

D. HERNÁNDEZ-HERNÁNDEZ (México)  
O. HERNÁNDEZ-LERMA (México)  
M. TAKSAR (Stony Brook, N.Y.)

## THE LINEAR PROGRAMMING APPROACH TO DETERMINISTIC OPTIMAL CONTROL PROBLEMS

*Abstract.* Given a deterministic optimal control problem (OCP) with value function, say  $J^*$ , we introduce a linear program ( $P$ ) and its dual ( $P^*$ ) whose values satisfy  $\sup(P^*) \leq \inf(P) \leq J^*(t, x)$ . Then we give conditions under which (i) there is *no duality gap*, i.e.  $\sup(P^*) = \inf(P)$ , and (ii) ( $P$ ) is *solvable* and it is *equivalent* to the (OCP) in the sense that  $\min(P) = J^*(t, x)$ .

**1. Introduction.** A time-honored approach to optimal control problems (OCPs) is via mathematical programming problems on suitable spaces. For instance, this approach can be used to obtain Pontryagin's maximum principle; see e.g. [3]. Another class of results has also been obtained for both deterministic and stochastic OCPs using convex programming methods [2, 5, 6].

This paper is concerned with the *linear programming* (LP) approach to deterministic, finite-horizon OCPs with value function  $J^*(t, x)$ —when the initial data is  $(t, x)$  [see (2.3)]. In this case, we first introduce a linear program ( $P$ ) and its dual ( $P^*$ ) for which

$$(1.1) \quad \sup(P^*) \leq \inf(P) \leq J^*(t, x),$$

where  $\sup(P^*)$  and  $\inf(P)$  denote the values of ( $P^*$ ) and ( $P$ ), respectively. Then we give conditions under which

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1991 *Mathematics Subject Classification*: Primary 49J15, 49M35.

*Key words and phrases*: optimal control, linear programming (in infinite-dimensional spaces), duality theory.

This research was partially supported by research grant 1332-E9206 from the Consejo Nacional de Ciencia y Tecnología, Mexico.

The work of the third author was supported in part by NSF Grant DMS 9301200 and NATO Grant CRG 900147.

(i) there is *no duality gap*, i.e.,

$$(1.2) \quad \sup(P^*) = \inf(P);$$

(ii) the linear program  $(P)$  is *solvable*, which means that  $(P)$  has an optimal solution (and we write  $\min(P)$  instead of  $\inf(P)$ ), and is *equivalent* to the OCP in the sense that

$$(1.3) \quad \min(P) = J^*(t, x).$$

*Related literature.* In recent papers [8, 9], we have obtained results similar to (1.1)–(1.3) for some discrete-time stochastic control problems on general Borel spaces. Our work is also related to the *convex programming* approach in [2, 5, 6] in that we use (LP) *duality* theory to get (1.1)–(1.3); in fact, to set our OCP we follow closely [5, 6]. Finally, we should mention that for several classes of OCPs (see e.g. [12, 13]) there is a well known, direct way—i.e., without going through the dual program  $(P^*)$ —to get (1.3); namely, one simply writes down the associated linear program  $(P)$  and then uses continuity/compactness arguments to get a minimizing sequence that converges to the optimal value. But of course, using duality, one gets more information on the OCP. For example, it turns out that the dual  $(P^*)$  is associated with the dynamic programming equation (DPE) in a sense to be precised in the Corollary to Theorem 5.1.

*Organization of the paper.* In Section 2 we introduce the OCP we are interested in, and recall some facts on the dynamic programming equation. Section 3 presents the linear programs  $(P)$  and  $(P^*)$  associated with the OCP. We also prove the consistency of these programs. In Section 4 we present the proof of (1.1)–(1.2), whereas the equality (1.3) is proved in Section 5. Finally, in Section 6 we introduce a particular approximation to the value function.

## 2. The optimal control problem

**Remark 2.1.** *Notation.* (a) If  $X$  is a generic metric space, then we denote by  $C(X)$  the space of real-valued continuous bounded functions with finite uniform norm  $\|\cdot\|$ . If  $b : X \rightarrow \mathbb{R}$  is a continuous function with  $b(\cdot) \geq 1$  (which we call a *bounding function*), then  $C_b(X)$  stands for the real vector space of all continuous functions  $v : X \rightarrow \mathbb{R}$  such that

$$\|v\|_b := \|v/b\| = \sup_{x \in X} |v(x)|/b(x) < \infty.$$

Let  $\mathcal{D}_b(X)$  be the *dual* of  $C_b(X)$ , i.e. the vector space of all bounded linear functionals on  $C_b(X)$ . If  $\xi \in \mathcal{D}_b(X)$  and  $v \in C_b(X)$ , we denote by  $\langle \xi, v \rangle$  the value of  $\xi$  at  $v$ .

(b) Let  $\mathcal{M}_b(X)$  be the vector space of all finite signed measures  $\mu$  on the Borel sets of  $X$  such that  $\|\mu\|_b := \int b d|\mu|$  is finite, where  $|\cdot|$  stands for

the total variation. Then, identifying  $\mu \in \mathcal{M}_b(X)$  with the linear functional  $v \rightarrow \langle \mu, v \rangle := \int v d\mu$  on  $C_b(X)$ , we see that  $\mathcal{M}_b(X) \subset \mathcal{D}_b(X)$  since

$$|\langle \mu, v \rangle| \leq \|v\|_b \|\mu\|_b.$$

(c) Let  $T$ ,  $0 < T < \infty$ , be the optimization horizon, and  $U \subset \mathbb{R}^n$  the control set, which is assumed to be compact. Define  $\Sigma := [0, T] \times \mathbb{R}^n$ ,  $S := \Sigma \times U$ .

If  $v$  is a function on  $\mathbb{R}^n$ , we consider it to be a function on  $\Sigma$ ,  $S$  or  $\mathbb{R}^n \times U$ , defining  $v(t, x) := v(x)$ ,  $v(t, x, u) := v(x)$  or  $v(x, u) := v(x)$  respectively.

For each  $t \in [0, T]$ , the set  $\mathcal{U}(t)$  of control processes is the set of Borel measurable functions  $\mathbf{u} : [t, T] \rightarrow U$ .

*The optimal control problem (OCP).* Let  $f : S \rightarrow \mathbb{R}^n$  be a given function, and consider the controlled system

$$(2.1) \quad \dot{x}(s) := f(s, x(s), \mathbf{u}(s)), \quad t < s \leq T, \quad x(t) = x,$$

where  $x \in \mathbb{R}^n$  and  $\mathbf{u} \in \mathcal{U}(t)$ . The OCP is then to minimize

$$(2.2) \quad J(t, x; \mathbf{u}) := \int_t^T l_0(s, x(s), \mathbf{u}(s)) ds + L_0(x(T))$$

over the pairs  $(x(\cdot), \mathbf{u}(\cdot))$  that satisfy Definition 2.2. The OCP's *value function*  $J^*$  is defined as

$$(2.3) \quad J^*(t, x) := \inf_{\mathcal{U}(t)} J(t, x; \mathbf{u}).$$

DEFINITION 2.2. A pair  $(x(\cdot), \mathbf{u}(\cdot))$  is said to be *admissible* for the initial data  $(t, x)$  if  $\mathbf{u}(\cdot) \in \mathcal{U}(t)$ , and  $x(\cdot)$  satisfies (2.1). We shall denote by  $\mathcal{P}(t, x)$  the family of all admissible pairs, given the initial data  $(t, x)$ .

Throughout the following we assume (H1)–(H3) below:

(H1)  $f$  belongs to  $C(S)$  and it is Lipschitz in  $x \in \mathbb{R}^n$ , uniformly in  $(t, u) \in [0, T] \times U$ , i.e.

$$\sup_S |f(t, x, u)| \leq K \quad \text{and} \quad |f(t, x, u) - f(t, y, u)| \leq c|x - y| \quad \forall x, y \in \mathbb{R}^n,$$

where  $c$  is some constant independent of  $(t, u)$ .

(H2)  $l_0$  and  $L_0$  are nonnegative, bounded away from zero, continuous functions on  $S$  and  $\mathbb{R}^n$  respectively, and there exists a real-valued continuous function  $b(x)$  on  $\mathbb{R}^n$  such that

$$\begin{aligned} l_0(t, x, u) &\leq b(x), \quad \forall (t, x, u) \in S, \\ L_0(x) &\leq b(x), \quad \forall x \in \mathbb{R}^n, \\ b(x)/l_0(t, x, u) &\in C(S), \quad \text{and} \quad b(x)/L_0(x) \in C(\mathbb{R}^n). \end{aligned}$$

(H3) There exist  $\varepsilon_0 > 0$  and  $c > 0$  such that for all  $|s - t|, |x - y| < \varepsilon_0$ ,

$$\begin{aligned} |b(y) - b(x)| &\leq c|y - x|b(x), \\ |l_0(t, x, u) - l_0(s, y, u)| &\leq c(|y - x| + |t - s|)b(x), \\ |L_0(y) - L_0(x)| &\leq c|y - x|b(x); \end{aligned}$$

without loss of generality we may take  $c$  to be the same as in (H1).

*The dynamic programming equation (DPE).* We write partial derivatives as  $D_0 := \partial/\partial t$  and  $D_i := \partial/\partial x_i$  for  $i = 1, \dots, n$ . Let  $b$  be as in (H2) and define  $C_b^1(\Sigma)$  as the Banach space consisting of all the functions  $\varphi \in C_b(\Sigma)$  with partial derivatives  $D_i\varphi$  in  $C_b(\Sigma)$  for all  $i = 0, 1, \dots, n$ , with

$$(2.4) \quad \|\varphi\|_b^1 := \|\varphi\|_b + \sum_{i=0}^n \|D_i\varphi\|_b < \infty.$$

For each  $\varphi \in C_b^1(\Sigma)$ , define  $A\varphi \in C_b(S)$  by

$$(2.5) \quad A\varphi(t, x, u) := D_0\varphi(t, x) + f(t, x, u) \cdot \nabla_x \varphi(t, x),$$

where  $\nabla_x \varphi$  is the  $x$ -gradient of  $\varphi$ . Then  $A : C_b^1(\Sigma) \rightarrow C_b(S)$  is a linear operator and it is obviously bounded, since

$$(2.6) \quad \|A\varphi\|_b \leq (1 + \|f\|)\|\varphi\|_b^1 \quad \forall \varphi \in C_b^1(\Sigma).$$

**DEFINITION 2.3.** A function  $\varphi$  in  $C_b^1(\Sigma)$  is said to be a smooth subsolution to the *dynamic programming equation* (DPE) if

$$A\varphi + l_0 \geq 0 \quad \text{on } [0, T] \times \mathbb{R}^n \times U, \quad \text{and} \quad \varphi(T, x) \leq L_0(x) \quad \forall x \in \mathbb{R}^n.$$

If  $\varphi$  is in  $C_b^1(\Sigma)$  and  $(x(\cdot), \mathbf{u}(\cdot)) \in \mathcal{P}(t, x)$ , then

$$\frac{d}{dt}\varphi(t, x(t)) = A\varphi(t, x(t), \mathbf{u}(t)),$$

so that

$$(2.7) \quad \int_t^T A\varphi(s, x(s), \mathbf{u}(s)) ds = \varphi(T, x(T)) - \varphi(t, x).$$

Therefore, if  $\varphi$  is a smooth subsolution to the DPE, then  $\varphi(t, x) \leq J(t, x; \mathbf{u})$ , and we see that  $\varphi$  and the value function are related by the inequality

$$(2.8) \quad \varphi(t, x) \leq J^*(t, x).$$

**3. The linear programming formulation.** We will use the linear programming terminology of [1], Chapter 3.

*Dual pairs.* Let  $b$  be the function in (H2)–(H3) and define the vector space  $\tilde{C}(S) := C_b(S) \times C_b(\mathbb{R}^n)$ , which consists of all pairs  $\tilde{l} = (l, L)$  of functions  $l \in C_b(S)$  and  $L \in C_b(\mathbb{R}^n)$ . (Note that condition (H2) implies that

$(l_0, L_0) \in \widetilde{C}(S)$ ). Moreover, let  $\mathcal{D}_b(S)$  and  $\mathcal{D}_b(\mathbb{R}^n)$  be the dual spaces of  $C_b(S)$  and  $C_b(\mathbb{R}^n)$  respectively, and define  $\widetilde{\mathcal{D}}(S)$  as the vector space consisting of pairs  $\widetilde{\xi} = (\xi_1, \xi_2)$  of functionals  $\xi_1 \in \mathcal{D}_b(S)$  and  $\xi_2 \in \mathcal{D}_b(\mathbb{R}^n)$ . Then  $(\widetilde{C}(S), \widetilde{\mathcal{D}}(S))$  is a dual pair with respect to the bilinear form

$$\langle \widetilde{\xi}, \widetilde{l} \rangle := \langle \xi_1, l \rangle + \langle \xi_2, L \rangle.$$

Let  $\mathcal{M}_b(S) \subset \mathcal{D}_b(S)$  and  $\mathcal{M}_b(\mathbb{R}^n) \subset \mathcal{D}_b(\mathbb{R}^n)$  be the spaces of measures introduced in Remark 2.1. Then each admissible pair  $(x(\cdot), \mathbf{u}(\cdot)) \in \mathcal{P}(t, x)$  defines a pair of measures  $\widetilde{M}^{\mathbf{u}} = (M^{\mathbf{u}}, N^{\mathbf{u}})$  in  $\mathcal{M}_b(S) \times \mathcal{M}_b(\mathbb{R}^n)$  by setting, for  $\widetilde{l} \in \widetilde{C}(S)$ ,

$$(3.1) \quad \langle \widetilde{M}^{\mathbf{u}}, \widetilde{l} \rangle = \langle M^{\mathbf{u}}, l \rangle + \langle N^{\mathbf{u}}, L \rangle = \int_t^T l(s, x(s), \mathbf{u}(s)) ds + L(x(T)).$$

That is,  $N^{\mathbf{u}}$  is the Dirac measure at  $x(T)$ , and  $M^{\mathbf{u}}$  satisfies

$$M^{\mathbf{u}}(A \times B \times C) = \int_{[t, T] \cap A} I_B(x(s)) I_C(\mathbf{u}(s)) ds,$$

where  $A, B$  and  $C$  are arbitrary Borel sets in  $[t, T]$ ,  $\mathbb{R}^n$  and  $U$  respectively. Note that condition (H1) implies that for each controlled process  $x(t)$ ,  $0 < t < T$ , defined by (2.1) belongs to a compact set. Thus  $\langle \widetilde{M}^{\mathbf{u}}, \widetilde{l} \rangle$  is well defined and finite for each  $\widetilde{l}$ . Furthermore, if  $\varphi \in C_b^1(\Sigma)$ , we may write (2.7) as

$$(3.2) \quad \langle (M^{\mathbf{u}}, N^{\mathbf{u}}), (-A\varphi, \varphi_T) \rangle = \varphi(t, x),$$

where  $\varphi_T(x) := \varphi(T, x)$ , for  $x \in \mathbb{R}^n$ , denotes the restriction of  $\varphi$  to  $\{T\} \times \mathbb{R}^n$ . On the other hand, from (2.2)–(2.3),

$$(3.3) \quad J^*(t, x) = \inf_{\mathcal{U}(t)} \langle (M^{\mathbf{u}}, N^{\mathbf{u}}), (l_0, L_0) \rangle.$$

We shall consider  $\widetilde{C}(S)$  and  $\widetilde{\mathcal{D}}(S)$  to be endowed with the norms

$$\|\widetilde{l}\|_* = \|(l, L)\|_* = \max\{\|l\|_b, \|L\|_b\}$$

and

$$\|\widetilde{\xi}\|_* = \|(\xi_1, \xi_2)\|_* = \max\{\|\xi_1\|_b, \|\xi_2\|_b\}.$$

In addition to  $(\widetilde{\mathcal{D}}(S), \widetilde{C}(S))$ , we also consider the dual pair  $(\mathcal{D}_b^1(\Sigma), C_b^1(\Sigma))$ , where  $\mathcal{D}_b^1(\Sigma)$  is the dual of  $C_b^1(\Sigma)$ .

Let  $\mathcal{L}_2 : C_b^1(\Sigma) \rightarrow \widetilde{C}(S)$  be the linear map defined by

$$(3.4) \quad \mathcal{L}_2 \varphi := (-A\varphi, \varphi_T), \quad \varphi \in C_b^1(\Sigma).$$

By (2.6),  $\mathcal{L}_2$  is continuous. We now define  $\mathcal{L}_1 : \widetilde{\mathcal{D}}(S) \rightarrow \mathcal{D}_b^1(\Sigma)$  as follows. First, for every  $\widetilde{\xi} = (\xi_1, \xi_2) \in \widetilde{\mathcal{D}}(S)$ , let  $T_{\widetilde{\xi}}$  be defined on  $C_b^1(\Sigma)$  as  $T_{\widetilde{\xi}}(\varphi) =$

$\langle \tilde{\xi}, \mathcal{L}_2 \varphi \rangle$ . Since  $\mathcal{L}_2$  is a continuous linear map, so is  $T_{\tilde{\xi}}$ . Therefore, there exists a unique  $\nu_{\tilde{\xi}} \in \mathcal{D}_b^1(\Sigma)$  such that

$$(3.5) \quad T_{\tilde{\xi}}(\varphi) = \langle \nu_{\tilde{\xi}}, \varphi \rangle \quad (= \langle \tilde{\xi}, \mathcal{L}_2 \varphi \rangle).$$

As this holds for every  $\tilde{\xi} \in \tilde{\mathcal{D}}(S)$ , we define  $\mathcal{L}_1 : \tilde{\mathcal{D}}(S) \rightarrow \mathcal{D}_b^1(\Sigma)$  as

$$(3.6) \quad \mathcal{L}_1 \tilde{\xi} := \nu_{\tilde{\xi}}$$

and note that  $\mathcal{L}_1$  is the *adjoint* of  $\mathcal{L}_2$ , i.e., from (3.5),

$$(3.7) \quad \langle \mathcal{L}_1 \tilde{\xi}, \varphi \rangle = \langle \tilde{\xi}, \mathcal{L}_2 \varphi \rangle \quad \forall \tilde{\xi} \in \tilde{\mathcal{D}}(S), \varphi \in C_b^1(\Sigma).$$

Moreover, from (3.7), (3.4) and (2.5), a direct calculation shows that

$$\|\mathcal{L}_1 \tilde{\xi}\|_b^1 = \sup\{|\langle \mathcal{L}_1 \tilde{\xi}, \varphi \rangle| : \|\varphi\|_b^1 \leq 1\} \leq (2 + \|f\|) \|\tilde{\xi}\|_*.$$

Thus,  $\mathcal{L}_1$  is a continuous linear map.

**Remark 3.1. Notation.** Given a real vector space  $X$  with a positive cone  $X^+$  we write  $x \geq 0$  whenever  $x \in X^+$ . Let  $\tilde{C}(S)^+ := \{\tilde{l} = (l, L) \in \tilde{C}(S) : l \geq 0, L \geq 0\}$  be the natural positive cone in  $\tilde{C}(S)$ , and

$$\tilde{\mathcal{D}}(S)^+ := \{\tilde{\xi} = (\xi_1, \xi_2) \in \tilde{\mathcal{D}}(S) : \langle \tilde{\xi}, \tilde{l} \rangle \geq 0 \forall \tilde{l} \in \tilde{C}(S)^+\}$$

the corresponding dual cone.

*Linear programs.* Let  $\tilde{l}_0$  be the pair  $(l_0, L_0) \in \tilde{C}(S)$ , and let  $\nu^0 := \delta_{(t,x)} \in \mathcal{D}_b^1(\Sigma)$  be the Dirac measure concentrated at the initial condition  $(t, x)$  of (2.1), that is,  $\langle \nu^0, \varphi \rangle = \varphi(t, x)$  for  $\varphi \in C_b^1(\Sigma)$ . Consider now the following linear program  $(P)$  and its dual  $(P^*)$ .

$(P)$  minimize  $\langle \tilde{\xi}, \tilde{l}_0 \rangle$ , subject to:

$$(3.8) \quad \mathcal{L}_1 \tilde{\xi} = \nu^0, \quad \tilde{\xi} \in \tilde{\mathcal{D}}(S)^+.$$

$(P^*)$  maximize  $\langle \nu^0, \varphi \rangle [= \varphi(t, x)]$ , subject to:

$$(3.9) \quad \mathcal{L}_2 \varphi \leq \tilde{l}_0, \quad \varphi \in C_b^1(\Sigma),$$

where the latter inequality is understood componentwise, i.e.,

$$-A\varphi \leq l_0 \quad \text{and} \quad \varphi_T \leq L_0.$$

Recall that  $\varphi_T(\cdot) := \varphi(T, \cdot)$  is the restriction of  $\varphi$  to  $\{T\} \times \mathbb{R}^n$ . Let  $F(P)$  (resp.  $F(P^*)$ ) be the set of feasible solutions to  $(P)$  (resp.  $(P^*)$ ); i.e.  $F(P)$  (resp.  $F(P^*)$ ) is the set of pairs  $\tilde{\xi} = (\xi_1, \xi_2)$  in  $\tilde{\mathcal{D}}(S)$  that satisfy (3.8) (resp. the set of functions  $\varphi \in C_b^1(\Sigma)$  that satisfy (3.9)).

*Consistency.* The linear program  $(P)$  is said to be *consistent* if  $F(P)$  is nonempty, and similarly for  $F(P^*)$ . The program  $(P^*)$  is consistent, since e.g.  $\varphi(\cdot) \equiv 0$  is in  $F(P^*)$ . On the other hand,  $(P)$  is also consistent since  $F(P)$  contains the set of all pairs  $\tilde{M}^u = (M^u, N^u) \geq 0$  such that

$(x(\cdot), \mathbf{u}(\cdot)) \in \mathcal{P}(t, x)$ ; see (3.1). Indeed, by (3.7), the equality  $\mathcal{L}_1 \widetilde{M}^{\mathbf{u}} = \nu^0$  in (3.8) holds if and only if

$$\langle \widetilde{M}^{\mathbf{u}}, \mathcal{L}_2 \varphi \rangle = \langle (M^{\mathbf{u}}, N^{\mathbf{u}}), (-A\varphi, \varphi_T) \rangle = \varphi(t, x) \quad \forall \varphi \in C_b^1(\Sigma),$$

which is the same as (3.2) for  $(\xi_1, \xi_2) = (M^{\mathbf{u}}, N^{\mathbf{u}})$ .

The latter also implies that, from (3.3),

$$J^*(t, x) = \inf_{\mathcal{U}(t, x)} \langle \widetilde{M}^{\mathbf{u}}, \widetilde{l}_0 \rangle \geq \inf_{F(P)} \langle \widetilde{\xi}, \widetilde{l}_0 \rangle =: \inf(P),$$

i.e. the value function  $J^*$  and the value,  $\inf(P)$ , of  $(P)$  are related by

$$J^*(t, x) \geq \inf(P).$$

Furthermore, denoting by  $\sup(P^*)$  the value of  $(P^*)$ , *weak duality* yields [1]

$$\inf(P) \geq \sup(P^*);$$

hence,

$$(3.10) \quad J^*(t, x) \geq \inf(P) \geq \sup(P^*).$$

**4. Absence of duality gap.** In this section we prove that there is *no duality gap* (see (4.1)) and that  $(P)$  is *solvable*. More precisely, we have the following theorem.

**THEOREM 4.1.** *If the hypotheses (H1)–(H3) hold, then there is no duality gap and  $(P)$  is solvable, i.e.*

$$(4.1) \quad \sup(P^*) = \inf(P),$$

and there exists an optimal solution  $\widetilde{\xi}^* \in \widetilde{\mathcal{D}}(S)$  for  $(P)$ , so that

$$\sup(P^*) = \min(P) = \langle \widetilde{\xi}^*, \widetilde{l}_0 \rangle.$$

**Proof.** We use Theorems 3.10 and 3.22 of [1], which state that if  $(P)$  is consistent with a finite value, and the set

$$(4.2) \quad D := \{(\mathcal{L}_1 \widetilde{\xi}, \langle \widetilde{\xi}, \widetilde{l}_0 \rangle) : \widetilde{\xi} \in \widetilde{\mathcal{D}}(S)^+\}$$

is closed in  $\mathcal{D}_b^1(\Sigma) \times \mathbb{R}$ , then there is no duality gap between  $(P)$  and  $(P^*)$ , and  $(P)$  is solvable. Thus, since we have seen that  $(P)$  is consistent, it suffices to show that the set  $D$  in (4.2) is closed. Let  $\Gamma$  be a directed set, and let  $\{\widetilde{\xi}_\gamma = (\xi_{1\gamma}, \xi_{2\gamma}) : \gamma \in \Gamma\}$  be a net in  $\widetilde{\mathcal{D}}(S)^+$  such that  $(\mathcal{L}_1 \widetilde{\xi}_\gamma, \langle \widetilde{\xi}_\gamma, \widetilde{l}_0 \rangle)$  converges to  $(\nu, r)$  in  $\mathcal{D}_b^1(\Sigma) \times \mathbb{R}$ , i.e.

$$(4.3) \quad r = \lim_{\Gamma} \langle \widetilde{\xi}_\gamma, \widetilde{l}_0 \rangle$$

and

$$(4.4) \quad \nu = \lim_{\Gamma} \mathcal{L}_1 \widetilde{\xi}_\gamma$$

in the weak topology  $\sigma(\mathcal{D}_b^1(\Sigma), C_b^1(\Sigma))$ . We wish to show that  $(\nu, r)$  is in  $D$ , i.e. there exists  $\tilde{\xi} = (\xi_1, \xi_2) \in \tilde{\mathcal{D}}(S)^+$  such that

$$(4.5) \quad r = \langle \tilde{\xi}, \tilde{l}_0 \rangle \quad \text{and} \quad \nu = \mathcal{L}_1 \tilde{\xi}.$$

By (4.3), given  $\varepsilon > 0$ , there exists  $\gamma(\varepsilon) \in \Gamma$  such that, for all  $\gamma \geq \gamma(\varepsilon)$ ,

$$(4.6) \quad r - \varepsilon \leq \langle \tilde{\xi}_\gamma, \tilde{l}_0 \rangle = \langle \xi_{1\gamma}, l_0 \rangle + \langle \xi_{2\gamma}, L_0 \rangle \leq r + \varepsilon.$$

Therefore, for any  $\gamma \geq \gamma(\varepsilon)$  and  $l \in C_b(S)$ ,

$$\begin{aligned} |\langle \xi_{1\gamma}, l \rangle| &\leq \langle \xi_{1\gamma}, |l| \rangle \leq \|l\|_b \langle \xi_{1\gamma}, b \rangle \\ &\leq \|l\|_b \langle \xi_{1\gamma}, l_0 \rangle \|b/l_0\| \quad \text{by (H2)} \\ &\leq \|l\|_b \|b/l_0\| (r + \varepsilon) \quad \text{by (4.6);} \end{aligned}$$

that is,  $\{\xi_{1\gamma} : \gamma \geq \gamma(\varepsilon)\}$  is a bounded family in  $\mathcal{D}_b(S)$ . Similarly,  $\{\xi_{2\gamma} : \gamma \geq \gamma(\varepsilon)\}$  is a bounded family in  $\mathcal{D}_b(\mathbb{R}^n)$ , since for all  $\gamma \geq \gamma(\varepsilon)$  and  $L \in C_b(\mathbb{R}^n)$ ,

$$\begin{aligned} |\langle \xi_{2\gamma}, L \rangle| &\leq \langle \xi_{2\gamma}, |L| \rangle \leq \|L\|_b \langle \xi_{2\gamma}, b \rangle \\ &\leq \|L\|_b \langle \xi_{2\gamma}, L_0 \rangle \|b/L_0\| \quad \text{by (H2)} \\ &\leq \|L\|_b \|b/L_0\| (r + \varepsilon) \quad \text{by (4.6).} \end{aligned}$$

Thus,  $\{\tilde{\xi}_\gamma : \gamma \geq \gamma(\varepsilon)\}$  is bounded and, therefore, there exists a directed set  $\Gamma' \subset \Gamma$  and a pair  $\tilde{\xi} = (\xi_1, \xi_2)$  such that  $\{\tilde{\xi}_\gamma : \gamma \in \Gamma'\}$  converges to  $\tilde{\xi}$ . This convergence, together with (4.3), yields  $\langle \tilde{\xi}, \tilde{l}_0 \rangle = r$ , whereas the continuity of  $\mathcal{L}_1$  and (4.4) give

$$\mathcal{L}_1 \tilde{\xi} = \mathcal{L}_1 \left( \lim_{\Gamma'} \tilde{\xi}_\gamma \right) = \lim_{\Gamma'} \mathcal{L}_1 \tilde{\xi}_\gamma = \nu.$$

That is, (4.5) holds. ■

**5. Equivalence of  $(P)$  and the OCP.** In this section we prove that the original OCP (2.1)–(2.3) and the linear program  $(P)$  are *equivalent* in the sense of the following theorem.

**THEOREM 5.1.** *Assume (H1)–(H3). Then  $\min(P) = J^*(t, x)$ .*

Moreover, from (4.1) and Theorem 5.1, we obtain  $J^*(t, x) = \sup(P^*)$ . In other words:

**COROLLARY.** *Under (H1)–(H3), the value function  $J^*$  is the supremum of the smooth subsolutions to the DPE.*

In the proof of Theorem 5.1 we use the following key result, which is proved in the next section.

**THEOREM 5.2.** *For every  $\varepsilon > 0$  there exist functions  $\tilde{J}_\varepsilon$ ,  $L_\varepsilon$  and  $\gamma_\varepsilon$ , with  $\tilde{J}_\varepsilon \in C_b^1(\Sigma)$ , such that*

$$(5.1) \quad \|\tilde{J}_\varepsilon - J^*\|_b \rightarrow 0 \quad \text{as } \varepsilon \rightarrow 0, \quad \tilde{J}_\varepsilon(T, x) = L_\varepsilon(x),$$

$$(5.2) \quad \|L_0 - L_\varepsilon\|_b \rightarrow 0 \quad \text{as } \varepsilon \rightarrow 0,$$

$$(5.3) \quad A\tilde{J}_\varepsilon + l_0 \geq \gamma_\varepsilon,$$

where

$$(5.4) \quad \|\gamma_\varepsilon\|_b \rightarrow 0 \quad \text{as } \varepsilon \rightarrow 0.$$

**Proof of Theorem 5.1.** From (3.10) and the solvability of  $(P)$  (Theorem 4.1), we know that  $\min(P) \leq J^*(t, x)$ . Suppose that  $\min(P) < J^*(t, x)$ . Then there exists  $\tilde{\xi} \in F(P)$  such that

$$(5.5) \quad \langle \tilde{\xi}, \tilde{l}_0 \rangle < J^*(t, x).$$

Thus, from (5.3),

$$\begin{aligned} \langle \tilde{\xi}, \tilde{l}_0 \rangle &\geq \langle \xi_1, -A\tilde{J}_\varepsilon + \gamma_\varepsilon \rangle + \langle \xi_2, L_\varepsilon \rangle + \langle \xi_2, L_0 - L_\varepsilon \rangle \\ &\geq \langle \xi_1, -A\tilde{J}_\varepsilon \rangle + \langle \xi_2, L_\varepsilon \rangle - \|\gamma_\varepsilon\|_b \|\xi_1\|_b - \|\xi_2\|_b \|L_0 - L_\varepsilon\|_b \\ &= \langle \tilde{\xi}, \mathcal{L}_2 \tilde{J}_\varepsilon \rangle - \|\gamma_\varepsilon\|_b \|\xi_1\|_b - \|\xi_2\|_b \|L_0 - L_\varepsilon\|_b \\ &= \langle \mathcal{L}_1 \tilde{\xi}, \tilde{J}_\varepsilon \rangle - \|\gamma_\varepsilon\|_b \|\xi_1\|_b - \|\xi_2\|_b \|L_0 - L_\varepsilon\|_b \\ &= \tilde{J}_\varepsilon(t, x) - \|\gamma_\varepsilon\|_b \|\xi_1\|_b - \|\xi_2\|_b \|L_0 - L_\varepsilon\|_b \quad \text{by (3.8)}. \end{aligned}$$

From (5.1)–(5.2) and (5.4), it follows that  $J^*(t, x) \leq \langle \tilde{\xi}, \tilde{l}_0 \rangle$ , which contradicts (5.5). ■

**6. Approximation of the value function.** In this section we prove the approximation Theorem 5.2. We will do this via several lemmas, from which we obtain a particular approximation to the optimal cost function. We first extend our control problem to a larger time interval.

Put

$$\begin{aligned} f(t, x, u) &:= f(0, x, u) \quad \text{and} \quad l_0(t, x, u) := l_0(0, x, u) \quad \text{if } t < 0; \\ f(t, x, u) &:= f(T, x, u) \quad \text{and} \quad l_0(t, x, u) := l_0(T, x, u) \quad \text{if } t > T. \end{aligned}$$

For each  $\varepsilon > 0$ , define  $\Sigma_\varepsilon := [-\varepsilon, T + \varepsilon] \times \mathbb{R}^n$ ,  $S_\varepsilon := \Sigma_\varepsilon \times U$ , and  $\mathcal{U}_\varepsilon(t)$  as the set of Borel measurable functions  $\mathbf{u} : [t, T + \varepsilon] \rightarrow U$ ,  $-\varepsilon \leq t < T + \varepsilon$ .

Note that, thus defined, the extensions of  $l_0$  and  $f$  to  $\Sigma_\varepsilon$  and  $S_\varepsilon$  satisfy (H1) and (H2).

Define

$$J_\varepsilon(t, x; \mathbf{u}) := \int_t^{T+\varepsilon} l_0(r, x(r), \mathbf{u}(r)) dr + L_0(x(T + \varepsilon)),$$

where

$$(6.1) \quad \begin{aligned} \dot{x}(r) &= f(r, x(r), \mathbf{u}(r)), & t < r \leq T + \varepsilon, \\ x(t) &= x. \end{aligned}$$

The value function  $J_\varepsilon^*$  is defined as

$$J_\varepsilon^*(t, x) := \inf_{\mathcal{U}_\varepsilon(t)} J_\varepsilon(t, x; \mathbf{u}).$$

Note that  $\varepsilon = 0$  yields the original OCP.

We shall now establish properties of the value function  $J_\varepsilon^*$ . Below,  $C$  stands for a generic constant whose values may be different in different formulas.

LEMMA 6.1. *There exists  $C$  such that for all  $\varepsilon < 1$ ,*

$$J_\varepsilon^*(t, x) \leq Cb(x) \quad \forall (t, x) \in \Sigma_\varepsilon.$$

PROOF. From (H3) it follows that

$$(6.2) \quad b(y) \leq b(x) (1 + c|y - x|) \leq b(x)e^{c|x-y|}$$

for all  $|x - y| < \varepsilon_0$ . By induction, one can show the validity of (6.2) for all  $x, y \in \mathbb{R}^n$ . From (6.1) and (H1) we obtain, for each  $\mathbf{u} \in \mathcal{U}_\varepsilon(t)$  and  $r \geq t$ ,

$$(6.3) \quad |x(r) - x| \leq K|r - t|.$$

Then, by (H2) and (6.2)–(6.3),

$$\begin{aligned} J_\varepsilon(t, x; \mathbf{u}) &\leq \int_t^{T+\varepsilon} b(x(r)) dr + b(x(T + \varepsilon)) \\ &\leq \int_t^{T+\varepsilon} b(x)e^{c|x(r)-x|} dr + b(x)e^{c|x(T+\varepsilon)-x|} \\ &\leq b(x) \left[ \int_t^{T+\varepsilon} e^{cK|r-t|} dr + e^{cK|T+\varepsilon-t|} \right] \leq Cb(x). \end{aligned}$$

Taking the infimum over  $\mathcal{U}_\varepsilon(t)$  yields the lemma. ■

LEMMA 6.2. *There exist  $\varepsilon_1 > 0$  and  $C > 0$  such that for all  $\varepsilon < 1$  and  $|x - y|, |s - t| < \varepsilon_1$ ,*

$$|J_\varepsilon^*(t, x) - J_\varepsilon^*(s, y)| \leq C[|x - y| + |s - t|]b(x).$$

PROOF. Assume  $t < s$  and let  $\mathbf{u} \in \mathcal{U}_\varepsilon(t)$  be an arbitrary control function. Put

$$\begin{aligned} \dot{x}_1(r) &= f(r, x_1(r), \mathbf{u}(r)), & t < r \leq T + \varepsilon, & \quad \text{with } x_1(t) = x, \\ \dot{x}_2(r) &= f(r, x_2(r), \mathbf{u}(r)), & s < r \leq T + \varepsilon, & \quad \text{with } x_2(s) = y. \end{aligned}$$

Then

$$\begin{aligned}
 (6.4) \quad & |J_\varepsilon(t, x; \mathbf{u}) - J_\varepsilon(s, y; \mathbf{u})| \\
 & \leq \left| \int_t^s l_0(r, x_1(r), \mathbf{u}(r)) dr \right| \\
 & \quad + \left| \int_s^{T+\varepsilon} [l_0(r, x_1(r), \mathbf{u}(r)) - l_0(r, x_2(r), \mathbf{u}(r))] dr \right| \\
 & \quad + |L_0(x_1(T + \varepsilon)) - L_0(x_2(T + \varepsilon))| \\
 & =: I_1 + I_2 + I_3.
 \end{aligned}$$

Using (6.2), (6.3) and (H2), we have

$$\begin{aligned}
 (6.5) \quad I_1 & \leq \int_t^s b(x_1(r)) dr \leq \int_t^s b(x) e^{c|x_1(r)-x|} dr \\
 & \leq b(x) \int_t^s e^{cK|r-t|} dr \leq b(x) e^{cK(T+2)} (s-t).
 \end{aligned}$$

We now majorize  $I_2$ . From (6.3),  $|x_1(s) - x| \leq K|s - t|$ ; hence

$$(6.6) \quad |x_1(s) - y| \leq |x - y| + K|s - t|.$$

Consequently, by (H1),

$$\begin{aligned}
 (6.7) \quad & |x_1(r) - x_2(r)| \\
 & = |x_1(s) - y| + \left| \int_s^r [f(z, x_1(z), \mathbf{u}(z)) - f(z, x_2(z), \mathbf{u}(z))] dz \right| \\
 & \leq |x - y| + K|t - s| + \int_s^r c|x_1(z) - x_2(z)| dz.
 \end{aligned}$$

Thus, Gronwall's inequality implies

$$(6.8) \quad |x_1(r) - x_2(r)| \leq [|x - y| + K|t - s|] e^{c|r-s|}.$$

Taking  $\varepsilon_1 < 1$  such that  $(K+1)\varepsilon_1 e^{c(T+2)} < \varepsilon_0$  we have (see condition (H3))

$$\begin{aligned}
 (6.9) \quad I_2 & \leq \int_s^{T+\varepsilon} |l_0(r, x_1(r), \mathbf{u}(r)) - l_0(r, x_2(r), \mathbf{u}(r))| dr \\
 & \leq \int_s^{T+\varepsilon} b(x_1(r)) [|x - y| + K|t - s|] e^{c(T+\varepsilon-s)} dr \\
 & \leq b(x) [|x - y| + K|t - s|] e^{c(T+2)} \int_s^{T+\varepsilon} e^{c|x_1(r)-x|} dr
 \end{aligned}$$

$$\begin{aligned}
&\leq b(x)[|x - y| + K|t - s|]e^{c(T+2)} \int_{-\varepsilon}^{T+\varepsilon} e^{cK|r-t|} dr \\
&= C[|x - y| + |t - s|]b(x).
\end{aligned}$$

Similarly, using (6.8), (6.2), (6.3) and (H3), we may majorize  $I_3$  as follows:

$$\begin{aligned}
(6.10) \quad I_3 &= |L_0(x_1(T + \varepsilon)) - L_0(x_2(T + \varepsilon))| \\
&\leq cb(x_1(T + \varepsilon))|x_2(T + \varepsilon) - x_1(T + \varepsilon)| \\
&\leq cb(x)e^{c|x_1(T+\varepsilon)-x|}(|x - y| + K|t - s|)e^{c(T+\varepsilon-s)} \\
&\leq cb(x)e^{cK|T+\varepsilon-t|}(|x - y| + |t - s|)(K + 1)e^{c(T+\varepsilon-s)} \\
&= Cb(x)(|x - y| + |t - s|).
\end{aligned}$$

Combining (6.4), (6.5), (6.9) and (6.10) and taking the supremum over all control functions  $\mathbf{u}(\cdot)$ , we complete the proof of the lemma, since

$$|J_\varepsilon^*(t, x) - J_\varepsilon^*(s, y)| \leq \sup_{\mathcal{U}_\varepsilon(t)} |J_\varepsilon(t, x; \mathbf{u}) - J_\varepsilon(s, y; \mathbf{u})|. \quad \blacksquare$$

**Remark 6.3.** From Lemma 6.2 it follows that  $J_\varepsilon^*$  is differentiable for almost all  $(t, x) \in \Sigma_\varepsilon$ , and  $|D_i J_\varepsilon^*(t, x)| \leq Cb(x)$ ,  $i = 0, 1, \dots, n$ .

**LEMMA 6.4.** *There exists  $C > 0$  such that for all  $(t, x) \in \Sigma$  and all sufficiently small  $\varepsilon > 0$ ,*

$$(6.11) \quad |J_\varepsilon^*(t, x) - J^*(t, x)| \leq C\varepsilon b(x).$$

**Proof.** Let  $0 \leq t \leq T$  and let  $\mathbf{u}(\cdot)$  be any control function in  $\mathcal{U}_\varepsilon(t)$ . Let

$$\begin{aligned}
\dot{x}(r) &= f(r, x(r), \mathbf{u}(r)), \quad t < r \leq T + \varepsilon, \\
x(t) &= x.
\end{aligned}$$

Then (H3) and the inequalities (6.2) and (6.3) show that for  $\varepsilon < 1$ ,

$$\begin{aligned}
(6.12) \quad |J_\varepsilon(t, x; \mathbf{u}) - J(t, x; \mathbf{u})| & \\
&\leq \int_T^{T+\varepsilon} l_0(r, x(r), \mathbf{u}(r)) dr + |L_0(x(T + \varepsilon)) - L_0(x(T))| \\
&\leq \int_T^{T+\varepsilon} b(x)e^{c|x(r)-x|} dr + cb(x(T))|x(T + \varepsilon) - x(T)| \\
&\leq b(x)e^{cK(T+\varepsilon)}\varepsilon + cb(x)e^{c|x(T)-x|}K\varepsilon \\
&\leq b(x)e^{cK(T+\varepsilon)}\varepsilon + cb(x)e^{cK|T-t|}K\varepsilon \leq C\varepsilon b(x).
\end{aligned}$$

Finally, as in the proof of Lemma 6.2, taking the supremum over all  $\mathbf{u}(\cdot)$ , we get (6.11).  $\blacksquare$

LEMMA 6.5. *There exist  $\varepsilon_2 > 0$  and  $C > 0$  such that for any  $\varepsilon < \varepsilon_2$ , any initial condition  $(t, x)$ , and any sufficiently small  $0 < h < \varepsilon$  and  $u \in U$ ,*

$$(6.13) \quad J_\varepsilon^*(t, x) \leq l_0(t, x, u)h + J_\varepsilon^*(t + h, x + f(t, x, u)h) + C\varepsilon hb(x).$$

Proof. Let  $u \in U$  be fixed and let

$$\begin{aligned} \dot{x}(r) &= f(r, x(r), u), & t < r \leq T + \varepsilon, \\ x(t) &= x. \end{aligned}$$

The dynamic programming principle [4, p. 9] implies

$$(6.14) \quad \begin{aligned} J_\varepsilon^*(t, x) &\leq \int_t^{t+h} l_0(r, x(r), u) dr + J_\varepsilon^*(t + h, x(t + h)) \\ &=: I_1 + I_2. \end{aligned}$$

Using (H3) and (6.3), we get

$$(6.15) \quad \begin{aligned} |I_1 - l_0(t, x, u)h| &\leq \int_t^{t+h} |l_0(r, x(r), u) - l_0(r, x, u)| dr \\ &\quad + \int_t^{t+h} |l_0(r, x, u) - l_0(t, x, u)| dr \\ &\leq \int_t^{t+h} c|x(r) - x|b(x) dr + \int_t^{t+h} cb(x)|r - t| dr \\ &\leq cb(x) \int_t^{t+h} K|r - t| dr + cb(x)\varepsilon h/2 \\ &\leq c(K + 1)\varepsilon hb(x)/2. \end{aligned}$$

By virtue of (H3), the inequality (6.15) is valid for  $h$  such that  $|x(r) - x| < \varepsilon_0$  for all  $t \leq r \leq t + h$ . This requirement is satisfied by choosing  $h \leq \varepsilon \leq \varepsilon_0/K$ . On the other hand, using Lemma 6.2, (H1) and (H3), we get

$$(6.16) \quad \begin{aligned} |I_2 - J_\varepsilon^*(t + h, x + f(t, x, u)h)| &\leq Cb(x)|x(t + h) - x - f(t, x, u)h| \\ &\leq Cb(x) \int_t^{t+h} |f(r, x(r), u) - f(t, x, u)| dr \\ &\leq Cb(x) \left[ \int_t^{t+h} |f(r, x(r), u) - f(r, x, u)| dr \right. \\ &\quad \left. + \int_t^{t+h} |f(r, x, u) - f(t, x, u)| dr \right] \end{aligned}$$

$$\begin{aligned} &\leq Cb(x) \left[ \int_t^{t+h} c|x(r) - x| dr + \varepsilon h \right] \\ &= Cb(x)(cKh^2/2 + \varepsilon h) \leq Cb(x)\varepsilon h(cK/2 + 1). \end{aligned}$$

In (6.16),  $h$  is chosen such that  $|f(r, x, u) - f(t, x, u)| < \varepsilon$  for  $r \in [t, t+h]$ . The inequalities (6.14)–(6.16) yield (6.13). ■

**Remark 6.6.** From Remark 6.3 it follows that subtracting  $J_\varepsilon^*(t, x)$  from both sides of (6.13), dividing by  $h$  and letting  $h \rightarrow 0$ , we get

$$(6.17) \quad 0 \leq l_0(t, x, u) + AJ_\varepsilon^*(t, x, u) + C\varepsilon b(x)$$

for almost all  $(t, x) \in \Sigma_\varepsilon$ , and all  $u \in U$ .

We shall now use  $J_\varepsilon^*$  to construct a smooth approximation of  $J^*$ . Let  $\varrho_\varepsilon(t, x)$  be an infinitely differentiable nonnegative function such that  $\varrho_\varepsilon(t, x) = 0$  if  $|t| + |x| > \varepsilon$  and

$$\int_{-\infty}^{\infty} \int_{\mathbb{R}^n} \varrho_\varepsilon(t, x) dx dt = 1.$$

For  $(t, x) \in \Sigma$  define the convolution

$$(6.18) \quad \begin{aligned} \tilde{J}_\varepsilon(t, x) &:= \varrho_\varepsilon * J_\varepsilon^*(t, x) = \int_{t-\varepsilon}^{t+\varepsilon} \int_{B_\varepsilon(x)} \varrho_\varepsilon(t-s, x-y) J_\varepsilon^*(s, y) dy ds \\ &= \int_{-\varepsilon}^{+\varepsilon} \int_{B_\varepsilon(0)} \varrho_\varepsilon(s, y) J_\varepsilon^*(t-s, x-y) dy ds, \end{aligned}$$

where  $B_\varepsilon(x)$  is the ball in  $\mathbb{R}^n$  with radius  $\varepsilon$  and center  $x$ .

**LEMMA 6.7.**  $\tilde{J}_\varepsilon$  belongs to  $C_b^1(\Sigma)$ .

**Proof.** Continuous differentiability of  $\tilde{J}_\varepsilon$  is obvious from its definition. On the other hand, applying Lemmas 6.1 and 6.2 to  $J_\varepsilon^*$ , we see that

$$(6.19) \quad \begin{aligned} \tilde{J}_\varepsilon(t, x) &\leq J_\varepsilon^*(t, x) + \sup_{|s-t|, |x-y| < \varepsilon} |J_\varepsilon^*(s, y) - J_\varepsilon^*(t, x)| \\ &\leq Cb(x) + 2C\varepsilon b(x) = (1 + 2\varepsilon)Cb(x). \end{aligned}$$

Let  $\varepsilon_1$  be as in Lemma 6.2. From (6.18) we see that for each  $\varepsilon < \varepsilon_1$  and each  $(t, x), (s, y)$  subject to  $|t-s|, |x-y| < \varepsilon$ ,

$$(6.20) \quad \begin{aligned} &|\tilde{J}_\varepsilon(t, x) - \tilde{J}_\varepsilon(s, y)| \\ &= \left| \int_{-\varepsilon}^{\varepsilon} \int_{B_\varepsilon(0)} \varrho_\varepsilon(r, z) [J_\varepsilon^*(t-r, x-z) - J_\varepsilon^*(s-r, y-z)] dz dr \right| \end{aligned}$$

$$\begin{aligned}
 &\leq \int_{-\varepsilon}^{\varepsilon} \int_{B_{\varepsilon}(0)} \varrho_{\varepsilon}(r, z) C(|s-t| + |x-y|) b(x) dz dr \\
 &= C(|s-t| + |x-y|) b(x).
 \end{aligned}$$

Inequality (6.20) shows that

$$(6.21) \quad |D_i \tilde{J}_{\varepsilon}| \leq Cb(x).$$

Combining (6.21) and (6.19), we get the statement of the lemma. ■

LEMMA 6.8.  $\|\tilde{J}_{\varepsilon} - J^*\|_b \rightarrow 0$  as  $\varepsilon \rightarrow 0$ .

PROOF. In view of Lemma 6.4, it is sufficient to show that

$$(6.22) \quad \|J_{\varepsilon}^* - \tilde{J}_{\varepsilon}\|_b \rightarrow 0 \quad \text{as } \varepsilon \rightarrow 0.$$

From (6.18),

$$\begin{aligned}
 (6.23) \quad &|\tilde{J}_{\varepsilon}(t, x) - J_{\varepsilon}^*(t, x)| \\
 &\leq \int_{-\varepsilon}^{\varepsilon} \int_{B_{\varepsilon}(0)} \varrho_{\varepsilon}(r, z) |J_{\varepsilon}^*(t-r, x-z) - J_{\varepsilon}^*(t, x)| dz dr \\
 &\leq \int_{-\varepsilon}^{\varepsilon} \int_{B_{\varepsilon}(0)} \varrho_{\varepsilon}(r, z) \sup_{|t-s|, |x-y| < \varepsilon} |J_{\varepsilon}^*(t-r, x-z) - J_{\varepsilon}^*(t, x)| dz dr \\
 &= \int_{-\varepsilon}^{\varepsilon} \int_{B_{\varepsilon}(0)} \varrho_{\varepsilon}(r, z) \sup_{|t-s|, |x-y| < \varepsilon} |J_{\varepsilon}^*(s, y) - J_{\varepsilon}^*(t, x)| dz dr \\
 &\leq \int_{-\varepsilon}^{\varepsilon} \int_{B_{\varepsilon}(0)} \varrho_{\varepsilon}(r, z) \left[ \sup_{|t-s|, |x-y| < \varepsilon} C(|t-s| + |x-y|) b(x) \right] dz dr \\
 &\leq 2C\varepsilon b(x),
 \end{aligned}$$

where the last inequality in (6.23) follows from Lemma 6.2. ■

To conclude this section, we shall use the previous lemmas to prove Theorem 5.2.

PROOF OF THEOREM 5.2. Let  $L_{\varepsilon}(x) := \tilde{J}_{\varepsilon}(x, T)$ . Then, from Lemma 6.8 and the equality  $J^*(x, T) = L_0(x)$ , we have

$$(6.24) \quad \|\tilde{J}_{\varepsilon} - J^*\|_b \rightarrow 0 \quad \text{and} \quad \|L_{\varepsilon} - L_0\|_b \rightarrow 0 \quad \text{as } \varepsilon \rightarrow 0,$$

which proves (5.1)–(5.2). Now, from (6.17) it follows that

$$(6.25) \quad 0 \leq l_0 * \varrho_{\varepsilon} + (AJ_{\varepsilon}^*) * \varrho_{\varepsilon} + C\varepsilon(b * \varrho_{\varepsilon}) \quad \text{on } S.$$

Thus, to complete the proof of the theorem it suffices to show that, as  $\varepsilon \rightarrow 0$ ,

- (i)  $\|(AJ_\varepsilon^*) * \varrho_\varepsilon - A\tilde{J}_\varepsilon\|_b \rightarrow 0$ ,
- (ii)  $\|l_0 * \varrho_\varepsilon - l_0\|_b \rightarrow 0$ , and
- (iii)  $\|b * \varrho_\varepsilon\|_b < \infty$ .

Fix  $\varepsilon < \varepsilon_2$  (where  $\varepsilon_2$  is the same as in Lemma 6.5) and  $(t, x, u) \in S$ . Then (i) follows from

$$\begin{aligned}
(6.26) \quad & \frac{1}{b(x)} |(AJ_\varepsilon^*) * \varrho_\varepsilon(t, x, u) - A\tilde{J}_\varepsilon(t, x, u)| \\
&= \frac{1}{b(x)} \left| \sum_{i=1}^n \int_{-\varepsilon}^{\varepsilon} \int_{B_\varepsilon(0)} f_i(t-r, x-z, u) D_i J_\varepsilon^*(t-r, x-z) \varrho_\varepsilon(r, z) dz dr \right. \\
&\quad \left. - \sum_{i=1}^n f_i(t, x, u) D_i \tilde{J}_\varepsilon(t, x) \right| \\
&= \frac{1}{b(x)} \sum_{i=1}^n \left| \int_{-\varepsilon}^{\varepsilon} \int_{B_\varepsilon(0)} [f_i(t-r, x-z, u) \right. \\
&\quad \left. - f_i(t, x, u)] D_i J_\varepsilon^*(t-r, x-z) \varrho_\varepsilon(r, z) dz dr \right| \\
&\leq \sum_{i=1}^n \delta(f_i) \|D_i J_\varepsilon^*\|_b,
\end{aligned}$$

where  $\delta(f_i)$  denotes the modulus of continuity of  $f_i$ .

We now prove (ii) using (H3):

$$\begin{aligned}
(6.27) \quad & \frac{1}{b(x)} |l_0 * \varrho_\varepsilon(t, x, u) - l_0(t, x, u)| \\
&\leq \frac{1}{b(x)} \int_{-\varepsilon}^{\varepsilon} \int_{B_\varepsilon(0)} |l_0(t-r, x-z, u) - l_0(t, x, u)| \varrho_\varepsilon(r, z) dz dr \\
&\leq \frac{1}{b(x)} \int_{-\varepsilon}^{\varepsilon} \int_{B_\varepsilon(0)} cb(x)[|r| + |z|] \varrho_\varepsilon(r, z) dz dr \leq 2c\varepsilon.
\end{aligned}$$

Finally, to prove (iii) we use (6.2):

$$(6.28) \quad \frac{1}{b(x)} \int_{B_\varepsilon(0)} b(x-z) \varrho_\varepsilon(z) dz \leq \frac{1}{b(x)} b(x) \int_{B_\varepsilon(0)} \varrho_\varepsilon(z) e^{c|z|} dz = \text{const.}$$

Combining (6.25)–(6.28), we get the statement of the theorem. ■

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Daniel Hernández-Hernández  
 Departamento de Matemáticas  
 UAM-I  
 Apartado postal 55-534  
 México D.F., Mexico

Onésimo Hernández-Lerma  
 Departamento de Matemáticas  
 CINVESTAV-IPN  
 Apartado postal 14-740  
 07000 México D.F., Mexico  
 E-mail: ohernand@math.cinvestav.mx

Michael Taksar  
 Department of Applied Mathematics  
 State University of New York at Stony Brook  
 Stony Brook, NY 11794, U.S.A.

*Received on 9.2.1995;  
 revised version on 29.8.1995*