty) \int_0^\infty e^{-s} f(\bar{y}(s), \bar{u}(x, s)) ds - \delta \\ & = J^N(x, \bar{u}) - \delta \cong v^N(x) - \delta. \end{aligned}$$

Thus,  $v^N(x) \leq \inf_{u \in \mathcal{A}_{ad}} J^N(x, u)$ . One can prove the other inequality similarly.  $\square$

The following lemma is an analogue of Lemma 3.2 in [11].

LEMMA 3.2. *Let  $v^{N-1} \in BUC(\bar{\theta})$  and (1.1)–(1.4), (A.2)–(A.4) hold. Then for any  $T$  positive, there is a positive function  $h_T$  and a projection  $\mathcal{P}_T(u)$  of any Borel measurable map  $u$  of  $\bar{\theta} \times [0, \infty)$  into  $U$  such that  $\mathcal{P}_T(u) \in \mathcal{A}_{ad}$  and*

$$(3.8) \quad |J_T^N(x, u) - J_T^N(x, \mathcal{P}_T(u))| \leq h_T(\sup \{ \text{dist}(y_0(x, 0, t, u), \bar{\theta}) : t \in [0, T] \})$$

where  $h_T$  is a continuous function with  $h_T(0) = 0$  and

$$(3.9) \quad J_T^N(x, u) = E \left\{ \int_0^{T \wedge T_1} e^{-s} f(y(x, s, u), u(x, s)) ds + e^{-T_1} v^{N-1}(Y_1) \chi_{[0, T_1]}(T_1) \right\}.$$

*Proof.* Define  $t_0(x, u) = \inf \{ t \geq 0 : y_0(x, 0, t, u) \in \partial \bar{\theta} \}$  or infinity. Let  $t^*$  and  $k$  be as in Lemma 3.2 of [11], i.e.

$$(3.10) \quad \begin{aligned} t^* &= \min \{ \rho / K(\bar{b}), l\beta / L(\bar{b})K(\bar{b}), \ln(1 + \beta l / 4K(\bar{b})) / L(\bar{b}) \}, \\ k &= 2 / l\rho \end{aligned}$$

where  $K(\bar{b}) = IK(b)$  and  $L(\bar{b}) = l^2K(b) + l^2L(b)$ . We now construct  $u^1$  as in Lemma 3.2 of [11]

$$(3.11) \quad u^1(x, t) = \begin{cases} u(x, t) & \text{if } t \leq t_0(x, u) \text{ or } t \geq t_0(x, u) + k\varepsilon_0(x, u), \\ \alpha(y_0(x, 0, t_0(x, u), u)) & \text{if } t_0(x, u) < t < t_0(x, u) + k\varepsilon_0(x, u) \end{cases}$$



where  $\alpha$  as in (A.2) and  $\varepsilon_0(x, u) = \sup \{ \text{dist}(y_0(x, 0, t, u), \bar{\theta}) : t \in [0, t^*] \}$ . Since  $x \rightarrow t_0(x, u)$  is a Borel measurable map  $u^1$  is measurable. Also in Lemma 3.2 of [11] it is proved that

$$(3.12) \quad y_0(x, 0, t, u^1) \in \bar{\theta} \quad \text{for all } t \in [0, t^*].$$

Now construct a sequence of strategies  $\{u^n : n = 1, 2, \dots\}$  by the following recursive formula

$$t_n(x, u^n) = \inf \{ t \geq nt^* : y_0(x, 0, t, u^n) \in \partial\theta \} \quad \text{or infinity,}$$

$$\varepsilon_n(x, u^n) = \sup_{t \in [0, (n+1)t^*]} [\text{dist}(y_0(x, 0, t, u^n), \bar{\theta})],$$

then

$$u^{n+1}(x, t) = \begin{cases} u^n(x, t) & \text{if } t \leq t_n(x, u^n) \quad \text{or } t \geq t_n(x, u^n) + k\varepsilon_n(x, u^n), \\ \alpha(y_0(x, 0, t_n(x, u^n), u^n)) & \text{if } t_n(x, u^n) < t < t_n(x, u^n) + k\varepsilon_n(x, u^n). \end{cases}$$

Iterate (3.12) to get  $y_0(x, 0, t, u^n) \in \bar{\theta}$  for  $t \in [0, nt^*]$ . We have to estimate the Lebesgue measure of the following set

$$(3.13) \quad M^n(x) = \{ t \in [0, nt^*] : u^n(x, t) \neq u(x, t) \}.$$

For every  $t$  we have

$$|y_0(x, 0, t, u^n) - y_0(x, 0, t, u)|$$

$$\leq \int_{[0, t] \cap M^n(x)} 2K(b) + \int_{[0, t] \setminus M^n(x)} L(b) |y_0(x, 0, s, u) - y_0(x, 0, s, u^n)| ds;$$

thus the Gronwall's inequality implies

$$\varepsilon_n(x, u^n) \leq \varepsilon_n(x, u) + 2K(b) e^{(n+1)L(b)t^*} \text{meas } M^n(x).$$

The construction of  $u^n$  yields

$$(3.14) \quad \text{meas } M^n(x) \leq k \sum_{i=0}^{n-1} \varepsilon_i(x, u^i)$$

$$\leq nk\varepsilon_{n-1}(x, u) + k2K(b) e^{nL(b)t^*} \sum_{i=0}^{n-1} \text{meas } M^i(x).$$

Iterate this inequality to obtain  $C(n)$ , depending only on  $n, K(b)$  and  $L(b)$ , such that

$$(3.15) \quad \text{meas } M^n(x) \leq C(n)\varepsilon_{n-1}(x, u).$$

Now, for given  $T$ , choose  $\bar{n}$  so that  $T \leq \bar{n}t^*$ . Then define  $\mathcal{P}_T u$  as

$$\mathcal{P}_T u(x, t) = \begin{cases} u^{\bar{n}}(x, t) & \text{for } t \leq T, \\ \tilde{u}(y_0(x, 0, T, u^{\bar{n}}), t - T) & \text{for } t > T \end{cases}$$

where  $\tilde{u}$  is any strategy in  $\mathcal{A}_{ad}$ .

Observe that for any  $u$

$$J_T^N(x, u) = \int_0^T \lambda(t)\Lambda(t) \left[ \int_0^t e^{-s} f(y(s), u(s)) ds + e^{-t} \int_{\bar{\theta}} v^{N-1}(z) Q(y(t), u(t), dz) \right] dt$$

$$+ \Lambda(T) \int_0^T e^{-s} f(y(s), u(s)) ds.$$

By using (1.1)–(1.4) one can show

$$(3.16) \quad |J_T^N(x, u) - J_T^N(x, \mathcal{P}_T(u))| \leq CT[d_T(x) + W_{v^{N-1}}(d_T(x)) + \text{meas } M^{\bar{\theta}}(x)]$$

where  $C$  is a positive constant and

$$\begin{aligned} d_T(x) &= \sup_{t \in [0, T]} \{|y_0(x, 0, t, u) - y_0(x, 0, t, \mathcal{P}_T(u))|\} \\ &\leq 2K(b) e^{L(b)T} \text{meas } M^{\bar{\theta}}(x). \end{aligned}$$

Plug this into (3.16) together with (3.15) to conclude Lemma 3.2.  $\square$

LEMMA 3.3. *Let (A.2)–(A.4) and (1.1)–(1.5) hold; then  $v^N \in BUC(\bar{\theta})$  and there is a  $\delta$ -optimal strategy  $u^*$  such that*

$$J^N(x, u^*) \leq v^N(x) + \delta \quad \text{for all } x \in \bar{\theta}.$$

*Proof.* It is proved that  $v^0 \in BUC(\bar{\theta})$  [11, Thm. 3.3]. Now suppose  $v^{N-1} \in BUC(\bar{\theta})$  and define

$$\omega(r) = \sup \{|v^N(x) - v^N(y)|: x, y \in \bar{\theta} \text{ and } |x - y| < r\} \quad \text{for } r > 0.$$

At the origin  $\omega(0) = \lim_{r \downarrow 0} \omega(r)$ . Using Lemmas 3.1 and 3.2, we can conclude, as in Theorem 3.3 of [11], that for some  $t$  positive,

$$(3.17) \quad \omega(r) \leq h_t(Cr) + e^{-t} \omega(\tilde{C}r) + Ctr$$

where  $\tilde{C} > 1$ ,  $C > 0$  and  $h_t$  is as in Lemma 3.2. Iterate (3.17) to obtain

$$\omega(\tilde{C}^{-n}) \leq e^{-nt} \omega(1) + \sum_{m=0}^{n-1} e^{-mt} [h_t(C\tilde{C}^{(m-n)}) + C\tilde{C}^{(m-n)}t].$$

Use dominated convergence theorem to get  $\lim_{n \rightarrow \infty} \omega(\tilde{C}^{-n}) = 0$ . Hence  $v^N \in BUC(\bar{\theta})$ .

Pick  $\{x_m: m = 1, 2, \dots\} \subset \bar{\theta}$  such that  $\bar{\theta} \subset \bigcup_m B(x_m, r)$  where  $r$  to be chosen. Then select  $\{u_n: n = 1, 2, \dots\} \subset \mathcal{A}_{ad}$

$$(3.18) \quad J^N(x_m, u_m) \leq v^N(x_m) + \frac{\delta}{2}.$$

Now define  $u$  as follows

$$u(x, t) = u_m(x_m, t) \quad \text{if } x \in \theta_m = \bigcup_{n=1}^m B(x_n, r) \setminus \bigcup_{n=1}^{m-1} B(x_n, r).$$

Let  $u^* = \mathcal{P}_T(u)$  where  $T$  to be chosen. Note that  $u^*$  depends both on  $r$  and  $T$  but this dependence is suppressed in the notation. For every  $x \in \theta_m$  we have

$$(3.19) \quad \begin{aligned} |J^N(x, u^*) - J^N(x_m, u)| &\leq |J_T^N(x, u^*) - J_T^N(x, u)| + |J_T^N(x, u) - J_T^N(x_m, u)| \\ &\quad + 2 \sup_{\substack{x \in \theta \\ u \in \mathcal{A}_{ad}}} |J^N(x, u) - J_T^N(x, u)| := I_1 + I_2 + I_3. \end{aligned}$$

The construction of  $u$  and standard ODE estimates yield

$$(3.20) \quad \sup_{\substack{x \in \theta_m \\ t \in [0, T]}} |y_0(x, 0; t, u) - y_0(x_m, 0; t, u)| \leq C(T)r$$

where  $C(T)$  is a positive constant. Since  $y_0(x_m, 0; t, u) \in \bar{\theta}$  for all  $t \geq 0$  above inequality implies that

$$(3.21) \quad \sup_{\substack{x \in \bar{\theta} \\ t \in [0, T]}} d(y_0(x, 0; t, u), \bar{\theta}) \leq C(T)r.$$

Now, in the case of  $I_1$  use (3.8), (3.21) and in the case of  $I_2$  use (3.20), (1.1)-(1.4) and the continuity of  $v^{N-1}$  to obtain

$$(3.22) \quad I_1 + I_2 \leq h^N(T, r)$$

where  $h^N \in C([0, \infty) \times [0, \infty))$  with  $\lim_{r \downarrow 0} h^N(T, r) = 0$  for every  $T$  and  $N$ . Also (3.2) and (3.9) imply

$$|J^N(x, u) - J^N_T(x, u)| = \left| E \left[ e^{-T_1} v^{N-1}(Y_1) \chi_{(T, \infty)}(T_1) + \int_{T \wedge T_1}^{T_1} e^{-s} f(y(x, s, u), u(x, s)) ds \right] \right| \leq e^{-T} [\|v^{N-1}\|_{L^\infty(\bar{\theta})} + K(f)].$$

Recall that  $K(f)$  is the sup-norm of  $f$  and it is easy to show that  $v^N$  is bounded by  $K(f)$  for every  $N$ . Hence we have

$$(3.23) \quad I_3 \leq 4K(f) e^{-T}.$$

Substitute (3.22)-(3.23) into (3.19) to get for all  $x_m \in \theta_m$

$$(3.24) \quad |J^N(x, u^*) - J^N(x_m, u)| \leq h^N(T, r) + 4K(f) e^{-T}.$$

The continuity of  $v^N$ , (3.18) and the above inequality imply

$$J^N(x, u^*) \leq v^N(x) + \frac{\delta}{2} + \omega_{v^N}(r) + h^N(T, r) + 4K(f) e^{-T}.$$

Recall that  $\lim_{r \downarrow 0} h^N(T, r) = 0$ ; thus we can choose  $T$  and  $r$  so that  $J^N(x, u^*) \leq v^N(x) + \delta$ .  $\square$

**THEOREM 3.4.** *If (A.2)-(A.4), (1.1)-(1.5) hold, then  $v \in BUC(\bar{\theta})$  and the dynamic programming relation (0.8) holds.*

*Proof.* Iterating the second assertion of the previous lemma, one gets

$$(3.25) \quad v^N(x) = \inf_{\{u_1, \dots, u_N\} \subset \mathcal{A}_{ad}} E \left\{ \sum_{n=0}^{N-1} \int_{T_n}^{T_{n+1}} e^{-t} f(y_0(Y_n, T_n, t, u_n), u_n(Y_n, t - T_n)) dt + \int_{T_N}^{\infty} e^{-t} f(y_0(Y_N, T_N, t, u_N), u_N(Y_N, t - T_N)) dt \right\}.$$

Now define  $v^\infty$  by

$$(3.26) \quad v^\infty(x) = \inf_{\{u_n: n=1, 2, \dots\} \subset \mathcal{A}_{ad}} E \left\{ \sum_{n=0}^{\infty} \int_{T_n}^{T_{n+1}} e^{-t} f(y_0(Y_n, T_n, t, u_n), u_n(Y_n, t - T_n)) dt \right\}.$$

Hence we have

$$\sup_{x \in \bar{\theta}} |v^N(x) - v^\infty(x)| \leq 2K(f) \sup_{\{u_1, \dots, u_N\} \subset \mathcal{A}_{ad}} E(e^{-T_N}).$$

To prove that  $v^N$  converges to  $v^\infty$  it suffices to show that  $E(e^{-T_N})$  is decreasing to zero independent of control.

Let  $\{u_n: n = 1, \dots\} \subset \mathcal{A}_{ad}$  and set  $\lambda_n(t) = \lambda(y_0(Y_{n-1}, 0, t, u_n), u_n(Y_{n-1}, t))$ .

$$\begin{aligned} E(e^{-T_n + T_{n-1}} | Y_1, \dots, Y_{n-1}, T_{n-1}) &= \int_0^\infty e^{-t} \lambda_n(t) \exp \left\{ - \int_0^t \lambda_n(s) ds \right\} dt \\ &= 1 - \int_0^\infty e^{-t} \exp \left\{ - \int_0^t \lambda_n(s) ds \right\} dt \\ &\leq 1 - \int_0^\infty e^{-(1+K(\lambda))t} dt := \gamma < 1. \end{aligned}$$

Observe that  $\gamma$  is independent of control and strictly less than one. Hence

$$(3.27) \quad \sup_{\{u_1, \dots, u_N\} \in \mathcal{A}_{ad}} E(e^{-T_N}) \leq \gamma^N.$$

Therefore  $v^N$  converges to  $v^\infty$  uniformly on  $\bar{\theta}$ . So  $v^\infty \in BUC(\bar{\theta})$  and  $v^\infty$  satisfies (0.8).

We now proceed to show that  $v^\infty = v$ . First observe that  $v^\infty \leq v$  because of the definitions of  $v^\infty$  and  $v$ . Also we can construct  $u^*$  as in the previous lemma such that for all  $x \in \bar{\theta}$

$$(3.28) \quad E \left\{ \int_0^{T_1} e^{-t} f(y_0(x, 0, t, u^*), u^*(x, t)) dt + e^{-T_1} v^\infty(Y_1) \right\} \leq v^\infty(x) + \delta.$$

Apply (3.28) at  $x = Y_1$  to obtain

$$v^\infty(Y_1) \geq -\delta + E \left\{ \int_0^{T_2 - T_1} e^{-t} f(y_0(Y_1, 0, t, u^*), u^*(Y_1, t)) dt + e^{-(T_2 - T_1)} v^\infty(Y_2) | Y_1, T_1 \right\}.$$

The above inequality and (3.28) yields

$$(3.29) \quad E \left\{ \sum_{n=0}^1 \int_{T_n}^{T_{n+1}} e^{-t} f(y_0(Y_n, T_n, t, u^*), u^*(Y_n, t - T_n)) dt + e^{-T_2} v^\infty(Y_2) \right\} \leq v^\infty(x) + \delta E \sum_{n=0}^1 e^{-T_n}.$$

Iterate this procedure to obtain

$$J(x, u^*) \leq v^\infty(x) + \delta E \left( \sum_{n=0}^{\infty} e^{-T_n} \right) \leq v^\infty(x) + \delta(1 - \gamma)^{-1}$$

where  $\gamma$  is as in (3.27).  $\square$

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