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Title	Optimal Control for Absolutely Continuous Stochastic Processes and the Mass Transportation Problem
Author(s)	Mikami, Toshio
Citation	Electronic Communications in Probability, 7, 199-213
Issue Date	2002
Doc URL	http://hdl.handle.net/2115/5927
Туре	article (author version)
Note(URL)	http://www.math.washington.edu/~ejpecp/ECP/viewarticle.php?id=1644
File Information	ECP7.pdf



# Optimal control for absolutely continuous stochastic processes and the mass transportation problem

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November 14, 2002

submitted January 15, 2002 Final version accepted October 28, 2002 AMS Subject classification: 93E20

Key words: Absolutely continuous stochastic process, mass transportation problem, Salisbury's problem, Markov control, zero-noise limit.

#### Abstract

We study the optimal control problem for  $\mathbf{R}^{d}$ -valued absolutely continuous stochastic processes with given marginal distributions at every time. When d = 1, we show the existence and the uniqueness of a minimizer which is a function of a time and an initial point. When d > 1, we show that a minimizer exists and that minimizers satisfy the same ordinary differential equation.

# 1 Introduction

Monge-Kantorovich problem (MKP for short) plays a crucial role in many fields and has been studied by many authors (see [2, 3, 7, 10, 12, 20] and the references therein).

Let  $h : \mathbf{R}^d \mapsto [0, \infty)$  be convex, and  $Q_0$  and  $Q_1$  be Borel probability measures on  $\mathbf{R}^d$ , and put

$$\mu_h(Q_0, Q_1) := \inf E[\int_0^1 h\left(\frac{d\phi(t)}{dt}\right) dt],\tag{1}$$

where the infimum is taken over all absolutely continuous stochastic processes  $\{\phi(t)\}_{0 \le t \le 1}$  for which  $P\phi(t)^{-1} = Q_t(t = 0, 1)$ . (In this paper we use the same notation P for different probability measures, for the sake of simplicity, when it is not confusing.)

As a special case of MKPs, we introduce the following problem (see e.g. [2, 3] and also [18]).

Does there exist a minimizer  $\{\phi^o(t)\}_{0 \le t \le 1}$ , of (1.1), which is a function of t and  $\phi^o(0)$ ?

Suppose that there exist  $p \in L^1([0,1] \times \mathbf{R}^d : \mathbf{R}, dtdx)$  and  $b(t,x) \in L^1([0,1] \times \mathbf{R}^d : \mathbf{R}^d, p(t,x)dtdx)$  such that the following holds: for any  $f \in C_o^{\infty}(\mathbf{R}^d)$  and any  $t \in [0,1]$ ,

$$\int_{\mathbf{R}^{d}} f(x)(p(t,x) - p(0,x))dx = \int_{0}^{t} ds \int_{\mathbf{R}^{d}} \langle \nabla f(x), b(s,x) \rangle p(s,x)dx,$$
  

$$p(t,x) \ge 0 \quad dx - \text{a.e.}, \qquad \int_{\mathbf{R}^{d}} p(t,x)dx = 1.$$
(2)

Here  $\langle \cdot, \cdot \rangle$  denotes the inner product in  $\mathbf{R}^d$  and  $\nabla f(x) := (\partial f(x) / \partial x_i)_{i=1}^d$ . Put, for  $n \ge 1$ ,

$$\mathbf{e}_{n} := \inf\{E[\int_{0}^{1} h\left(\frac{dY(t)}{dt}\right) dt] : \{Y(t)\}_{0 \le t \le 1} \in A_{n}\},\tag{3}$$

where  $A_n$  is the set of all absolutely continuous stochastic processes  $\{Y(t)\}_{0 \le t \le 1}$ for which  $P(Y(t) \in dx) = p(t, x)dx$  for all  $t = 0, 1/n, \dots, 1$ .

Then the minimizer of  $\mathbf{e}_n$  can be constructed by those of

$$\mu_{\frac{h(n\cdot)}{n}}\left(p\left(\frac{k}{n},x\right)dx, p\left(\frac{k+1}{n},x\right)dx\right) \quad (k=0,\cdots,n-1)$$

(see (1.1) for notation). As  $n \to \infty$ ,  $\mathbf{e}_n$  formally converges to

$$\mathbf{e} := \inf\{E[\int_0^1 h\left(\frac{dY(t)}{dt}\right)dt] : \{Y(t)\}_{0 \le t \le 1} \in A\},\tag{4}$$

where A is the set of all absolutely continuous stochastic processes  $\{Y(t)\}_{0 \le t \le 1}$ for which  $P(Y(t) \in dx) = p(t, x)dx$  for all  $t \in [0, 1]$ .

In this sense, the minimizer of  $\mathbf{e}$  can be considered as the continuum limit of those of  $\mathbf{e}_n$  as  $n \to \infty$ .

In this paper, instead of h(u), we would like to consider more general function  $L(t, x; u) : [0, 1] \times \mathbf{R}^d \times \mathbf{R}^d \mapsto [0, \infty)$  which is convex in u, and study the minimizers of

$$\mathbf{e}^{0} := \inf\{E[\int_{0}^{1} L\left(t, Y(t); \frac{dY(t)}{dt}\right) dt] : \{Y(t)\}_{0 \le t \le 1} \in A\}.$$
(5)

**Remark 1** It is easy to see that the set  $A_n$  is not empty, but it is not trivial to show that the set A is not empty if b in (1.2) is not smooth. As a similar problem, that of the construction of a Markov diffusion process  $\{X(t)\}_{0 \le t \le 1}$ such that  $PX(t)^{-1}$  satisfies a given Fokker-Planck equation with nonsmooth coefficients is known and has been studied by many authors (see [4], [5], [15], [19] and the references therein).

We would also like to point out that (1.1) and (1.5) can be formally considered as the zero-noise limits of h-path processes and variational processes, respectively, when  $h = L = |u|^2$  (see [8] and [15], respectively).

More generally, we have the following.

Let  $(\Omega, \mathbf{B}, P)$  be a probability space, and  $\{\mathbf{B}_t\}_{t\geq 0}$  be a right continuous, increasing family of sub  $\sigma$ -fields of  $\mathbf{B}$ , and  $X_o$  be a  $\mathbf{R}^d$ -valued,  $\mathbf{B}_0$ -adapted random variable such that  $PX_o^{-1}(dx) = p(0, x)dx$ , and  $\{W(t)\}_{t\geq 0}$  denote a d-dimensional  $(\mathbf{B}_t)$ -Wiener process (see e.g. [11] or [13]).

For  $\varepsilon > 0$  and a  $\mathbb{R}^d$ -valued  $(\mathbb{B}_t)$ -progressively measurable  $\{u(t)\}_{0 \le t \le 1}$ , put

$$X^{\varepsilon,u}(t) := X_o + \int_0^t u(s)ds + \varepsilon W(t) \quad (t \in [0,1]).$$
(6)

Put also

$$\mathbf{e}^{\varepsilon} := \inf\{E[\int_0^1 L(t, X^{\varepsilon, u}(t); u(t))dt] : \{u(t)\}_{0 \le t \le 1} \in A^{\varepsilon}\} \quad (\varepsilon > 0), \qquad (7)$$

where  $A^{\varepsilon} := \{\{u(t)\}_{0 \le t \le 1} : P(X^{\varepsilon, u}(t) \in dx) = p(t, x) dx (0 \le t \le 1)\};$  and

$$\tilde{\mathbf{e}}^{\varepsilon} := \inf\{\int_0^1 \int_{\mathbf{R}^d} L(t, y; B(t, y)) p(t, y) dt dy : B \in \tilde{A}^{\varepsilon}\} \quad (\varepsilon \ge 0), \qquad (8)$$

where  $\tilde{A}^{\varepsilon}$  is the set of all  $B(t, x) : [0, 1] \times \mathbf{R}^d \mapsto \mathbf{R}^d$  for which the following holds: for any  $f \in C_o^{\infty}(\mathbf{R}^d)$  and any  $t \in [0, 1]$ ,

$$\int_{\mathbf{R}^d} f(x)(p(t,x) - p(0,x))dx$$
  
=  $\int_0^t ds \int_{\mathbf{R}^d} \left(\frac{\varepsilon^2 \Delta f(x)}{2} + \langle \nabla f(x), B(s,x) \rangle \right) p(s,x)dx.$ 

Then we expect that the following holds:

$$\mathbf{e}^{\varepsilon} = \tilde{\mathbf{e}}^{\varepsilon} \to \mathbf{e}^{0} = \tilde{\mathbf{e}}^{0} \quad (\text{as } \varepsilon \to 0).$$
<sup>(9)</sup>

In this paper we show that the set A is not empty and (1.9) holds, and that a minimizer of  $\mathbf{e}^0$  exists when the cost function L(t, x; u) grows at least of order of  $|u|^2$  as  $u \to \infty$  (see Theorem 1 in section 2).

We also show that the minimizers satisfy the same ordinary differential equation (ODE for short) when L is strictly convex in u (see Theorem 2 in section 2). (In this paper we say that a function  $\{\psi(t)\}_{0 \le t \le 1}$  satisfies an ODE if and only if it is absolutely continuous and  $d\psi(t)/dt$  is a function of t and  $\psi(t)$ , dt-a.e..)

When d = 1, we show the uniqueness of the minimizer of  $e^0$  (see Corollary 1 in section 2).

Since a stochastic process which satisfies an ODE is not always nonrandom, we would also like to know if the minimizer is a function of a time and an initial point. In fact, the following is known as Salisbury's problem (SP for short).

Is a continuous strong Markov process which is of bounded variation in time a function of an initial point and a time?

If  $x(t)_{0 \le t \le 1}$  is a **R**-valued strong Markov process, and if there exists a Borel measurable function f, on **R**, such that  $x(t) = x(0) + \int_0^t f(x(s)) ds$  $(0 \le t \le 1)$ , then SP has been solved positively by Çinlar and Jacod (see [6]). When d > 1, a counter example is known (see [21]). When d = 1, we give a positive answer to SP for time-inhomogeneous stochastic processes (see Proposition 2 in section 4). This is a slight generalization of [6] where they made use of the result on time changes of Markov processes, in that the stochastic processes under consideration are time-inhomogeneous and need not be Markovian. In particular, we show, when d = 1, that  $\{Y(t)\}_{0 \le t \le 1}, \in A$ , which satisfies an ODE is unique and nonrandom. It will be used to show that the unique minimizer of  $\mathbf{e}^0$  is a function of an initial point and of a time when d = 1 (see Corollary 1 and Theorem 3 in section 2).

**Remark 2** When d > 1,  $\{Y(t)\}_{0 \le t \le 1}$ ,  $\in A$ , which satisfies an ODE is not unique (see Proposition 1 in section 2).

When  $L(t, x; u) = |u|^2$  and p(t, x) satisfies the Fokker-Planck equation with sufficiently smooth coefficients, the optimization problem (1.5) was considered in [16] where the minimizer exists uniquely and is a function of a time and an initial point, and where we used a different approach which depends on the form of  $L(t, x; u) = |u|^2$ .

Our main tool in the proof is the weak convergence method, the result on the construction of a Markov diffusion process from a family of marginal distributions, and the theory of Copulas.

In section 2 we state our main result. We first consider the case where a cost function L(t, x; u) grows at least of order of  $|u|^2$  as  $u \to \infty$  and  $d \ge 1$ . Next we restrict our attention to the case where L is a function of u and d = 1. The proof is given in section 3. We discuss SP in section 4.

### 2 Main result

In this section we give our main result.

We state assumptions before we state the result when  $d \ge 1$ .

(H.0).  $\tilde{\mathbf{e}}^0$  is finite (see (1.8) for notation).

(H.1).  $L(t, x; u) : [0, 1] \times \mathbf{R}^d \times \mathbf{R}^d \mapsto [0, \infty)$  is convex in u, and as  $h, \delta \downarrow 0$ ,

$$R(h,\delta) := \sup \left\{ \frac{L(t,x;u) - L(s,y;u)}{1 + L(s,y;u)} : |t-s| < h, |x-y| < \delta, u \in \mathbf{R}^d \right\} \downarrow 0.$$

(H.2). There exists  $q \ge 2$  such that the following holds:

$$0 < \liminf_{|u| \to \infty} \frac{\inf\{L(t, x; u) : (t, x) \in [0, 1] \times \mathbf{R}^d\}}{|u|^q},$$
(10)

$$\sup\left\{\frac{\sup_{z\in\partial_u L(t,x;u)}|z|}{(1+|u|)^{q-1}}:(t,x,u)\in[0,1]\times\mathbf{R}^d\times\mathbf{R}^d\right\}\equiv C_{\nabla L}<\infty,\qquad(11)$$

where  $\partial_u L(t, x; u) := \{z \in \mathbf{R}^d : L(t, x; v) - L(t, x; u) \ge \langle z, v - u \rangle \text{ for all } v \in \mathbf{R}^d\}$   $(t \in [0, 1], x, u \in \mathbf{R}^d).$ (H.3).  $p(t, \cdot)$  is absolutely continuous dt-a.e., and for q in (H.2),

$$\int_0^1 \int_{\mathbf{R}^d} \left| \frac{\nabla_x p(t,x)}{p(t,x)} \right|^q p(t,x) dt dx < \infty.$$
(12)

**Remark 3** If (H.0) does not hold, then  $e^0$  in (1.5) is infinite. (H.1) implies the continuity of  $L(\cdot, \cdot; u)$  for each  $u \in \mathbb{R}^d$ . (H.2) holds if  $L(t, x; u) = |u|^q$ . We need (H.3) to make use of the result on the construction of a Markov diffusion process of which the marginal distribution at time t is p(t, x)dx $(0 \le t \le 1)$ . (2.3) holds if b(t, x) in (1.2) is twice continuously differentiable with bounded derivatives up to the second order, and if p(0, x) is absolutely continuous, and if the following holds:

$$\int_{\mathbf{R}^d} \left| \frac{\nabla_x p(0,x)}{p(0,x)} \right|^q p(0,x) dx < \infty.$$
(13)

The following theorem implies the existence of a minimizer of  $e^0$  (see (1.5)-(1.8) for notations).

**Theorem 1** Suppose that (H.0)-(H.3) hold. Then the sets  $A^{\varepsilon}$  ( $\varepsilon > 0$ ) and A are not empty, and the following holds:

$$\tilde{\mathbf{e}}^{\varepsilon} = \mathbf{e}^{\varepsilon} \to \mathbf{e}^0 = \tilde{\mathbf{e}}^0 \quad (as \ \varepsilon \to 0).$$
 (14)

In particular, for any  $\{u^{\varepsilon}(t)\}_{0 \le t \le 1}$ ,  $\in A^{\varepsilon}(\varepsilon > 0)$ , for which

$$\lim_{\varepsilon \to 0} E[\int_0^1 L(t, X^{\varepsilon, u^\varepsilon}(t); u^\varepsilon(t)) dt] = \mathbf{e}^0,$$
(15)

 $\{\{X^{\varepsilon,u^{\varepsilon}}(t)\}_{0\leq t\leq 1}\}_{\varepsilon>0}$  is tight in  $C([0,1]:\mathbf{R}^d)$ , and any weak limit point of  $\{X^{\varepsilon,u^{\varepsilon}}(t)\}_{0\leq t\leq 1}$  as  $\varepsilon \to 0$  is a minimizer of  $\mathbf{e}^0$ .

The following theorem implies the uniqueness of the minimizer of  $\tilde{\mathbf{e}}^0$  and that of the ODE which is satisfied by the minimizers of  $\mathbf{e}^0$ .

**Theorem 2** Suppose that (H.0)-(H.3) hold. Then for any minimizer  $\{X(t)\}_{0 \le t \le 1}$ of  $\mathbf{e}^0$ ,  $b^X(t,x) := E[dX(t)/dt|(t,X(t) = x)]$  is a minimizer of  $\tilde{\mathbf{e}}^0$ . Suppose in addition that L is strictly convex in u. Then  $\tilde{\mathbf{e}}^0$  has the unique minimizer  $b^o(t,x)$  and the following holds: for any minimizer  $\{X(t)\}_{0 \le t \le 1}$  of  $\mathbf{e}^0$ ,

$$X(t) = X(0) + \int_0^t b^o(s, X(s)) ds \quad \text{for all } t \in [0, 1], \quad a.s..$$
(16)

**Remark 4** By Theorems 1 and 2, if (H.0) with  $L = |u|^2$  and (H.3) with q = 2 hold, then there exists a stochastic process  $\{X(t)\}_{0 \le t \le 1}, \in A$ , which satisfies an ODE.

Since  $b \in \tilde{A}^0$  is not always the gradient, in x, of a function, the following implies that the set  $\tilde{A}^0$  does not always consist of only one point.

**Proposition 1** Suppose that  $L = |u|^2$ , and that (H.0) and (H.3) with q = 2 hold, and that for any M > 0,

$$ess.inf\{p(t,x) : t \in [0,1], |x| \le M\} > 0.$$
(17)

Then the unique minimizer of  $\tilde{\mathbf{e}}^0$  can be written as  $\nabla_x V(t, x)$ , where  $V(t, \cdot) \in H^1_{loc}(\mathbf{R}^d : \mathbf{R}) dt$ -a.e..

We next consider the one-dimensional case. Put

$$F_t(x) := \int_{(-\infty,x]} p(t,y) dy \quad (t \in [0,1], x \in \mathbf{R}),$$
$$F_t^{-1}(u) := \sup\{y \in \mathbf{R} : F_t(y) < u\} \quad (t \in [0,1], 0 < u < 1).$$

(H.3)'. d = 1, and  $F_t(x)$  is differentiable and has the locally bounded first partial derivatives on  $[0, 1] \times \mathbf{R}$ .

By Proposition 2 in section 4, we obtain the following.

**Corollary 1** Suppose that (H.0)-(H.3) and (H.3)' hold, and that L is strictly convex in u. Then the minimizer  $\{X(t)\}_{0 \le t \le 1}$  of  $\mathbf{e}^0$  is unique. Moreover,  $\lim_{s \in \mathbf{Q} \cap [0,1], s \to t} F_s^{-1}(F_0(X(0)))$  exists and is equal to X(t) for all  $t \in [0,1]$  a.s..

The theory of copulas allows us to treat a different set of assumptions by a different method (see (1.3)-(1.4) for notations).

(H.0)'.  $\{\mathbf{e}_n\}_{n\geq 1}$  is bounded.

(H.1)'.  $h : \mathbf{R} \mapsto [0, \infty)$  is even and convex.

(H.2)'. There exists r > 1 such that the following holds:

$$0 < \liminf_{|u| \to \infty} \frac{h(u)}{|u|^r}.$$
(18)

(H.3)". d = 1, and p(t, x) is positive on  $[0, 1] \times \mathbf{R}$ .

**Theorem 3** Suppose that (H.0)'-(H.2)' and (H.3)'' hold. Then  $\{F_t^{-1}(F_0(x))\}_{0 \le t \le 1}$ on  $(\mathbf{R}, \mathbf{B}(\mathbf{R}), p(0, x)dx)$  belongs to the set A and is a minimizer of  $\mathbf{e}$ . Suppose in addition that (H.3)' holds. Then  $\{F_t^{-1}(F_0(x))\}_{0 \le t \le 1}$  is the unique minimizer, of  $\mathbf{e}$ , that satisfies an ODE.

**Remark 5** If  $\{\mathbf{e}_n\}_{n\geq 1}$  is unbounded, then so is  $\mathbf{e}$ . By (H.1)',  $\{\overline{X}(t) := F_t^{-1}(F_0(x))\}_{0\leq t\leq 1}$  satisfies the following (see e.g. [20, Chap. 3.1]): for any t and  $s \in [0, 1]$ ,

$$\mu_h(p(s,x)dx, p(t,x)dx) = E_0[h(\overline{X}(t) - \overline{X}(s))]$$
(19)

(see (1.1) for notation), where we put  $P_0(dx) := p(0, x)dx$ . Indeed,

$$\overline{X}(t) = F_t^{-1}(F_s(\overline{X}(s))) \tag{20}$$

since for a distribution F on  $\mathbf{R}$ ,

$$F(F^{-1}(u)) = u \quad (0 < u < 1)$$
(21)

 $(see \ e. \ g. \ [17]).$ 

# 3 Proof of the result

In this section we prove the result given in section 2.

Before we give the proof of Theorem 1, we state and prove three technical lemmas.

**Lemma 1** Suppose that (H.2) holds. Then for any  $\varepsilon > 0$ ,  $\tilde{\mathbf{e}}^{\varepsilon} = \mathbf{e}^{\varepsilon}$ .

(Proof). For any  $B^{\varepsilon} \in \tilde{A}^{\varepsilon}$  for which  $\int_{0}^{1} \int_{\mathbf{R}^{d}} L(t, x; B^{\varepsilon}(t, x))p(t, x)dtdx$  is finite, there exists a Markov process  $\{Z^{\varepsilon}(t)\}_{0 \le t \le 1}$  such that the following holds:

$$Z^{\varepsilon}(t) = X_o + \int_0^t B^{\varepsilon}(s, Z^{\varepsilon}(s)) ds + \varepsilon W(t), \qquad (22)$$

$$P(Z^{\varepsilon}(t) \in dx) = p(t, x)dx \quad (0 \le t \le 1),$$
(23)

since  $\int_0^1 \int_{\mathbf{R}^d} |B^{\varepsilon}(t,x)|^2 p(t,x) dt dx$  is finite by (H.2) (see [4] and [5]). This implies that  $\{B^{\varepsilon}(t,Z^{\varepsilon}(t))\}_{0 \le t \le 1} \in A^{\varepsilon}$ , and that the following holds:

$$\int_0^1 \int_{\mathbf{R}^d} L(t,x; B^{\varepsilon}(t,x)) p(t,x) dt dx = \int_0^1 E[L(t, Z^{\varepsilon}(t); B^{\varepsilon}(t, Z^{\varepsilon}(t)))] dt, \quad (24)$$

from which  $\mathbf{e}^{\varepsilon} \leq \tilde{\mathbf{e}}^{\varepsilon}$ .

We next show that  $\mathbf{e}^{\varepsilon} \geq \tilde{\mathbf{e}}^{\varepsilon}$ .

For any  $\{u^{\varepsilon}(t)\}_{0 \leq t \leq 1} \in A^{\varepsilon}, b^{\varepsilon, u^{\varepsilon}}(t, x) := E[u^{\varepsilon}(t)|(t, X^{\varepsilon, u^{\varepsilon}}(t) = x)] \in \tilde{A}^{\varepsilon}.$ Indeed, for any  $f \in C_o^{\infty}(\mathbf{R}^d)$  and any  $t \in [0, 1]$ , by the Itô formula,

$$\int_{\mathbf{R}^{d}} f(x)(p(t,x) - p(0,x))dx = E[f(X^{\varepsilon,u^{\varepsilon}}(t)) - f(X^{\varepsilon,u^{\varepsilon}}(0))] \quad (25)$$

$$= \int_{0}^{t} E\left[\frac{\varepsilon^{2}}{2} \Delta f(X^{\varepsilon,u^{\varepsilon}}(s)) + \langle \nabla f(X^{\varepsilon,u^{\varepsilon}}(s)), u^{\varepsilon}(s) \rangle\right] ds$$

$$= \int_{0}^{t} E\left[\frac{\varepsilon^{2}}{2} \Delta f(X^{\varepsilon,u^{\varepsilon}}(s)) + \langle \nabla f(X^{\varepsilon,u^{\varepsilon}}(s)), b^{\varepsilon,u^{\varepsilon}}(s, X^{\varepsilon,u^{\varepsilon}}(s)) \rangle\right] ds$$

$$= \int_{0}^{t} ds \int_{\mathbf{R}^{d}} \left(\frac{\varepsilon^{2}}{2} \Delta f(x) + \langle \nabla f(x), b^{\varepsilon,u^{\varepsilon}}(s, x) \rangle\right) p(s, x) dx.$$

The following completes the proof: by Jensen's inequality,

$$\int_{0}^{1} E[L(t, X^{\varepsilon, u^{\varepsilon}}(t); u^{\varepsilon}(t))]dt$$

$$\geq \int_{0}^{1} E[L(t, X^{\varepsilon, u^{\varepsilon}}(t); b^{\varepsilon, u^{\varepsilon}}(t, X^{\varepsilon, u^{\varepsilon}}(t)))]dt$$

$$= \int_{0}^{1} \int_{\mathbf{R}^{d}} L(t, x; b^{\varepsilon, u^{\varepsilon}}(t, x))p(t, x)dtdx.$$
(26)

Q. E. D.

The following lemma can be shown by the standard argument and the proof is omitted (see [13, p. 17, Theorem 4.2 and p. 33, Theorem 6.10]).

**Lemma 2** For any  $\{u^{\varepsilon}(t)\}_{0 \le t \le 1} \in A^{\varepsilon} \ (\varepsilon > 0)$  for which  $\{E[\int_0^1 |u^{\varepsilon}(t)|^2 dt]\}_{\varepsilon > 0}$  is bounded,  $\{\{X^{\varepsilon, u^{\varepsilon}}(t)\}_{0 \le t \le 1}\}_{\varepsilon > 0}$  is tight in  $C([0, 1] : \mathbf{R}^d)$ .

**Lemma 3** For any  $\{u^{\varepsilon_n}(t)\}_{0\leq t\leq 1} \in A^{\varepsilon_n} \ (n\geq 1) \ (\varepsilon_n \to 0 \ as \ n\to \infty) \ such that \ \{E[\int_0^1 |u^{\varepsilon_n}(t)|^2 dt]\}_{n\geq 1} \ is \ bounded \ and \ that \ \{X_n(t) := X^{\varepsilon_n, u^{\varepsilon_n}}(t)\}_{0\leq t\leq 1} \ weakly \ converges \ as \ n\to\infty, \ the \ weak \ limit \ \{X(t)\}_{0\leq t\leq 1} \ in \ C([0,1]: \mathbf{R}^d) \ is \ absolutely \ continuous.$ 

(Proof). We only have to show the following: for any  $\delta > 0$  and any  $m \ge 2$ ,  $n \ge 1$  and any  $s_{i,j}, t_{i,j} \in \mathbf{Q}$  for which  $0 \le s_{i,j} \le t_{i,j} \le s_{i,j+1} \le t_{i,j+1} \le 1$  $(1 \le i \le n, 1 \le j \le m-1)$  and for which  $\sum_{j=1}^{m} |t_{i,j} - s_{i,j}| \le \delta$   $(1 \le i \le n)$ ,

$$E[\max_{1 \le i \le n} (\sum_{j=1}^{m} |X(t_{i,j}) - X(s_{i,j})|)^2] \le \delta \liminf_{k \to \infty} E[\int_0^1 |u^{\varepsilon_k}(t)|^2 dt].$$
(27)

Indeed, by the monotone convergence theorem and by the continuity of  $\{X(t)\}_{0 \le t \le 1}$ , (3.6) implies that, for all  $m \ge 2$ ,

$$E[\sup\{(\sum_{j=1}^{m} |X(t_j) - X(s_j)|)^2 : \sum_{j=1}^{m} |t_j - s_j| \le \delta$$

$$, 0 \le s_j \le t_j \le s_{j+1} \le t_{j+1} \le 1(1 \le j \le m - 1)\}]$$

$$\le \delta \liminf_{k \to \infty} E[\int_0^1 |u^{\varepsilon_k}(t)|^2 dt].$$
(28)

The left hand side of (3.7) converges, as  $m \to \infty$ , to

$$E[\sup\{(\sum_{j=1}^{m} |X(t_j) - X(s_j)|)^2 : \sum_{j=1}^{m} |t_j - s_j| \le \delta, m \ge 2$$

$$, 0 \le s_j \le t_j \le s_{j+1} \le t_{j+1} \le 1 (1 \le j \le m - 1)\}]$$
(29)

since the integrand on the left hand side of (3.7) is nondecreasing in m.

Hence by Fatou's lemma,

$$\lim_{\delta \to 0} (\sup\{(\sum_{j=1}^{m} |X(t_j) - X(s_j)|)^2 : \sum_{j=1}^{m} |t_j - s_j| \le \delta, m \ge 2$$
(30)  
,  $0 \le s_j \le t_j \le s_{j+1} \le t_{j+1} \le 1 (1 \le j \le m - 1)\}) = 0$  a.s.,

since the integrand in (3.8) is nondecreasing in  $\delta > 0$  and henceforth is convergent as  $\delta \to 0$ .

To complete the proof, we prove (3.6). By Jensen's inequality, for  $i = 1, \dots, n$  for which  $\sum_{j=1}^{m} |t_{i,j} - s_{i,j}| > 0$ ,

$$\left(\sum_{j=1}^{m} |X(t_{i,j}) - X(s_{i,j})|\right)^{2}$$

$$\leq \left(\sum_{j=1}^{m} |t_{i,j} - s_{i,j}|\right) \sum_{1 \le j \le m, s_{i,j} < t_{i,j}} \left|\frac{X(t_{i,j}) - X(s_{i,j})}{t_{i,j} - s_{i,j}}\right|^{2} (t_{i,j} - s_{i,j}).$$
(31)

Put  $A_{mn} := \{t_{i,j}, s_{i,j}; 1 \leq i \leq n, 1 \leq j \leq m\}$  and  $\{t_k\}_{1 \leq k \leq \#(A_{mn})} := A_{mn}$ so that  $t_k < t_{k+1}$  for  $k = 1, \dots, \#(A_{mn}) - 1$ , where  $\#(A_{mn})$  denotes the cardinal number of the set  $A_{mn}$ . Then, by Jensen's inequality,

$$\sum_{1 \le j \le m, s_{i,j} < t_{i,j}} \left| \frac{X(t_{i,j}) - X(s_{i,j})}{t_{i,j} - s_{i,j}} \right|^2 (t_{i,j} - s_{i,j})$$

$$\le \sum_{1 \le k \le \#(A_{mn}) - 1} \left| \frac{X(t_k) - X(t_{k+1})}{t_{k+1} - t_k} \right|^2 (t_{k+1} - t_k).$$
(32)

The following completes the proof: for any  $k = 1, \dots, \#(A_{mn}) - 1$ ,

$$E\left[\left|\frac{X(t_{k}) - X(t_{k+1})}{t_{k+1} - t_{k}}\right|^{2}\right] \leq \liminf_{\ell \to \infty} E\left[\left|\frac{X_{\ell}(t_{k}) - X_{\ell}(t_{k+1})}{t_{k+1} - t_{k}}\right|^{2}\right]$$
(33)  
$$\leq \frac{1}{t_{k+1} - t_{k}}\liminf_{\ell \to \infty} E\left[\int_{t_{k}}^{t_{k+1}} |u^{\varepsilon_{\ell}}(t)|^{2} dt\right].$$

Q. E. D.

We prove Theorem 1 by Lemmas 1-3.

(Proof of Theorem 1). The proof of (2.5) is divided into the following:

$$\limsup_{\varepsilon \to 0} \tilde{\mathbf{e}}^{\varepsilon} \leq \tilde{\mathbf{e}}^{0}, \tag{34}$$

$$\liminf_{\varepsilon \to 0} \mathbf{e}^{\varepsilon} \geq \mathbf{e}^{0}, \tag{35}$$

since  $\mathbf{e}^{\varepsilon} = \tilde{\mathbf{e}}^{\varepsilon}$  by Lemma 1, and since  $\mathbf{e}^0 \ge \tilde{\mathbf{e}}^0$  in the same way as in the proof of the inequality  $\mathbf{e}^{\varepsilon} \geq \tilde{\mathbf{e}}^{\varepsilon}$  (see (3.4)-(3.5)).

We first prove (3.13). For  $B \in \tilde{A^0}$  for which  $\int_0^1 \int_{\mathbf{R}^d} L(t,x;B(t,x))p(t,x)dtdx$ is finite and  $\varepsilon > 0$ ,  $B(t, x) + \varepsilon^2 \nabla p(t, x) / (2p(t, x)) \in \tilde{A}^{\varepsilon}$ . Indeed, for any  $f \in C_o^{\infty}(\mathbf{R}^d)$  and any  $t \in [0, 1]$ ,

$$\begin{split} &\int_{\mathbf{R}^d} f(x)(p(t,x) - p(0,x))dx \\ &= \int_0^t ds \int_{\mathbf{R}^d} < \nabla f(x), B(s,x) > p(s,x)dx \\ &= \int_0^t ds \int_{\mathbf{R}^d} \left(\frac{\varepsilon^2}{2} \Delta f(x) + \left\langle \nabla f(x), B(s,x) + \frac{\varepsilon^2 \nabla p(s,x)}{2p(s,x)} \right\rangle \right) p(s,x)dx. \end{split}$$

For any  $t \in [0, 1]$ ,  $x, u, v \in \mathbf{R}^d$ , and  $z \in \partial_u L(t, x; u + v)$ , by (2.2),

$$L(t, x; u + v) \le L(t, x; u) - \langle z, v \rangle$$

$$\le L(t, x; u) + C_{\nabla L} (1 + |u + v|)^{q-1} |v|.$$
(36)

Putting u = B(t, x) and  $v = \varepsilon^2 \nabla p(t, x)/(2p(t, x))$  in (3.15), we have

$$\tilde{\mathbf{e}}^{\varepsilon} \leq \int_{0}^{1} \int_{\mathbf{R}^{d}} L\left(t, x; B(t, x) + \frac{\varepsilon^{2} \nabla p(t, x)}{2p(t, x)}\right) p(t, x) dt dx \tag{37}$$

$$\leq \int_{0}^{1} \int_{\mathbf{R}^{d}} C_{\nabla L} \left(1 + \left|B(t, x) + \frac{\varepsilon^{2} \nabla p(t, x)}{2p(t, x)}\right|\right)^{q-1} \left|\frac{\varepsilon^{2} \nabla p(t, x)}{2p(t, x)}\right| p(t, x) dt dx + \int_{0}^{1} \int_{\mathbf{R}^{d}} L(t, x; B(t, x)) p(t, x) dt dx$$

$$\rightarrow \int_{0}^{1} \int_{\mathbf{R}^{d}} L(t, x; B(t, x)) p(t, x) dt dx \quad (\text{as } \varepsilon \to 0)$$

by (2.1) and (H.3), where we used the following in the last line of (3.16):

$$\frac{q-1}{q} + \frac{1}{q} = 1.$$

Next we prove (3.14). By Lemmas 2-3, we only have to show the following: for any  $\{u^{\varepsilon_n}(t)\}_{0 \le t \le 1} \in A^{\varepsilon_n} \ (n \ge 1) \ (\varepsilon_n \to 0 \text{ as } n \to \infty)$  for which  $\{X_n(t) := X^{\varepsilon_n, u^{\varepsilon_n}}(t)\}_{0 \le t \le 1}$  weakly converges, as  $n \to \infty$ , to a stochastic process  $\{X(t)\}_{0 \le t \le 1}$ , and for which  $\{E[\int_0^1 L(t, X_n(t); u^{\varepsilon_n}(t))dt]\}_{n \ge 1}$  is bounded,

$$\liminf_{n \to \infty} E\left[\int_0^1 L(t, X_n(t); u^{\varepsilon_n}(t))dt\right] \ge E\left[\int_0^1 L\left(t, X(t); \frac{dX(t)}{dt}\right)dt\right].$$
(38)

We prove (3.17). For  $\alpha \in (0, 1)$  and  $\delta > 0$ ,

$$E\left[\int_{0}^{1} L(t, X_{n}(t); u^{\varepsilon_{n}}(t))dt\right]$$

$$\geq \frac{1}{1 + R(\alpha, \delta)} E\left[\int_{0}^{1-\alpha} dsL\left(s, X_{n}(s); \frac{1}{\alpha} \int_{s}^{s+\alpha} u^{\varepsilon_{n}}(t)dt\right) \\; \sup_{0 \leq t, s \leq 1, |t-s| < \alpha} |X_{n}(t) - X_{n}(s)| < \delta\right] - R(\alpha, \delta).$$
(39)

Indeed, if  $\sup_{0 \le t,s \le 1,|t-s| < \alpha} |X_n(t) - X_n(s)| < \delta$ , then for  $s \in [0, 1 - \alpha]$ , by Jensen's inequality and (H.1),

$$L\left(s, X_{n}(s); \frac{1}{\alpha} \int_{s}^{s+\alpha} u^{\varepsilon_{n}}(t) dt\right) \leq \frac{1}{\alpha} \int_{s}^{s+\alpha} L(s, X_{n}(s); u^{\varepsilon_{n}}(t)) dt \quad (40)$$
  
$$\leq R(\alpha, \delta) + \frac{1 + R(\alpha, \delta)}{\alpha} \int_{s}^{s+\alpha} L(t, X_{n}(t); u^{\varepsilon_{n}}(t)) dt.$$

Hence putting  $u = \int_s^{s+\alpha} u^{\varepsilon_n}(t) dt / \alpha$  and  $v = (X_n(s+\alpha) - X_n(s) - \int_s^{s+\alpha} u^{\varepsilon_n}(t) dt) / \alpha$  in (3.15), we have, from (3.18),

$$E\left[\int_{0}^{1} L(t, X_{n}(t); u^{\varepsilon_{n}}(t))dt\right]$$

$$\geq \frac{1}{1 + R(\alpha, \delta)} E\left[\int_{0}^{1-\alpha} L\left(s, X_{n}(s); \frac{X_{n}(s+\alpha) - X_{n}(s)}{\alpha}\right)ds$$

$$; \sup_{0 \le t, s \le 1, |t-s| < \alpha} |X_{n}(t) - X_{n}(s)| < \delta\right]$$

$$- E\left[\int_{0}^{1-\alpha} C_{\nabla L}\left(1 + \left|\frac{X_{n}(s+\alpha) - X_{n}(s)}{\alpha}\right|\right)^{q-1} \times \left|\frac{\varepsilon_{n}}{\alpha}(W(s+\alpha) - W(s))\right|ds\right] - R(\alpha, \delta).$$

$$(41)$$

Letting  $n \to \infty$  and then  $\alpha \to 0$  and  $\delta \to 0$  in (3.20), we obtain (3.17).

Indeed, by Skorohod's theorem (see e.g. [13]), taking a new probability space, we can assume that  $\{X_n(t)\}_{0 \le t \le 1}$  converges, as  $n \to \infty$ , to  $\{X(t)\}_{0 \le t \le 1}$  in sup norm, a.s., and that the following holds: for any  $\beta \in (0, \delta/3)$ , by (H.1),

$$\begin{aligned} (1+R(0,\beta))E[\int_{0}^{1-\alpha}L\Big(s,X_{n}(s);\frac{X_{n}(s+\alpha)-X_{n}(s)}{\alpha}\Big)ds\\ &;\sup_{0\leq t,s\leq 1,|t-s|<\alpha}|X_{n}(t)-X_{n}(s)|<\delta]\\ \geq & E[\int_{0}^{1-\alpha}L\Big(s,X(s);\frac{X_{n}(s+\alpha)-X_{n}(s)}{\alpha}\Big)ds;\sup_{0\leq t\leq 1}|X(t)-X_{n}(t)|<\beta\\ &,\sup_{0\leq t,s\leq 1,|t-s|<\alpha}|X(t)-X(s)|<\beta]-R(0,\beta). \end{aligned}$$

The limit of the right-hand side of this inequality as  $n \to \infty$ , and  $\alpha \to 0$ and then  $\beta \to 0$  is dominated by  $E[\int_0^1 L(s, X(s); dX(s)/ds)ds]$  from below by Fatou's lemma. The second mean value on the right hand side of (3.20) can be shown to converge to zero as  $n \to \infty$  in the same way as in (3.16) by (2.1).

(H.0) and (2.5) implies that the set A and  $A^{\varepsilon}$  ( $\varepsilon > 0$ ) are not empty. (2.5) and (3.17) completes the proof.

(Proof of Theorem 2).  $b^X(t, x)$  is a minimizer of  $\tilde{\mathbf{e}}^0$  by (2.5) in the same way as in (3.4)-(3.5).

We prove the uniqueness of the minimizer of  $\tilde{\mathbf{e}}^0$ . Suppose that  $b^o(t, x)$  is also a minimizer of  $\tilde{\mathbf{e}}^0$ . Then for any  $\lambda \in (0, 1)$ ,  $\lambda b^X + (1 - \lambda)b^o \in \tilde{A}^0$ , and

$$\tilde{\mathbf{e}}^{0} \leq \int_{0}^{1} \int_{\mathbf{R}^{d}} L(t, y; \lambda b^{X}(t, y) + (1 - \lambda)b^{o}(t, y))p(t, y)dtdy \qquad (42)$$

$$\leq \lambda \int_{0}^{1} \int_{\mathbf{R}^{d}} L(t, y; b^{X}(t, y))p(t, y)dtdy$$

$$+ (1 - \lambda) \int_{0}^{1} \int_{\mathbf{R}^{d}} L(t, y; b^{o}(t, y))p(t, y)dtdy = \tilde{\mathbf{e}}^{0}.$$

By the strict convexity of L in u,

$$b^{X}(t,x) = b^{o}(t,x), \quad p(t,x)dtdx - a.e..$$
 (43)

We prove (2.7). Since L is strictly convex in u, the following holds:

$$\frac{dX(t)}{dt} = b^X(t, X(t)) \quad dtdP - a.e.$$
(44)

by (2.5) (see (3.5)). By (3.22),

$$E[\sup_{0 \le t \le 1} |X(t) - X(0) - \int_0^t b^o(s, X(s))ds|]$$

$$\leq \int_0^1 E[|b^X(s, X(s)) - b^o(s, X(s))|]ds = 0.$$
Q. E. D.

(Proof of Proposition 1). From [15],  $\tilde{\mathbf{e}}^{\varepsilon} = \mathbf{e}^{\varepsilon}$  for  $\varepsilon > 0$ , and the minimizer of  $\tilde{\mathbf{e}}^{\varepsilon}$  can be written as  $\nabla_x \Phi^{\varepsilon}(t, x)$ , where  $\Phi^{\varepsilon}(t, \cdot) \in H^1_{loc}(\mathbf{R}^d : \mathbf{R})$  dt-a.e.. Since  $\{\nabla_x \Phi^{\varepsilon}\}_{0 < \varepsilon < 1}$  is strongly bounded in  $L^2([0, 1] \times \mathbf{R}^d : \mathbf{R}^d, p(t, x) dt dx)$  by (2.5), it is weakly compact in  $L^2([0, 1] \times \mathbf{R}^d : \mathbf{R}^d, p(t, x) dt dx)$  (see [9, p. 639]). We denote a weak limit point by  $\Psi$ . Then  $\Psi$  is the unique minimizer of  $\tilde{\mathbf{e}}^0$ . Indeed,  $\Psi \in \tilde{A}^0$ , and by (2.5) and Fatou's lemma,

$$\tilde{\mathbf{e}}^{0} = \lim_{\varepsilon \to 0} \int_{0}^{1} \int_{\mathbf{R}^{d}} |\nabla_{x} \Phi^{\varepsilon}(t, y)|^{2} p(t, y) dt dy \qquad (46)$$

$$\geq \int_{0}^{1} \int_{\mathbf{R}^{d}} |\Psi(t, y)|^{2} p(t, y) dt dy \geq \tilde{\mathbf{e}}^{0}.$$

In particular,  $\{\nabla_x \Phi^{\varepsilon}\}_{0 < \varepsilon < 1}$  converges, as  $\varepsilon \to 0$ , to  $\Psi$ , strongly in  $L^2([0, 1] \times \mathbf{R}^d : \mathbf{R}^d, p(t, x) dt dx)$ , which completes the proof in the same way as in [15, Proposition 3.1].

Q. E. D.

**Remark 6** If V(t, x) and p(t, x) in Proposition 1 are sufficiently smooth, then

$$\nabla_x \Phi^{\varepsilon}(t,x) = \nabla_x V(t,x) + \frac{\varepsilon^2 \nabla_x p(t,x)}{2p(t,x)}$$

(see [16, section 1]).

(Proof of Theorem 3). Put for  $t \in [0, 1]$ ,  $x \in \mathbf{R}$  and  $n \ge 1$ ,

$$Y(t,x) = F_t^{-1}(F_0(x)), (47)$$

$$Y_n(t,x) = Y\left(\frac{[nt]}{n},x\right)$$

$$+n\left(t - \frac{[nt]}{n}\right)\left(Y\left(\frac{[nt]+1}{n},x\right) - Y\left(\frac{[nt]}{n},x\right)\right),$$

$$(48)$$

where [nt] denotes the integer part of nt.

Then by (H.3)",  $Y(\cdot, x) \in C([0, 1] : \mathbf{R}), P_0(dx) := p(0, x)dx - a.s.$ , and

$$\lim_{n \to \infty} Y_n(t, x) = Y(t, x) \quad (0 \le t \le 1), \quad P_0 - a.s.,$$
(49)

and

$$\mathbf{e}_n = E_0 \left[ \int_0^1 h\left(\frac{dY_n(t,x)}{dt}\right) dt \right] \quad (n \ge 1)$$
(50)

(see Remark 5 in section 2 and [11, p. 35, Exam. 8.1]).

Hence in the same way as in the proof of Lemma 3, we can show that the following holds: for any  $\delta > 0$ 

$$E_{0}[\sup\{(\sum_{j=1}^{m}|Y(t_{j},x)-Y(s_{j},x)|)^{r}:\sum_{j=1}^{m}|t_{j}-s_{j}| \leq \delta, m \geq 2 \quad (51)$$
  
$$, 0 \leq s_{j} \leq t_{j} \leq s_{j+1} \leq t_{j+1} \leq 1(1 \leq j \leq m-1)\}]$$
  
$$\leq \delta^{r-1}\liminf_{n \to \infty} E_{0}[\int_{0}^{1} \left|\frac{dY_{n}(t,x)}{dt}\right|^{r} dt],$$

which implies that  $Y(\cdot, x)$  is absolutely continuous  $P_0 - a.s.$ , by (H.0)' and (H.2)'. In particular,  $\{Y(t, x)\}_{0 \le t \le 1}$  on  $(\mathbf{R}, \mathbf{B}(\mathbf{R}), P_0)$  belongs to the set A.

For  $n \ge 1$  and  $\alpha \in (0, 1)$ , by Jensen's inequality and (H.1)',

$$\infty > \sup_{m \ge 1} \mathbf{e}_m \ge \mathbf{e}_n \ge E_0 \left[ \int_0^{1-\alpha} ds \left( \frac{1}{\alpha} \int_s^{s+\alpha} h\left( \frac{dY_n(t,x)}{dt} \right) dt \right) \right] \qquad (52)$$
$$\ge E_0 \left[ \int_0^{1-\alpha} h\left( \frac{Y_n(s+\alpha,x) - Y_n(s,x)}{\alpha} \right) ds \right].$$

Let  $n \to \infty$  and then  $\alpha \to 0$  in (3.31). Then the proof of the first part is over by Fatou's lemma since  $\sup_{m\geq 1} \mathbf{e}_m \leq \mathbf{e}$ .

The following together with Proposition 2 in section 4 completes the proof: by (2.12),

$$Y(t,x) = Y(0,x) + \int_0^t \frac{\partial F_s^{-1}(F_s(Y(s,x)))}{\partial s} ds \quad (0 \le t \le 1) \quad P_0 - a.s..$$
Q. E. D

# 4 Appendix

In this section we solve SP positively for **R**-valued, time-inhomogeneous stochastic processes.

**Proposition 2** Suppose that (H.3)' holds, and that there exists  $\{Y(t)\}_{0 \le t \le 1}$ ,  $\in A$ , which satisfies

$$Y(t) = Y(0) + \int_0^t b^Y(s, Y(s)) ds \quad (0 \le t \le 1) \ a.s.$$
(53)

for some  $b^{Y}(t,x) \in L^{1}([0,1] \times \mathbf{R} : \mathbf{R}, p(t,x)dtdx)$ . Then the following holds:

$$Y(t) = F_t^{-1}(F_0(Y(0))) \quad (t \in \mathbf{Q} \cap [0, 1]) \quad a.s..$$
(54)

In particular,  $\lim_{s \in \mathbf{Q} \cap [0,1], s \to t} F_s^{-1}(F_0(Y(0)))$  exists and is equal to Y(t) for all  $t \in [0,1]$  a.s..

**Remark 7** If  $F_0$  is not continuous, then SP does not always have a positive answer. For example, put  $Y(t) \equiv tY(\omega)$  for a **R**-valued random variable  $Y(\omega)$  on a probability space. Then dY(t)/dt = Y(t)/t for t > 0. But, of course, Y(t) is not a function of t and  $Y(0) \equiv 0$ .

(Proof of Proposition 2). It is easy to see that the following holds:

$$F_t(Y(t)) = F_0(Y(0)) \quad (t \in [0, 1]) \text{ a.s.}.$$
 (55)

Indeed,

$$\frac{\partial F_t(x)}{\partial t} = -b^Y(t,x)p(t,x), \quad dtdx - a.e.$$

since  $b^{Y}(t,x) = b(t,x), p(t,x)dtdx - a.e.$ , and henceforth by (H.3)'

$$E[\sup_{0 \le t \le 1} |F_t(Y(t)) - F_0(Y(0))|]$$
  
$$\leq \int_0^1 E[\left|\frac{\partial F_s(Y(s))}{\partial s} + p(s, Y(s))b^Y(s, Y(s))\right|]ds = 0.$$

Since  $\{Y(t)\}_{0 \le t \le 1}$  is continuous, the proof is over by (4.3) and by the following:

$$P(F_t^{-1}(F_t(Y(t))) = Y(t)(t \in [0, 1] \cap \mathbf{Q})) = 1.$$
(56)

We prove (4.4). For  $(t, x) \in [0, 1] \times \mathbf{R}$  for which  $F_t(x) \in (0, 1)$ ,

$$F_t^{-1}(F_t(x)) \le x,$$

and for  $t \in [0, 1]$ , the set  $\{x \in \mathbf{R} : F_t^{-1}(F_t(x)) < x, F_t(x) \in (0, 1)\}$  can be written as a union of at most countably many disjoint intervals of the form (a, b] for which  $P(a < Y(t) \le b) = 0$ , provided that it is not empty.

Indeed, if  $F_t^{-1}(F_t(x)) < \overline{x}$  and if  $F_t(x) \in (0,1)$ , then

$$\{y \in \mathbf{R} : F_t^{-1}(F_t(y)) < y, F_t(y) = F_t(x)\}$$
  
=  $(F_t^{-1}(F_t(x)), \sup\{y \in \mathbf{R} : F_t(y) = F_t(x)\}].$ 

Q. E. D.

(Acknowledgement) We would like to thank Prof. M. Takeda for a useful discussion on Salisbury's problem.

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