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# Randomization method and backward SDEs for optimal control of partially observed path-dependent stochastic systems

Elena BANDINI\*    Andrea COSSO†    Marco FUHRMAN‡    Huyên PHAM§

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## Abstract

We consider a unifying framework for stochastic control problem including the following features: partial observation, path-dependence (both with respect to the state and the control), and without any non-degeneracy condition on the stochastic differential equation (SDE) for the controlled state process, driven by a Wiener process. In this context, we develop a general methodology, referred to as the randomization method, studied in [23] for classical Markovian control under full observation, and consisting basically in replacing the control by an exogenous process independent of the driving noise of the SDE. Our first main result is to prove the equivalence between the primal control problem and the randomized control problem where optimization is performed over change of equivalent probability measures affecting the characteristics of the exogenous process. The randomized problem turns out to be associated by duality and separation argument to a backward SDE, which leads to the so-called randomized dynamic programming principle and randomized equation in terms of the path-dependent filter, and then characterizes the value function of the primal problem. In particular, classical optimal control problems with partial observation affected by non-degenerate Gaussian noise fall within the scope of our framework, and are treated by means of an associated backward SDE.

**Keywords:** Path-dependent controlled SDEs, partial observation, randomization of controls, randomized filter, backward SDEs.

**AMS 2010 subject classification:** 60H10, 60G57, 93E11, 93E20.

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# 1 Introduction

Let us start with the classical stochastic optimal control problem with full observation, characterized by the gain functional and value function

$$v(t, x) = \sup_{\alpha} J(t, x, \alpha), \quad J(t, x, \alpha) = \mathbb{E} \left[ \int_t^T f(s, X_s^{t,x,\alpha}, \alpha_s) ds + g(X_T^{t,x,\alpha}) \right], \quad (1.1)$$

where the supremum is taken over the set of progressive processes  $\alpha$  valued in a Borel space  $A$ , and  $X^{t,x,\alpha}$  evolves according to the controlled stochastic differential equation (SDE)

$$dX_s^{t,x,\alpha} = b(s, X_s^{t,x,\alpha}, \alpha_s) ds + \sigma(s, X_s^{t,x,\alpha}, \alpha_s) dW_s, \quad t \leq s \leq T, \quad (1.2)$$

with  $X_t^{t,x,\alpha} = x \in \mathbb{R}^n$ . Here  $W = (W_t)_{t \geq 0}$  is a  $d$ -dimensional Brownian motion on a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  with a filtration  $\mathbb{F} = (\mathcal{F}_t)_{t \geq 0}$  and the coefficients  $b: [0, T] \times \mathbb{R}^n \times A \rightarrow \mathbb{R}^n$ ,  $\sigma: [0, T] \times \mathbb{R}^n \times A \rightarrow \mathbb{R}^{n \times d}$ ,  $f: [0, T] \times \mathbb{R}^n \times A \rightarrow \mathbb{R}$ ,  $g: \mathbb{R}^n \rightarrow \mathbb{R}$  satisfy standard assumptions to be precised later on. The *dynamic programming method* then consists in proving the *dynamic programming principle*, which allows to relate the value function  $v$  to the Hamilton-Jacobi-Bellman (HJB) equation (or *dynamic programming equation*):

$$\begin{cases} \frac{\partial v}{\partial t}(t, x) + \sup_{a \in A} \{ \mathcal{L}^a v(t, x) + f(t, x, a) \} = 0, & (t, x) \in [0, T] \times \mathbb{R}^n, \\ v(T, x) = g(x), & x \in \mathbb{R}^n, \end{cases} \quad (1.3)$$

where (we denote by  $\cdot$  the scalar product between two vectors in  $\mathbb{R}^n$  and by  $^\top$  the transpose operator)

$$\mathcal{L}^a v(t, x) = b(t, x, a) \cdot D_x v(t, x) + \frac{1}{2} \text{tr} [\sigma \sigma^\top(t, x, a) D_x^2 v(t, x)].$$

In general,  $v$  turns out to be the unique viscosity solution to the HJB equation (1.3), see e.g. [12] or [28]. One key feature of the dynamic programming method is that the knowledge of  $v$  allows, at least in principle, to find an optimal control for problem (1.1), although in practice this can be done only in some special cases. Alternatively, the *Pontryagin maximum principle* provides a set of necessary, and sometimes sufficient, conditions in terms of a system of adjoint backward stochastic differential equations for an optimal control, see [31]. These very powerful and well-known methodologies break down (in the sense that at least one of them can not be directly implemented as sketched above) when we face control problems which present the following additional features:

- *partial observation*:  $\alpha$  is required to be adapted to a smaller filtration than  $\mathbb{F}$ , typically the one generated by an observation process;
- *path-dependence in the state*: the coefficients  $b$ ,  $\sigma$ ,  $f$ ,  $g$  depend (in a non-anticipative way) on the entire trajectory of  $X^{t,x,\alpha}$ , not only on its present value;
- *path-dependence in the control*: the coefficients  $b$ ,  $\sigma$ ,  $f$  depend on the past values of the control process  $\alpha$ , not only on its present value.

We refer to the last two features also as memory effects, and in this case (1.2) becomes a path-dependent (or hereditary) stochastic differential equation.

The reason for studying the above generalizations comes from the applications (e.g. to mathematical economics and finance or control engineering), which demand increasingly realistic models.

From a theoretical point of view, they represent very challenging problems with still many open questions. In the literature, an effective approach consists in reformulating the control problem in a new setting, where the dynamic programming method or maximum principle can then be implemented. For example, stochastic control problems with partial observation are shown to be equivalent, via a *separation principle* (see e.g. [11], [7], [17] or [3]) relying on results from nonlinear filtering, to full observation problems formulated on a different filtered probability space, with the filtration generated by the observation process; the conditional distribution of the state process, solution to a filtering equation, becomes a new state variable. On the other hand, stochastic control problems with delay in the state (a particular case of path-dependence) are embedded in an artificial infinite-dimensional space hosting the new state variable, comprising the present value of the state process and its past trajectory (moving window); the recovered Markovianity allows then to implement the dynamic programming method. Control problems with delay in the control are dealt with in a similar way, usually with additional difficulties. We refer for instance to [14], [15]. However, these reformulations of the original problem are strongly dependent on the specific features of the control problem at hand and often involve delicate and somewhat arbitrary choices, such as the function spaces that become the state space for the reformulated problem. Moreover, they generally require additional and sometimes artificial assumptions on the coefficients. Finally all these reformulations share the common feature that eventually the state variable has an infinite-dimensional component. This makes more difficult the rigorous derivation of a “dynamic programming equation” satisfied by the value function, or even providing a well-defined notion of solution to this equation, a difficult task that can in general be accomplished only under specific set of assumptions: we refer for example to [26], [25], [3], [16] for the optimal control of Zakai equation and the related dynamic programming equation and Pontryagin maximum principle in infinite dimensions, and to the book [10] for a recent overview of stochastic control problem with delay in state and control.

The aim of this paper is to develop a general methodology in a unifying framework for the study of stochastic optimal control problems as those mentioned above, which we refer to as the *randomization method*, introduced in [23] for the classical Markovian model (1.1), but earlier considered in [22] in connection with impulse control and in [5], [8], [9] on optimal switching problems. In the present paper we consider a quite general control problem where all the features introduced above, i.e. partial observation and path-dependence on the state and the control, are considered simultaneously, namely

$$dX_t = b_t(X, \alpha) dt + \sigma_t(X, \alpha) dB_t, \quad X_0 = x_0, \quad (1.4)$$

for  $t \in [0, T]$ , with gain functional and value defined by

$$J(\alpha) = \mathbb{E} \left[ \int_0^T f_t(X, \alpha) dt + g(X) \right], \quad v_0 = \sup_{\alpha} J(\alpha) \quad (1.5)$$

where the coefficients  $b, \sigma, f, g$  depend on the whole trajectories of  $X$  and  $\alpha$  in a non-anticipative way. The partial observation character is modeled as follows: in the Wiener process  $B$  we distinguish two components (possibly multidimensional) and write it in the form  $B = (V, W)$ . We suppose that the controller chooses the control actions at any time on the bases of the past observations of the component  $W$  alone. Thus, the control process  $\alpha$  is required to be adapted to the filtration generated by  $W$  and the supremum in (1.5) is taken over such controls. This formulation of a

partial observation problem is general enough to include large classes of optimization models with latent factors of interest in mathematical finance: see section 2.3.1 below. Moreover, the classical optimal control problem with partial observation, as presented for instance in the book [3], also falls under the scope of our results after a standard reformulation based on the so-called reference probability method, in which the observation process  $W$  is turned into a Wiener process by a change of measure: see subsection 2.3.2 where a typical observation process, perturbed by a non-degenerate Gaussian noise, is introduced.

In order to present the randomization method applied to the problem (1.4)-(1.5), we assume for simplicity that  $A$  is a subset of a Euclidean space and we take a finite measure  $\lambda$  on  $A$  with full support. Then, enlarging the original probability space if needed, we introduce a Poisson random measure  $\mu$  on  $\mathbb{R}_+ \times A$  with intensity  $\lambda(da)$  and independent of the Brownian motion  $B$ . Then we consider the stepwise process  $I$  associated with  $\mu$  and replace the control process  $\alpha$  by  $I$ , thus arriving at the following dynamics:

$$\begin{cases} dX_t = b_t(X, I) dt + \sigma_t(X, I) dB_t, \\ I_t = a_0 + \int_0^t \int_A (a - I_{s-}) \mu(ds da). \end{cases}$$

Next we consider an auxiliary optimization problem, called *randomized* or *dual* problem (in contrast to the starting optimal control problem with partial observation which we refer to also as *primal problem*), which consists in optimizing among equivalent changes of probability measures which only affect the intensity measure of  $\mu$  but not the law of  $W$ . In the randomized problem, an admissible control is a bounded positive map  $\nu$  defined on  $\Omega \times \mathbb{R}_+ \times A$ , which is predictable with respect to the filtration  $\mathbb{F}^{W, \mu}$  generated by  $W$  and  $\mu$ . Given  $\nu$ , by means of an absolutely continuous change of measure of Girsanov type we construct a probability measure  $\mathbb{P}^\nu$  such that the compensator of  $\mu$  is given by  $\nu_t(a)\lambda(da)dt$  and  $W$  remains a Brownian motion under  $\mathbb{P}^\nu$ . Then we introduce the gain and the value as

$$J^{\mathcal{R}}(\nu) = \mathbb{E}^\nu \left[ \int_0^T f_t(X, I) dt + g(X) \right], \quad v_0^{\mathcal{R}} = \sup_\nu J^{\mathcal{R}}(\nu),$$

where  $\mathbb{E}^\nu$  denotes the expectation under  $\mathbb{P}^\nu$ .

One of our main results states that the two control problems presented above are equivalent, in the sense that they share the same value:

$$v_0 = v_0^{\mathcal{R}}. \tag{1.6}$$

See Theorem 3.1, where some additional comments can be found.

Such equivalence result has important implications that will be addressed in Section 5. Indeed, it will be shown that the randomized control problem is associated by duality to the following backward stochastic differential equation (BSDE), with nonpositive jumps, which then also characterizes the value function of the initial control problem (1.5). For any bounded measurable functional  $\varphi$  on the space of continuous paths define

$$\rho_t(\varphi) = \mathbb{E}[\varphi(X_{\cdot \wedge t}) \mid \mathcal{F}_t^{W, \mu}],$$

and consider the BSDE

$$\begin{cases} Y_t = \rho_T(g) + \int_t^T \rho_s(f_s(\cdot, I)) ds + K_T - K_t - \int_t^T Z_s dW_s - \int_t^T \int_A U_s(a) \mu(ds da), \\ U_t(a) \leq 0, \end{cases} \quad (1.7)$$

In Theorem 5.1, which is another of our main results, we prove that there exists a unique minimal solution  $(Y, Z, U, K)$  to (1.7) (i.e. among all solutions we take the minimal one in terms of the  $Y$ -component) in a suitable space of stochastic processes adapted to the filtration  $\mathbb{F}^{W, \mu}$ , and moreover

$$Y_0 = v_0^{\mathcal{R}}, \quad \text{and more generally} \quad Y_t = \operatorname{ess\,sup}_{\nu} \mathbb{E}^{\nu} \left[ \int_t^T \rho_s(f_s(\cdot, I)) ds + \rho_T(g) \mid \mathcal{F}_t^{W, \mu} \right]. \quad (1.8)$$

The BSDE (1.7) is called the *randomized equation*, and corresponds to the HJB equation (1.3) of the classical Markovian framework. Note that the introduction of the measure-valued process  $\rho$  and its occurrence in the generator and the terminal condition of the BSDE is reminiscent of the so-called *separation principle* in classical optimal control with partial observation. We shall study in a companion paper [2] how one can also derive such kind of HJB equation in the context of partial observation Markovian control problems. An important feature of our randomization approach is that it does not rely on dynamic programming principle, thus circumventing delicate issues of measurable selection arguments, especially when dealing with path-dependence in state and control. Moreover, our BSDE representation opens perspective to build a new probabilistic numerical scheme for solving optimal control of partially observed SDE. Finally, we would like to point out that Theorems 3.1 and 5.1 are stated in quite a general framework, since no non-degeneracy condition is required on the diffusion coefficient  $\sigma$ . In particular when  $\sigma = 0$ , this includes the case of deterministic control problem with a path-dependent state dynamics and delay on control. When the diffusion coefficient of the Brownian motion  $V$  is zero, meaning that the dynamics of  $X$  is driven only by  $W$ , we are reduced to the case of full observation control problem. Therefore, we have provided a general equivalence and representation result in a unifying framework embedding classical cases in stochastic control theory.

In Section 5 we also prove a verification theorem (Theorem 5.2) in the context of the randomization method. Namely we formulate, in terms of the randomized equation (1.7), a sufficient condition for the existence of an *optimal feedback control* for our primal problem. In the classical Markovian framework (1.1) this result reduces to the standard verification theorem (see subsection 5.3 for more details).

The equality  $Y_0 = v_0$ , which follows from (1.6) and (1.8), provides a BSDE representation of the value function of a stochastic optimization problem, which includes as a special case the classical optimal control problem with partial observation. As far as we know, this is the first time that BSDE techniques allow such a probabilistic representation in a general framework. The reason is that, even for the simplest case when only the drift of the state equation is controlled, after the usual reformulation as a full observation control problem for a filtering equation (for instance, for a controlled Zakai equation) the corresponding semilinear HJB equation (see [3] or [16]) does not fall into the class of semilinear equations addressed by the standard theory of BSDEs (see e.g. [27]) where the generator has a particular structure condition, namely the dependence on the gradient has to have a particular form which involves the diffusion coefficient. The randomization method allows us to represent the solution to semilinear HJB equation with quadratic growth on

the gradient (see [6]) and to fully non-linear equations without any structure condition and without any non degeneracy condition on the diffusion coefficient, using a BSDE, in our present case the equation (1.7).

We conclude with a comparison of two related papers and one final comment.

An equivalence result similar to (1.6) and a corresponding BSDE representation can also be found in [23]. However, in that paper the equality (1.6) was proved only in the Markovian case with full observation and by a completely different method, namely by viscosity solution techniques applied to the HJB equation. Indeed the interest in [23] was focused on providing a nonlinear Feynman-Kac formula for the HJB equation (which was much more general and included also nonlocal terms) in order to design probabilistic numerical methods, that were later developed in [20] and [21]. It is our hope that similar numerical schemes may be adapted to the study of partially observable control problems, and this will be the focus of future works.

We also mention the article [13] where an equivalence result like (1.6) was proved, by purely probabilistic arguments, for an optimal control problem in the presence of path-dependence in the state variable. In [13] only the case of full observation was addressed and there was no memory effect with respect to the control. However, the main difference with respect to our setting is that in [13] the primal problem was formulated in a weak form, i.e. taking the supremum of the gain functional (1.5) also over all possible choices of the probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . This simplifies many arguments, and in particular makes the inequality  $v_0 \geq v_0^{\mathcal{R}}$  trivial. We have chosen in the present paper a strong formulation, i.e. with a fixed probability space, of our control problem, at the expense of additional technical difficulties. This is probably a more natural setting, especially in connection with modeling applications. Moreover, it is the customary setting for the Pontryagin maximum principle and for other classes of optimization problems like optimal stopping and switching.

The rest of the paper is organized as follows. In Section 2 we formulate the general optimal control problem (1.4)-(1.5) (the primal problem) with partial observation and path-dependence in the state and the control. We then present two motivating particular cases: in subsection 2.3.1 a general optimization model with latent factors and uncontrolled observation process, which finds usual applications in mathematical finance; in subsection 2.3.2 a classical optimal control problem with partial observation (but including also path-dependence). Then, in Section 3 we implement the randomization method in order to derive the randomized stochastic optimal control problem (or simply *randomized problem*) associated with the primal problem. We state in Theorem 3.1 the fundamental equivalence result between the primal and randomized problem. Section 4 is entirely devoted to the proof of Theorem 3.1, which requires for both inequalities sharp approximation results and suitable constructions with marked point processes. In Section 5 we show a separation principle for the randomized control problem using nonlinear filtering arguments, and then relate by duality the separated randomized problem to a constrained BSDE, which may be viewed consequently as the randomized equation for the primal control problem. We finally present a verification theorem for our primal problem using the randomized equation, which gives sufficient conditions for the existence of an optimal feedback control for the partial observation problem.

## 2 General formulation and applications

### 2.1 Basic notation and assumptions

In the following we will consider controlled stochastic equations of the form

$$dX_t^\alpha = b_t(X^\alpha, \alpha) dt + \sigma_t(X^\alpha, \alpha) dB_t, \quad (2.1)$$

for  $t \in [0, T]$ , where  $T > 0$  is a fixed deterministic and finite terminal time, and gain functionals

$$J(\alpha) = \mathbb{E} \left[ \int_0^T f_t(X^\alpha, \alpha) dt + g(X^\alpha) \right].$$

The initial condition in (2.1) is  $X_0^\alpha = x_0$ , a given random variable with law denoted  $\rho_0$ . Before formulating precise assumptions let us explain informally the meaning of several terms occurring in these expressions. The controlled process  $X^\alpha$  takes values in  $\mathbb{R}^n$  while  $B$  is a Wiener process in  $\mathbb{R}^{m+d}$ . We write  $B = (V, W)$  when we need to distinguish the first  $m$  components of  $B$  from the other  $d$  components. The control process, denoted by  $\alpha$ , takes values in a set  $A$  of control actions. The partial observation available to the controller will be described by imposing that the control process should be adapted to the filtration generated by the process  $W$  alone. Our formulation includes path-dependent (or hereditary) systems, i.e. it allows for the presence of memory effects both on the state and the control. Indeed, the coefficients  $b, \sigma, f, g$  depend on the whole trajectory of  $X^\alpha$  and  $\alpha$ . The dependence will be non-anticipative, in the sense that their values at time  $t$  depend on the values  $X_s^\alpha$  and  $\alpha_s$  for  $s \in [0, t]$ : this is expressed below in a standard way by requiring that they should be progressive with respect to some canonical filtration on spaces of paths.

Now let us come to precise assumptions and notations. Let us denote by  $\mathbf{C}_n$  the space of continuous paths from  $[0, T]$  to  $\mathbb{R}^n$ , equipped with the usual supremum norm  $\|x\|_\infty = x_T^*$ , where we set  $x_t^* := \sup_{s \in [0, t]} |x(s)|$ , for  $t \in [0, T]$  and  $x \in \mathbf{C}_n$ . We define the filtration  $(\mathcal{C}_t^n)_{t \in [0, T]}$ , where  $\mathcal{C}_t^n$  is the  $\sigma$ -algebra generated by the canonical coordinate maps  $\mathbf{C}_n \rightarrow \mathbb{R}^n$ ,  $x(\cdot) \mapsto x(s)$  up to time  $t$ , namely

$$\mathcal{C}_t^n := \sigma\{x(\cdot) \mapsto x(s) : s \in [0, t]\},$$

and we denote  $Prog(\mathbf{C}_n)$  the progressive  $\sigma$ -algebra on  $[0, T] \times \mathbf{C}_n$  with respect to  $(\mathcal{C}_t^n)$ .

We will require that the space of control actions  $A$  is a Borel space. We recall that a Borel space  $A$  is a topological space homeomorphic to a Borel subset of a Polish space (some authors use the terminology Lusin space). When needed,  $A$  will be endowed with its Borel  $\sigma$ -algebra  $\mathcal{B}(A)$ . We denote by  $\mathbf{M}_A$  the space of Borel measurable paths  $a : [0, T] \rightarrow A$ , we introduce the filtration  $(\mathcal{M}_t^A)_{t \in [0, T]}$ , where  $\mathcal{M}_t^A$  is the  $\sigma$ -algebra

$$\mathcal{M}_t^A := \sigma\{a(\cdot) \mapsto a(s) : s \in [0, t]\}$$

and we denote  $Prog(\mathbf{C}_n \times \mathbf{M}_A)$  the progressive  $\sigma$ -algebra on  $[0, T] \times \mathbf{C}_n$  with respect to the filtration  $(\mathcal{C}_t^n \otimes \mathcal{M}_t^A)_{t \in [0, T]}$ .

#### (A1)

- (i)  $A$  is a Borel space.



(ii) The functions  $b, \sigma, f$  are defined on  $[0, T] \times \mathbf{C}_n \times \mathbf{M}_A$  with values in  $\mathbb{R}^n, \mathbb{R}^{n \times (m+d)}$  and  $\mathbb{R}$  respectively, are assumed to be  $Prog(\mathbf{C}_n \times \mathbf{M}_A)$ -measurable (see also Remark 2.1 below).

(iii) The function  $g$  is continuous on  $\mathbf{C}_n$ , with respect to the supremum norm. The functions  $b, \sigma$  and  $f$  are assumed to satisfy the following sequential continuity condition: whenever  $x_k, x \in \mathbf{C}_n, \alpha_k, \alpha \in \mathbf{M}_A, \|x_k - x\|_\infty \rightarrow 0, \alpha_k(t) \rightarrow \alpha(t)$  for  $dt$ -a.e.  $t \in [0, T]$  as  $k \rightarrow \infty$  we have

$$b_t(x_k, \alpha_k) \rightarrow b_t(x, \alpha), \quad \sigma_t(x_k, \alpha_k) \rightarrow \sigma_t(x', \alpha), \quad f_t(x_k, \alpha_k) \rightarrow f_t(x, \alpha) \quad \text{for } dt\text{-a.e. } t \in [0, T].$$

(iv) There exist nonnegative constants  $L$  and  $r$  such that

$$|b_t(x, a) - b_t(x', a)| + |\sigma_t(x, a) - \sigma_t(x', a)| \leq L(x - x')_t^*, \quad (2.2)$$

$$|b_t(0, a)| + |\sigma_t(0, a)| \leq L, \quad (2.3)$$

$$|f_t(x, a)| + |g(x)| \leq L(1 + \|x\|_\infty^r), \quad (2.4)$$

for all  $(t, x, x', a) \in [0, T] \times \mathbf{C}_n \times \mathbf{C}_n \times \mathbf{M}_A$ .

(v)  $\rho_0$  is a probability measure on the Borel subsets of  $\mathbb{R}^n$ .

**Remark 2.1** The measurability condition **(A1)**-(ii) is assumed because it guarantees the following property, which is easily deduced:

(ii)' Whenever  $(\Omega, \mathcal{F}, \mathbb{P})$  is a probability space with a filtration  $\mathbb{F}$ , and  $\alpha$  and  $X^\alpha$  are  $\mathbb{F}$ -progressive processes with values in  $A$  and  $\mathbb{R}^n$  respectively, then the process  $(b_t(X^\alpha, \alpha), \sigma_t(X^\alpha, \alpha), f_t(X^\alpha, \alpha))_{t \in [0, T]}$  is also  $\mathbb{F}$ -progressive.

All the results in this paper still hold, with the same proofs, if property (ii)' is assumed to hold instead of (ii). There are cases when (ii)' is easy to be checked directly.

We finally note that the function  $g$ , being continuous, is also  $\mathcal{C}_T^n$ -measurable.  $\square$

**Remark 2.2** Assumption **(A1)** allows us to model various memory effects of the control on the state process, including important and usual cases of delay in the control. For instance suppose that  $A$  is a bounded Borel subset of a Banach space and  $\bar{b}: A \rightarrow \mathbb{R}^n$  is Lipschitz continuous. Then we may consider a weighted combination of pure delays:

$$b_t(x, a) = \bar{b} \left( \sum_{i=1}^q \pi_i(t) a(t - \delta_i) \right),$$

where  $0 < \delta_1 < \dots < \delta_q < T$ ,  $\pi_i$  are bounded measurable real-valued functions and we use the convention that  $\alpha_t = \bar{\alpha}$  (a fixed element of  $A$ ) if  $t < 0$ . We may also allow the delays  $\delta_i$  to depend on  $t$  in an appropriate way. Alternatively, we may have

$$b_t(x, \alpha) = \bar{b} \left( \int_0^t \pi(t, s) a(s) ds \right),$$

with  $\pi$  bounded measurable and real-valued. Note that in the latter case the measurability condition **(A1)**-(i) fails in general, since the  $\sigma$ -algebras  $\mathcal{M}_t^A$  are determined by a countable number of times, but the property (i)' in the previous remark is easy to verify.

Clearly, we may address more complicated situations which are combinations of the two previous cases and may also include a dependence on the path  $x$ .  $\square$

**Remark 2.3** We mention that no non-degeneracy assumption on the diffusion coefficient  $\sigma$  is imposed, and in particular, some lines or columns of  $\sigma$  may be equal to zero. We can then consider a priori more general model than (2.1) by adding dependence of the coefficients  $b, \sigma$  on another diffusion process  $M$ , for example an unobserved and uncontrolled factor (see Application in subsection 2.3.1). This generality is only apparent since it can be embedded in a standard way in our framework by considering the enlarged state process  $(X, M)$ .  $\square$

## 2.2 Formulation of the partially observed control problem

We assume that  $A, b, \sigma, f, g, \rho_0$  are given and satisfy the assumptions **(A1)**. We formulate a control problem fixing a setting  $(\Omega, \mathcal{F}, \mathbb{P}, \mathbb{F}, V, W, x_0)$ , where  $(\Omega, \mathcal{F}, \mathbb{P})$  is a complete probability space with a right-continuous and  $\mathbb{P}$ -complete filtration  $\mathbb{F} = (\mathcal{F}_t)_{t \geq 0}$ ,  $V$  and  $W$  are processes with values in  $\mathbb{R}^m$  and  $\mathbb{R}^d$  respectively, such that  $B = (V, W)$  is an  $\mathbb{R}^{m+d}$ -valued standard Wiener process with respect to  $\mathbb{F}$  and  $\mathbb{P}$ , and  $x_0$  is an  $\mathbb{R}^n$ -valued random variable, with law  $\rho_0$  under  $\mathbb{P}$ , which is assumed to be  $\mathcal{F}_0$ -measurable and to satisfy  $\mathbb{E}|x_0|^p < \infty$  for some  $p \in [1, \infty)$ ,  $p \geq 2r$  with  $r$  as in (2.4). Note that  $V$  and  $W$  are also standard Wiener processes and that  $V, W, x_0$  are all independent.

Let us denote  $\mathbb{F}^W = (\mathcal{F}_t^W)_{t \geq 0}$  the right-continuous and  $\mathbb{P}$ -complete filtration generated by  $W$ . An admissible control process is any  $\mathbb{F}^W$ -progressive process  $\alpha$  with values in  $A$ . The set of admissible control processes is denoted by  $\mathcal{A}^W$ . The controlled equation has the form

$$dX_t^\alpha = b_t(X^\alpha, \alpha) dt + \sigma_t(X^\alpha, \alpha) dB_t \quad (2.5)$$

on the interval  $[0, T]$  with initial condition  $X_0^\alpha = x_0$ , and the gain functional is

$$J(\alpha) = \mathbb{E} \left[ \int_0^T f_t(X^\alpha, \alpha) dt + g(X^\alpha) \right]. \quad (2.6)$$

Since we assume that **(A1)** holds, by standard results (see e.g. [29] Thm V. 11.2, or [19] Theorem 14.23), there exists a unique  $\mathbb{F}$ -adapted strong solution  $X^\alpha = (X_t^\alpha)_{0 \leq t \leq T}$  to (2.5) with continuous trajectories and such that (with the same  $p$  for which  $\mathbb{E}|x_0|^p < \infty$ )

$$\mathbb{E} \left[ \sup_{t \in [0, T]} |X_t^\alpha|^p \right] < \infty.$$

The stochastic optimal control problem under partial observation consists in maximizing  $J(\alpha)$  over all  $\alpha \in \mathcal{A}^W$ :

$$v_0 = \inf_{\alpha \in \mathcal{A}^W} J(\alpha). \quad (2.7)$$

**Remark 2.4** Let  $\mathbb{F}^B = (\mathcal{F}_t^B)_{t \geq 0}$  be the right-continuous and  $\mathbb{P}$ -complete filtration generated by  $B$ . Then  $B$  is clearly an  $\mathbb{F}^B$ -Brownian motion, the processes  $\alpha$  and  $X^\alpha$  are  $\mathbb{F}^B$ -progressive and the filtration  $\mathbb{F}$  does not play any role in determining  $J(\alpha)$  and  $v_0$ . So we might assume from the beginning that  $\mathbb{F} = \mathbb{F}^B$  and even that  $\mathcal{F} = \mathcal{F}_\infty^B$  whenever convenient, but in the sequel we keep the previous framework unless explicitly mentioned.  $\square$

## 2.3 Two basic applications

In this paragraph, we address two classical optimal control problems with partial observation, and we show that they can be recast in the form outlined in the previous subsection.

### 2.3.1 Model with latent factors and uncontrolled observation process

Let  $(\Omega, \mathcal{F}, \bar{\mathbb{P}})$  be a complete probability space with a right-continuous and  $\bar{\mathbb{P}}$ -complete filtration  $\mathbb{F} = (\mathcal{F}_t)_{t \geq 0}$ . Let  $V, \bar{W}$  be independent standard Wiener processes with respect to  $\mathbb{F}$ , with values in  $\mathbb{R}^m$  and  $\mathbb{R}^d$  respectively. We assume that a controller, for instance a financial agent, wants to optimize her/his position, described by an  $\bar{n}$ -dimensional stochastic process  $\bar{X}^\alpha$  solution on the interval  $[0, T]$  to an equation of the form

$$d\bar{X}_t^\alpha = \bar{b}_t(\bar{X}^\alpha, M, O, \alpha) dt + \bar{\sigma}_t^1(\bar{X}^\alpha, M, O, \alpha) dV_t + \bar{\sigma}_t^2(\bar{X}^\alpha, M, O, \alpha) d\bar{W}_t \quad (2.8)$$

with coefficients  $\bar{b}, \bar{\sigma}^1, \bar{\sigma}^2$  defined on  $[0, T] \times \mathbf{C}_{\bar{n}+\bar{m}+d} \times \mathbf{M}_A$  valued in  $\mathbb{R}^{\bar{n}}, \mathbb{R}^{\bar{n} \times m}, \mathbb{R}^{\bar{n} \times d}$  respectively, and  $Prog(\mathbf{C}_{\bar{n}+\bar{m}+d} \times \mathbf{M}_A)$ -measurable. Here, the process  $M$  valued in  $\mathbb{R}^{\bar{m}}$  represents a latent factor that can influence the dynamics of  $\bar{X}^\alpha$ , and is governed by a dynamics in the form:

$$dM_t = \bar{\beta}_t(M) dt + \gamma_t^1(M) dV_t + \gamma_t^2(M) d\bar{W}_t, \quad (2.9)$$

for some coefficients  $\bar{\beta}, \gamma^1, \gamma^2$  defined on  $[0, T] \times \mathbf{C}_{\bar{m}}$  valued in  $\mathbb{R}^{\bar{m}}, \mathbb{R}^{\bar{m} \times m}, \mathbb{R}^{\bar{m} \times d}$  respectively, and  $Prog(\mathbf{C}_{\bar{m}})$ -measurable. The process  $M$  is not directly observed, and actually the agent takes her/his decisions based on a noisy observation represented by a process  $O$  in  $\mathbb{R}^d$  solution to an equation of the form

$$dO_t = h_t(M, O) dt + k_t(O) d\bar{W}_t, \quad t \in [0, T], \quad (2.10)$$

for some coefficients  $h$  and  $k$  defined on  $[0, T] \times \mathbf{C}_{\bar{m}+d}$  and  $[0, T] \times \mathbf{C}_d$ ,  $Prog(\mathbf{C}_{\bar{m}+d})$ -measurable and  $Prog(\mathbf{C}_d)$ -measurable, valued in  $\mathbb{R}^d$  and  $\mathbb{R}^{d \times d}$  respectively. For instance,  $O_t$  may be related to the market price of financial risky assets at time  $t$ . We denote  $\mathbb{F}^O = (\mathcal{F}_t^O)_{t \geq 0}$  the right-continuous and  $\bar{\mathbb{P}}$ -complete filtration generated by  $O$ . An admissible control process, representing for instance the agent's investment strategy, is any  $\mathbb{F}^O$ -progressive process  $\alpha$  with values in the Borel space  $A$ .

The agent wishes to maximize, among all admissible control processes, a gain functional of the form

$$J(\alpha) = \bar{\mathbb{E}} \left[ \int_0^T \bar{f}_t(\bar{X}^\alpha, M, O, \alpha) dt + \bar{g}(\bar{X}^\alpha, M, O) \right],$$

where  $\bar{\mathbb{E}}$  denotes expectation with respect to  $\bar{\mathbb{P}}$ , for real-valued coefficients  $\bar{f}, \bar{g}$  defined on  $[0, T] \times \mathbf{C}_{\bar{n}+\bar{m}+d} \times \mathbf{M}_A$  and  $\mathbf{C}_{\bar{n}+\bar{m}+d}$ ,  $Prog(\mathbf{C}_{\bar{n}+\bar{m}+d} \times \mathbf{M}_A)$ -measurable and  $\mathcal{C}_T^{\bar{n}+\bar{m}+d}$ -measurable, respectively.

In order to put this problem in the form addressed in the previous subsection we make a change of probability measure and pass from the ‘‘physical’’ probability  $\bar{\mathbb{P}}$  to a ‘‘reference’’ probability  $\mathbb{P}$ . Assuming that  $k_t(y)$  is invertible for all  $t \in [0, T]$  and  $y \in \mathbf{C}_d$ , and that the process  $\{k_t^{-1}(O)h_t(M, O), 0 \leq t \leq T\}$  is bounded, we define a process  $Z$  setting

$$Z_t^{-1} = \exp \left( - \int_0^t k_s(O)^{-1} h_s(M, O) d\bar{W}_s - \frac{1}{2} \int_0^t |k_s(O)^{-1} h_s(M, O)|^2 ds \right), \quad t \in [0, T].$$

The process  $Z^{-1}$  is a martingale under  $\bar{\mathbb{P}}$ , and by the Girsanov theorem, under the probability  $\mathbb{P}(d\omega) = Z_T(\omega)^{-1} \bar{\mathbb{P}}(d\omega)$  the pair  $(V, W)$  is a standard Wiener process in  $\mathbb{R}^{d+m}$  with respect to  $\mathbb{F}$ , where  $W_t = \bar{W}_t + \int_0^t k_s(O)^{-1} h_s(M, O) ds$ ,  $t \in [0, T]$ . We denote by  $\mathbb{F}^W = (\mathcal{F}_t^W)_{t \in [0, T]}$  the right-continuous and  $\mathbb{P}$ -complete filtration generated by  $W$ , and see that the observation process  $O$  is a solution under  $\mathbb{P}$  to the equation:

$$dO_t = k_t(O) dW_t. \quad (2.11)$$

Assuming a Lipschitz condition on  $k$ , i.e. there exists a constant  $K$  such that

$$|k_t(y) - k_t(y^1)| \leq K(y - y^1)_t^*,$$

for all  $(t, y, y^1) \in [0, T] \times \mathbf{C}_d \times \mathbf{C}_d$ , we deduce that  $O$  must be  $\mathbb{F}^W$ -adapted and therefore that  $\mathcal{F}_t^O \subset \mathcal{F}_t^W$  for  $t \in [0, T]$ . On the other hand, since  $W_t = \int_0^t k_s(O)^{-1} dO_s$ , the opposite inclusion also holds and we conclude that  $\mathbb{F}^O = \mathbb{F}^W$ . Moreover, it is easily checked that  $Z$  is a  $\mathbb{P}$ -martingale satisfying the equation

$$dZ_t = Z_t k_t(O)^{-1} h_t(M, O) dW_t, \quad (2.12)$$

and that the equation (2.8)-(2.9) for  $(\bar{X}^\alpha, M)$  can be re-written under  $\mathbb{P}$  as

$$\begin{aligned} d\bar{X}_t^\alpha &= [\bar{b}_t(\bar{X}^\alpha, M, O, \alpha) - \bar{\sigma}_t^2(\bar{X}^\alpha, M, O, \alpha) k_t(O)^{-1} h_t(M, O)] dt \\ &\quad + \bar{\sigma}_t^1(\bar{X}^\alpha, M, O, \alpha) dV_t + \bar{\sigma}_t^2(\bar{X}^\alpha, M, O, \alpha) dW_t, \end{aligned} \quad (2.13)$$

$$dM_t = [\bar{\beta}_t(M) - \gamma_t^2(M) k_t(O)^{-1} h_t(M, O)] dt + \gamma_t^1(M) dV_t + \gamma_t^2(M) dW_t, \quad (2.14)$$

while the gain functional is re-written as an expectation under  $\mathbb{P}$  from the Bayes formula:

$$J(\alpha) = \mathbb{E} \left[ \int_0^T Z_t \bar{f}_t(\bar{X}^\alpha, M, O, \alpha) dt + Z_T \bar{g}(\bar{X}^\alpha, M, O) \right]. \quad (2.15)$$

Now let us define the four-component process  $X^\alpha = (\bar{X}^\alpha, M, O, Z)$  and note that the equations (2.11)-(2.12)-(2.13)-(2.14) specify a controlled stochastic equation for  $X^\alpha$  of the form (2.5) (with the obvious choice of  $b$  and  $\sigma$  in that equation). Similarly, the gain functional (2.15) can be put in the form (2.6) (with the obvious choice of  $f$  and  $g$ ). Moreover, one easily checks that requirements in **(A1)** are satisfied for suitable assumptions on  $\bar{b}$ ,  $\bar{\sigma}^1$ ,  $\bar{\sigma}^2$ ,  $k$ ,  $h$ ,  $\bar{\beta}$ ,  $\gamma^1$ ,  $\gamma^2$ ,  $\bar{f}$  and  $\bar{g}$ .

**Example 2.1** As an example of financial application, let us mention the case of a risky asset whose price  $S_t$  satisfies

$$dS_t = S_t(\rho(M_t) dt + \sigma_t(S) d\bar{W}_t)$$

for a scalar Brownian motion  $\bar{W}$ , a volatility which is a functional of the past values of  $S$ , and an unobserved return process  $M$  governed by (2.9). We assume that  $\rho$ ,  $\sigma_t(\cdot)$  and  $\sigma_t^{-1}(\cdot)$  are bounded functions. The wealth  $\bar{X}_t^\alpha$  of an investor that invests a fraction  $\alpha_t$  of her/his wealth in this asset (and the rest in a risk-free asset with interest rate  $r$ ) evolves according to the self-financing equation:

$$\begin{aligned} d\bar{X}_t^\alpha &= \alpha_t \bar{X}_t^\alpha \frac{dS_t}{S_t} + (1 - \alpha_t) \bar{X}_t^\alpha r dt \\ &= \bar{X}_t^\alpha [r + \alpha_t(\rho(M_t) - r)] dt + \bar{X}_t^\alpha \alpha_t \sigma_t(S) d\bar{W}_t \end{aligned} \quad (2.16)$$

The investor typically observes the risky price process or equivalently the log-price process  $O_t := \log S_t$  that solves the equation

$$dO_t = \left( \rho(M_t) - \frac{\sigma_t(S)^2}{2} \right) dt + \sigma_t(S) d\bar{W}_t,$$

which can be put in the form (2.10) setting  $k_t(y) = \sigma_t(\exp(y))$  and  $h_t(z, y) = \rho(z) - k_t(y)^2/2$ . Notice that the wealth process is  $\mathbb{F}^O$ -adapted, since it is solution to equation (2.16). Therefore, when choosing the investment strategy  $\alpha$  the investor gains no additional information by observing the wealth process, and so it is reasonable to impose the condition that  $\alpha$  should be adapted to the filtration  $\mathbb{F}^O$  alone, rather than to the one generated by  $O$  and  $\bar{X}^\alpha$ .  $\square$

### 2.3.2 A classical partially observed control problem

In the previous example the observed process  $O$  was not affected by the choice of the control. We next remove this restriction, adopting a classical approach which consists in starting with the “reference” probability  $\mathbb{P}$  and introducing the “physical” probability later, as presented e.g. in the book [3].

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a complete probability space with a right-continuous and  $\mathbb{P}$ -complete filtration  $\mathbb{F} = (\mathcal{F}_t)_{t \geq 0}$ . Let  $V, W$  be independent standard Wiener processes with respect to  $\mathbb{F}$ , with values in  $\mathbb{R}^m$  and  $\mathbb{R}^d$  respectively, and consider the observation process solution to the equation in  $\mathbb{R}^d$

$$dO_t = k_t(O) dW_t, \quad (2.17)$$

where  $k_t(y)$  is defined on  $[0, T] \times \mathbf{C}_d$ ,  $Prog(\mathbf{C}_d)$ -measurable, Lipschitz in  $y$ , and invertible with bounded inverse. Similarly as in the previous paragraph, we see that  $\mathbb{F}^W = \mathbb{F}^O$ , and an admissible control process is any  $\mathbb{F}^W$ -progressive process  $\alpha$  with values in a Borel space  $A$ .

We are given coefficients  $\bar{b}, h, \bar{\sigma}^1, \bar{\sigma}^2$  defined on  $[0, T] \times \mathbf{C}_{\bar{n}+d} \times \mathbf{M}_A$ , valued in  $\mathbb{R}^{\bar{n}}, \mathbb{R}^d, \mathbb{R}^{\bar{n} \times m}, \mathbb{R}^{\bar{n} \times d}$  respectively, and  $Prog(\mathbf{C}_{\bar{n}+d} \times \mathbf{M}_A)$ -measurable. Then, for any admissible control process  $\alpha$ , let the process  $\bar{X}^\alpha$  be defined as the solution to the equation in  $\mathbb{R}^{\bar{n}}$ :

$$\begin{aligned} d\bar{X}_t^\alpha &= [\bar{b}_t(\bar{X}^\alpha, O, \alpha) - \bar{\sigma}_t^2(\bar{X}^\alpha, O, \alpha) k_t(O)^{-1} h_t(\bar{X}^\alpha, O, \alpha)] dt \\ &\quad + \bar{\sigma}_t^1(\bar{X}^\alpha, O, \alpha) dV_t + \bar{\sigma}_t^2(\bar{X}^\alpha, O, \alpha) dW_t. \end{aligned} \quad (2.18)$$

We introduce the gain functional  $J(\alpha)$  associated to a control  $\alpha$  by means of a change of probability in the following way. Assuming that the function  $k^{-1}h$  is bounded, let us define for any admissible control process  $\alpha$ , the  $\mathbb{P}$ -martingale:

$$Z_t^\alpha = \exp \left( \int_0^t k_s(O)^{-1} h_s(\bar{X}^\alpha, O, \alpha) dW_s - \frac{1}{2} \int_0^t |k_s(O)^{-1} h_s(\bar{X}^\alpha, O, \alpha)|^2 ds \right),$$

solution to the equation

$$dZ_t^\alpha = Z_t^\alpha k_t(O)^{-1} h_t(\bar{X}^\alpha, O, \alpha) dW_t, \quad (2.19)$$

and introduce the “physical” probability  $\mathbb{P}^\alpha$  setting  $\mathbb{P}^\alpha(d\omega) = Z_T^\alpha(\omega) \mathbb{P}(d\omega)$ . Given real-valued coefficients  $\bar{f}, \bar{g}$  defined on  $[0, T] \times \mathbf{C}_{\bar{n}+d} \times \mathbf{M}_A$  and  $\mathbf{C}_{\bar{n}+d}$ ,  $Prog(\mathbf{C}_{\bar{n}+d} \times \mathbf{M}_A)$ -measurable and  $\mathcal{C}_T^{\bar{n}+d}$ -measurable, respectively, the gain functional is then defined as

$$J(\alpha) = \mathbb{E}^\alpha \left[ \int_0^T \bar{f}_t(\bar{X}^\alpha, O, \alpha) dt + \bar{g}(\bar{X}^\alpha, O) \right].$$

The interpretation of this formulation is the following. By defining the process  $W^\alpha$  as

$$W_t^\alpha = W_t - \int_0^s k_s(O)^{-1} h_s(\bar{X}^\alpha, O, \alpha) ds, \quad t \in [0, T],$$

for any admissible control process  $\alpha$ , we see, by the Girsanov theorem, that the pair  $(V, W^\alpha)$  is a standard Wiener process in  $\mathbb{R}^{m+d}$  under the probability  $\mathbb{P}^\alpha$  and with respect to  $\mathbb{F}$ . Moreover, the dynamics of  $(\bar{X}^\alpha, O)$  is written under  $\mathbb{P}^\alpha$  as:

$$d\bar{X}_t^\alpha = \bar{b}_t(\bar{X}^\alpha, O, \alpha) dt + \bar{\sigma}_t^1(\bar{X}^\alpha, O, \alpha) dV_t + \bar{\sigma}_t^2(\bar{X}^\alpha, O, \alpha) dW_t^\alpha,$$

$$dO_t = h_t(\bar{X}^\alpha, O, \alpha) dt + k_t(O) dW_t^\alpha.$$

We then obtain a classical controlled state equation, and an observation process perturbed by noise and also affected by the choice of the control.

Finally, we notice that this problem is recast in the framework of subsection 2.2 by rewriting from Bayes formula and the  $\mathbb{P}$ -martingale property of  $Z^\alpha$ , the gain functional as an expectation under  $\mathbb{P}$ :

$$J(\alpha) = \mathbb{E} \left[ \int_0^T Z_t^\alpha \bar{f}_t(\bar{X}^\alpha, O, \alpha) dt + Z_T^\alpha \bar{g}(\bar{X}^\alpha, O) \right]. \quad (2.20)$$

Thus, by defining the three-component process  $X^\alpha = (\bar{X}^\alpha, Z^\alpha, O)$ , we see that the equations (2.17)-(2.18)-(2.19) specify a controlled stochastic equation for  $X^\alpha$  of the form (2.5), and the gain functional (2.20) can be put in the form (2.6).

### 3 The randomized stochastic optimal control problem

We still assume that  $A, b, \sigma, f, g, \rho_0$  are given and satisfy the assumptions **(A1)**. We implement the randomization method and formulate the randomized stochastic optimal control problem associated with the control problem of subsection 2.2. To this end we assume we are also given  $\lambda, a_0$  satisfying the following conditions, which are assumed to hold from now on:

#### **(A2)**

- (i)  $\lambda$  is a finite positive measure on  $(A, \mathcal{B}(A))$  with full topological support.
- (ii)  $a_0$  is a fixed, deterministic point in  $A$ .

We anticipate that  $\lambda$  will play the role of an intensity measure and  $a_0$  will be the starting point of some auxiliary process introduced later. Notice that the initial problem (2.7) does not depend on  $\lambda, a_0$ , which only appear in order to give a randomized representation of the partially observed control problem. In this sense, **(A2)** is not a restriction imposed on the original problem and we have the choice to fix  $a_0 \in A$  and an intensity measure  $\lambda$  satisfying this condition.

#### 3.1 Formulation of the randomized control problem

The randomized control problem is formulated fixing a setting  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}}, \hat{V}, \hat{W}, \hat{\mu}, \hat{x}_0)$ , where  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}})$  is an arbitrary complete probability space with independent random elements  $\hat{V}, \hat{W}, \hat{\mu}, \hat{x}_0$ . The random variable  $\hat{x}_0$  is  $\mathbb{R}^n$ -valued, with law  $\rho_0$  under  $\hat{\mathbb{P}}$ , and it is assumed to satisfy  $\hat{\mathbb{E}}|\hat{x}_0|^p < \infty$  for some  $p \in [1, \infty)$ ,  $p \geq 2r$  with  $r$  as in (2.4). The process  $\hat{B} := (\hat{V}, \hat{W})$  is a standard Wiener process in  $\mathbb{R}^{m+d}$  under  $\hat{\mathbb{P}}$ .  $\hat{\mu}$  is a Poisson random measure on  $A$  with intensity  $\lambda(da)$  under  $\hat{\mathbb{P}}$ ; thus,  $\hat{\mu}$  is a sum of Dirac measures of the form  $\hat{\mu} = \sum_{n \geq 1} \delta_{(\hat{S}_n, \hat{\eta}_n)}$ , where  $(\hat{\eta}_n)_{n \geq 1}$  is a sequence of  $A$ -valued random variables and  $(\hat{S}_n)_{n \geq 1}$  is a strictly increasing sequence of random variables with values in  $(0, \infty)$ , and for any  $C \in \mathcal{B}(A)$  the process  $\hat{\mu}((0, t] \times C) - t\lambda(C)$ ,  $t \geq 0$ , is a  $\hat{\mathbb{P}}$ -martingale. We also define the  $A$ -valued process

$$\hat{I}_t = \sum_{n \geq 0} \hat{\eta}_n 1_{[\hat{S}_n, \hat{S}_{n+1})}(t), \quad t \geq 0, \quad (3.1)$$

where we use the convention that  $\hat{S}_0 = 0$  and  $\hat{I}_0 = a_0$ , the point in assumption **(A2)**-(ii). Notice that the sum in (3.1) is formal and that, when  $A$  is a subset of a linear space, formula (3.1) can be written as

$$\hat{I}_t = a_0 + \int_0^t \int_A (a - \hat{I}_{s-}) \hat{\mu}(ds da), \quad t \geq 0.$$

Let  $\hat{X}$  be the solution to the equation

$$d\hat{X}_t = b_t(\hat{X}, \hat{I}) dt + \sigma_t(\hat{X}, \hat{I}) dB_t, \quad (3.2)$$

for  $t \in [0, T]$ , starting from  $\hat{X}_0 = \hat{x}_0$ . We define two filtrations  $\mathbb{F}^{\hat{W}, \hat{\mu}} = (\mathcal{F}_t^{\hat{W}, \hat{\mu}})_{t \geq 0}$  and  $\mathbb{F}^{\hat{x}_0, \hat{B}, \hat{\mu}} = (\mathcal{F}_t^{\hat{x}_0, \hat{B}, \hat{\mu}})_{t \geq 0}$  setting

$$\begin{aligned} \mathcal{F}_t^{\hat{W}, \hat{\mu}} &= \sigma(\hat{W}_s, \hat{\mu}((0, s] \times C) : s \in [0, t], C \in \mathcal{B}(A)) \vee \mathcal{N}, \\ \mathcal{F}_t^{\hat{x}_0, \hat{B}, \hat{\mu}} &= \sigma(\hat{x}_0, \hat{B}_s, \hat{\mu}((0, s] \times C) : s \in [0, t], C \in \mathcal{B}(A)) \vee \mathcal{N}, \end{aligned} \quad (3.3)$$

where  $\mathcal{N}$  denotes the family of  $\hat{\mathbb{P}}$ -null sets of  $\hat{\mathcal{F}}$ . We denote  $\mathcal{P}(\mathbb{F}^{\hat{W}, \hat{\mu}})$ ,  $\mathcal{P}(\mathbb{F}^{\hat{x}_0, \hat{B}, \hat{\mu}})$  the corresponding predictable  $\sigma$ -algebras.

Under **(A1)** it is well-known (see e.g. Theorem 14.23 in [19]) that there exists a unique  $\mathbb{F}^{\hat{x}_0, \hat{B}, \hat{\mu}}$ -adapted strong solution  $\hat{X} = (\hat{X}_t)_{0 \leq t \leq T}$  to (3.2), satisfying  $\hat{X}_0 = \hat{x}_0$ , with continuous trajectories and such that (with the same  $p$  for which  $\hat{\mathbb{E}}|\hat{x}_0|^p < \infty$ )

$$\hat{\mathbb{E}} \left[ \sup_{t \in [0, T]} |\hat{X}_t|^p \right] < \infty. \quad (3.4)$$

We can now define the randomized optimal control problem as follows: the set  $\hat{\mathcal{V}}$  of admissible controls consists of all  $\hat{\nu} = \hat{\nu}_t(\hat{\omega}, a) : \hat{\Omega} \times \mathbb{R}_+ \times A \rightarrow (0, \infty)$ , which are  $\mathcal{P}(\mathbb{F}^{\hat{W}, \hat{\mu}}) \otimes \mathcal{B}(A)$ -measurable and bounded. Then the Doléans exponential process

$$\begin{aligned} \kappa_t^{\hat{\nu}} &= \mathcal{E}_t \left( \int_0^t \int_A (\hat{\nu}_s(a) - 1) (\mu(ds da) - \lambda(da) ds) \right) \\ &= \exp \left( \int_0^t \int_A (1 - \hat{\nu}_s(a)) \lambda(da) ds \right) \prod_{\hat{S}_n \leq t} \nu_{\hat{S}_n}(\hat{\eta}_n), \quad t \geq 0, \end{aligned} \quad (3.5)$$

is a martingale with respect to  $\hat{\mathbb{P}}$  and  $\mathbb{F}^{\hat{W}, \hat{\mu}}$ , and we can define a new probability setting  $\hat{\mathbb{P}}^{\hat{\nu}}(d\hat{\omega}) = \kappa_T^{\hat{\nu}}(\hat{\omega}) \hat{\mathbb{P}}(d\hat{\omega})$ . From the Girsanov theorem for multivariate point processes ([18]) it follows that under  $\hat{\mathbb{P}}^{\hat{\nu}}$  the  $\mathbb{F}^{\hat{W}, \hat{\mu}}$ -compensator of  $\hat{\mu}$  on the set  $[0, T] \times A$  is the random measure  $\hat{\nu}_t(a) \lambda(da) dt$ . Notice that  $\hat{B}$  remains a Brownian motion under  $\hat{\mathbb{P}}^{\hat{\nu}}$ , and using (2.2)-(2.3) we can generalize estimate (3.4) as follows

$$\sup_{\hat{\nu} \in \hat{\mathcal{V}}} \hat{\mathbb{E}}^{\hat{\nu}} \left[ \sup_{t \in [0, T]} |\hat{X}_t|^p \right] < \infty, \quad (3.6)$$

where  $\hat{\mathbb{E}}^{\hat{\nu}}$  denotes the expectation with respect to  $\hat{\mathbb{P}}^{\hat{\nu}}$ . We finally introduce the gain functional of the randomized control problem

$$J^{\mathcal{R}}(\hat{\nu}) = \hat{\mathbb{E}}^{\hat{\nu}} \left[ \int_0^T f_t(\hat{X}, \hat{I}) dt + g(\hat{X}) \right]. \quad (3.7)$$

The randomized stochastic optimal control problem consists in maximizing  $J^{\mathcal{R}}(\hat{\nu})$  over all  $\hat{\nu} \in \hat{\mathcal{V}}$ . Its value is defined as

$$v_0^{\mathcal{R}} = \sup_{\hat{\nu} \in \hat{\mathcal{V}}} J^{\mathcal{R}}(\hat{\nu}). \quad (3.8)$$

**Remark 3.1** Let us define  $\hat{\mathcal{V}}_{\text{inf} > 0} = \{\hat{\nu} \in \hat{\mathcal{V}} : \inf_{\hat{\Omega} \times [0, T] \times A} \hat{\nu} > 0\}$ . Then

$$\mathcal{U}_0^{\mathcal{R}} = \sup_{\hat{\nu} \in \hat{\mathcal{V}}_{\text{inf} > 0}} J^{\mathcal{R}}(\hat{\nu}). \quad (3.9)$$

Indeed, given  $\hat{\nu} \in \hat{\mathcal{V}}$  and  $\epsilon > 0$ , define  $\hat{\nu}^\epsilon = \hat{\nu} \vee \epsilon \in \hat{\mathcal{V}}_{\text{inf} > 0}$  and write the gain (3.7) in the form

$$J^{\mathcal{R}}(\hat{\nu}^\epsilon) = \hat{\mathbb{E}} \left[ \kappa_T^{\hat{\nu}^\epsilon} \left( \int_0^T f_t(\hat{X}, \hat{I}) dt + g(\hat{X}) \right) \right].$$

It is easy to see that  $J^{\mathcal{R}}(\hat{\nu}^\epsilon) \rightarrow J^{\mathcal{R}}(\hat{\nu})$  as  $\epsilon \rightarrow 0$ , which implies  $\mathcal{U}_0^{\mathcal{R}} = \sup_{\hat{\nu} \in \hat{\mathcal{V}}} J^{\mathcal{R}}(\hat{\nu}) \leq \sup_{\hat{\nu} \in \hat{\mathcal{V}}_{\text{inf} > 0}} J^{\mathcal{R}}(\hat{\nu})$ . The other inequality being obvious, we obtain (3.9).  $\square$

**Remark 3.2** We end this section noting that a randomized control problem can be constructed starting from the initial control problem with partial observation. Indeed, let  $(\Omega, \mathcal{F}, \mathbb{P}, \mathbb{F}, V, W, x_0)$  be the setting for the stochastic optimal control problem formulated in subsection 2.2. Suppose that  $(\Omega', \mathcal{F}', \mathbb{P}')$  is another probability space where a Poisson random measure  $\mu$  with intensity  $\lambda$  is defined. Then we define  $\bar{\Omega} = \Omega \times \Omega'$ , we denote by  $\bar{\mathcal{F}}$  the completion of  $\mathcal{F} \otimes \mathcal{F}'$  with respect to  $\mathbb{P} \otimes \mathbb{P}'$  and by  $\bar{\mathbb{P}}$  the extension of  $\mathbb{P} \otimes \mathbb{P}'$  to  $\bar{\mathcal{F}}$ . The random elements  $V, W, x_0$  in  $\Omega$  and the random measure  $\mu$  in  $\Omega'$  have obvious extensions to  $\bar{\Omega}$ , that will be denoted by the same symbols. Clearly,  $(\bar{\Omega}, \bar{\mathcal{F}}, \bar{\mathbb{P}}, V, W, \mu, x_0)$  is a setting for a randomized control problem as formulated before, that we call *product extension* of the setting  $(\Omega, \mathcal{F}, \mathbb{P}, V, W, x_0)$  for the initial control problem (2.7).

We note that the initial formulation of a randomized setting  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}}, \hat{V}, \hat{W}, \hat{\mu}, \hat{x}_0)$  was more general, since it was not required that  $\hat{\Omega}$  should be a product space  $\Omega \times \Omega'$  and, even if it were the case, it was not required that the process  $\hat{B} = (\hat{V}, \hat{W})$  should depend only on  $\omega \in \Omega$  while the random measure  $\hat{\mu}$  should depend only on  $\omega' \in \Omega'$ .  $\square$

### 3.2 The value of the randomized control problem

In this section it is our purpose to show that the value  $\mathcal{U}_0^{\mathcal{R}}$  of the randomized control problem defined in (3.8) does not depend on the specific setting  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}}, \hat{V}, \hat{W}, \hat{\mu}, \hat{x}_0)$ , so that it is just a functional of the (deterministic) elements  $A, b, \sigma, f, g, \rho_0, \lambda, a_0$ . Later on, in Theorem 3.1, we will prove that in fact  $\mathcal{U}_0^{\mathcal{R}}$  does not depend on the choice of  $\lambda$  and  $a_0$  either.

So let now  $(\tilde{\Omega}, \tilde{\mathcal{F}}, \tilde{\mathbb{P}}, \tilde{V}, \tilde{W}, \tilde{\mu}, \tilde{x}_0)$  be another setting for the randomized control problem, as in Section 3.1, and let  $\tilde{\mathbb{F}}^{\tilde{W}, \tilde{\mu}}, \tilde{\mathbb{F}}^{\tilde{x}_0, \tilde{B}, \tilde{\mu}}, \tilde{X}, \tilde{I}, \tilde{\mathcal{V}}$  be defined in analogy with what was done before. So, for any admissible control  $\tilde{\nu} \in \tilde{\mathcal{V}}$ , we also define  $\kappa^{\tilde{\nu}}$  and the probability  $d\tilde{\mathbb{P}}^{\tilde{\nu}} = \kappa_T^{\tilde{\nu}} d\tilde{\mathbb{P}}$  as well as the gain and the value

$$\tilde{J}^{\mathcal{R}}(\tilde{\nu}) = \tilde{\mathbb{E}}^{\tilde{\nu}} \left[ \int_0^T f_t(\tilde{X}, \tilde{I}) dt + g(\tilde{X}) \right], \quad \tilde{\mathcal{U}}_0^{\mathcal{R}} = \sup_{\tilde{\nu} \in \tilde{\mathcal{V}}} \tilde{J}^{\mathcal{R}}(\tilde{\nu}).$$

We recall that the gain functional and value for the setting  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}}, \hat{V}, \hat{W}, \hat{\mu}, \hat{x}_0)$  was defined in (3.7) and (3.8) and denoted by  $J^{\mathcal{R}}$  and  $\mathcal{U}_0^{\mathcal{R}}$  rather than  $\hat{J}^{\mathcal{R}}$  and  $\hat{\mathcal{U}}_0^{\mathcal{R}}$ , to simplify the notation in the following sections.

**Proposition 3.1** *With the previous notation, we have  $\mathcal{U}_0^{\mathcal{R}} = \tilde{\mathcal{U}}_0^{\mathcal{R}}$ . In other words,  $\mathcal{U}_0^{\mathcal{R}}$  only depends on the objects  $A, b, \sigma, f, g, \rho_0, \lambda, a_0$  appearing in the assumptions **(A1)** and **(A2)**.*



**Proof.** It is enough to prove that  $v_0^{\mathcal{R}} \leq \tilde{v}_0^{\mathcal{R}}$ , since the opposite inequality is established by the same arguments. Writing the gain  $J^{\mathcal{R}}(\hat{\nu})$  defined in (3.7) in the form

$$J^{\mathcal{R}}(\hat{\nu}) = \hat{\mathbb{E}} \left[ \kappa_T^{\hat{\nu}} \left( \int_0^T f_t(\hat{X}, \hat{I}) dt + g(\hat{X}) \right) \right],$$

recalling the definition (3.5) of the process  $\kappa^{\hat{\nu}}$  and noting that the process  $\hat{I}$  is completely determined by  $\hat{\mu}$ , we see that  $J^{\mathcal{R}}(\hat{\nu})$  only depends on the (joint) law of  $(\hat{X}, \hat{\mu}, \hat{\nu})$  under  $\hat{\mathbb{P}}$ . Since, however,  $\hat{X}$  is the solution to equation (3.2) with initial condition  $\hat{X}_0 = \hat{x}_0$ , it is easy to check that under our assumptions the law of  $(\hat{X}, \hat{\mu}, \hat{\nu})$  only depends on the law of  $(\hat{x}_0, \hat{V}, \hat{W}, \hat{\mu}, \hat{\nu})$ . Since  $\hat{x}_0$ ,  $\hat{V}$  and  $(\hat{W}, \hat{\mu}, \hat{\nu})$  are all independent, and the laws of  $\hat{x}_0$  and  $\hat{V}$  are fixed (since  $\hat{V}$  is a standard Wiener process and  $\hat{x}_0$  has law  $\rho_0$ ) we conclude that  $J^{\mathcal{R}}(\hat{\nu})$  only depends on the law of  $(\hat{W}, \hat{\mu}, \hat{\nu})$  under  $\hat{\mathbb{P}}$ . Similarly,  $\tilde{J}^{\mathcal{R}}(\tilde{\nu})$  only depends on the law of  $(\tilde{W}, \tilde{\mu}, \tilde{\nu})$  under  $\tilde{\mathbb{P}}$ .

Next we claim that, given  $\hat{\nu} \in \hat{\mathcal{V}}$  there exists  $\tilde{\nu} \in \tilde{\mathcal{V}}$  such that the law of  $(\hat{W}, \hat{\mu}, \hat{\nu})$  under  $\hat{\mathbb{P}}$  is the same as the law of  $(\tilde{W}, \tilde{\mu}, \tilde{\nu})$  under  $\tilde{\mathbb{P}}$ . Assuming the claim for a moment, it follows from the previous discussion that for this choice of  $\tilde{\nu}$  we have

$$J^{\mathcal{R}}(\hat{\nu}) = \tilde{J}^{\mathcal{R}}(\tilde{\nu}) \leq \tilde{v}_0^{\mathcal{R}},$$

and taking the supremum over  $\hat{\nu} \in \hat{\mathcal{V}}$  we deduce that  $v_0^{\mathcal{R}} \leq \tilde{v}_0^{\mathcal{R}}$ , which proves the result.

It only remains to prove the claim. By a monotone class argument we may suppose that  $\hat{\nu}_t(a) = k(a) \phi_t \psi_t$ , where  $k$  is a  $\mathcal{B}(A)$ -measurable,  $\phi$  is  $\mathbb{F}^{\hat{W}}$ -predictable and  $\psi$  is  $\mathbb{F}^{\hat{\mu}}$ -predictable (where these filtrations are the ones generated by  $\hat{W}$  and  $\hat{\mu}$  respectively). We may further suppose that

$$\phi_t = 1_{(t_0, t_1]}(t) \phi_0(\hat{W}_{s_1}, \dots, \hat{W}_{s_h})$$

for an integer  $h$  and deterministic times  $0 \leq s_1 \leq \dots \leq s_h \leq t_0 < t_1$  and a Borel function  $\phi_0$  on  $\mathbb{R}^h$ , since this class of processes generates the predictable  $\sigma$ -algebra of  $\mathbb{F}^{\hat{W}}$ , and that

$$\psi_t = 1_{(\hat{s}_n, \hat{s}_{n+1}]}(t) \psi_0(\hat{S}_1, \dots, \hat{S}_n, \hat{\eta}_1, \dots, \hat{\eta}_n, t)$$

for an integer  $n \geq 1$  and a Borel function  $\psi_0$  on  $\mathbb{R}^{2n+1}$ , since this class of processes generates the predictable  $\sigma$ -algebra of  $\mathbb{F}^{\hat{\mu}}$  (see [18], Lemma (3.3)). It is immediate to verify that the required process  $\tilde{\nu}$  can be defined setting

$$\tilde{\nu}_t(a) = k(a) 1_{(t_0, t_1]}(t) \phi_0(\tilde{W}_{s_1}, \dots, \tilde{W}_{s_h}) 1_{(\tilde{s}_n, \tilde{s}_{n+1}]}(t) \psi_0(\tilde{S}_1, \dots, \tilde{S}_n, \tilde{\eta}_1, \dots, \tilde{\eta}_n, t),$$

where  $(\tilde{S}_n, \tilde{\eta}_n)_{n \geq 1}$  are associated to the measure  $\tilde{\mu}$ , i.e.  $\tilde{\mu} = \sum_{n \geq 1} \delta_{(\tilde{s}_n, \tilde{\eta}_n)}$ .  $\square$

### 3.3 Equivalence of the partially observed and the randomized control problem

We can now state one of the main results of the paper.

**Theorem 3.1** *Assume that (A1) and (A2) are satisfied. Then the values of the partially observed control problem and of the randomized control problem are equal:*

$$v_0 = v_0^{\mathcal{R}}, \tag{3.10}$$

where  $v_0$  and  $v_0^{\mathcal{R}}$  are defined by (2.7) and (3.8) respectively. This common value only depends on the objects  $A, b, \sigma, f, g, \rho_0$  appearing in assumption (A1).

The last sentence follows immediately from Proposition 3.1, from the equality  $v_0 = v_0^{\mathcal{R}}$  and from the obvious fact that  $v_0$  cannot depend on  $\lambda, a_0$  introduced in assumption **(A2)**. The proof of the equality is contained in the next section.

Before giving the proof of Theorem 3.1, let us discuss the significance of this equivalence result. The randomized control problem involves an uncontrolled state process  $(X, I)$  solution to (3.1)-(3.2), and the optimization is done over a set of equivalent probability measures whose effect is to change the characteristics (the intensity) of the auxiliary randomized process  $I$  without impacting on the Brownian motion  $B$  driving  $X$ . Therefore, the equivalence result (3.10) means that by achieving such optimization in the randomized problem, we perform the same value as in the original control problem where controls affect directly the drift and diffusion of the state process. As explained in the Introduction, such equivalence result has important implications that will be addressed in Section 5 where it is shown that the randomized control problem is associated by duality to a backward stochastic differential equation (with nonpositive jumps), called the *randomized equation*, which then characterizes the value function of the initial control problem (2.7).

## 4 Proof of Theorem 3.1

The proof is split into two parts, corresponding to the inequalities  $v_0^{\mathcal{R}} \leq v_0$  and  $v_0 \leq v_0^{\mathcal{R}}$ . In the sequel, **(A1)** and **(A2)** are always assumed to hold.

Before starting with the rigorous proof, let us have a look at the main points.

- $v_0^{\mathcal{R}} \leq v_0$ . First, we prove that the value of the primal problem  $v_0$  does not change if we reformulate it on the enlarged probability space where the randomized problem lives, taking the supremum over  $\mathcal{A}^{W, \mu'}$ , which is the set of controls  $\bar{\alpha}$  progressively measurable with respect to the filtration generated by  $W$  and the Poisson random measure  $\mu'$  (Lemma 4.1; actually, we take  $\bar{\alpha}$  progressively measurable with respect to an even larger filtration, denoted  $\mathbb{F}^{W, \mu'_{\infty}}$ ). Second, we prove that for every  $\nu \in \mathcal{V}_{\text{inf}>0}$  there exists  $\bar{\alpha}^{\nu} \in \mathcal{A}^{W, \mu'}$  such that  $\mathcal{L}_{\mathbb{P}^{\nu}}(x_0, B, I) = \mathcal{L}_{\mathbb{P}}(x_0, B, \bar{\alpha}^{\nu})$  (Proposition 4.1). This result is a direct consequence of the key Lemma 4.3. From  $\mathcal{L}_{\mathbb{P}^{\nu}}(x_0, B, I) = \mathcal{L}_{\mathbb{P}}(x_0, B, \bar{\alpha}^{\nu})$  we obtain that  $J^{\mathcal{R}}(\nu) = \bar{J}(\bar{\alpha}^{\nu})$ , namely

$$v_0^{\mathcal{R}} := \sup_{\nu \in \mathcal{V}_{\text{inf}>0}} J^{\mathcal{R}}(\nu) = \sup_{\nu \in \mathcal{V}_{\text{inf}>0}} \bar{J}(\bar{\alpha}^{\nu}).$$

Since  $v_0 = \sup_{\bar{\alpha} \in \mathcal{A}^{W, \mu'}} \bar{J}(\bar{\alpha})$  by Lemma 4.1, and every  $\bar{\alpha}^{\nu}$  belongs to  $\mathcal{A}^{W, \mu'}$ , we easily obtain the inequality  $v_0^{\mathcal{R}} \leq v_0$ .

- $v_0 \leq v_0^{\mathcal{R}}$ . The proof of this inequality is based on a “density” result (which corresponds to the key Proposition A.1) in the spirit of Lemma 3.2.6 in [24]. Roughly speaking, we prove that the class  $\{\bar{\alpha}^{\nu} : \nu \in \mathcal{V}_{\text{inf}>0}\}$  is dense in  $\mathcal{A}^{W, \mu'}$ , with respect to the metric  $\tilde{\rho}$  defined in (4.17) (the same metric used in Lemma 3.2.6 in [24]). Then, the inequality  $v_0 \leq v_0^{\mathcal{R}}$  follows from the stability Lemma 4.4, which states that, under Assumption **(A1)**, the gain functional is continuous with respect to the metric  $\tilde{\rho}$ .

### 4.1 Proof of the inequality $v_0^{\mathcal{R}} \leq v_0$

We note at the outset that the requirement that  $\lambda$  has full support will not be used in the proof of the inequality  $v_0^{\mathcal{R}} \leq v_0$ .

Let  $(\Omega, \mathcal{F}, \mathbb{P}, \mathbb{F}, V, W, x_0)$  be a setting for the stochastic optimal control problem with partial observation formulated in subsection 2.2. We construct a setting for a randomized control problem in the form of a product extension as described at the end of Section 3.1.

Let  $\lambda$  be a Borel measure on  $A$  satisfying **(A2)**. As a first step, we need to construct a suitable surjective measurable map  $\pi : \mathbb{R} \rightarrow A$  and to introduce a properly chosen measure  $\lambda'$  on the Borel subsets of the real line such that in particular  $\lambda = \lambda' \circ \pi^{-1}$ . We also recall that the space of control actions  $A$  is assumed to be a Borel space and it is known that any such space is either finite or countable (with the discrete topology) or isomorphic, as a measurable space, to the real line (or equivalently to the half line  $(0, \infty)$ ): see e.g. [4], Corollary 7.16.1.

Let us denote by  $A_c$  the subset of  $A$  consisting of all points  $a \in A$  such that  $\lambda(\{a\}) > 0$ , and let  $A_{nc} = A \setminus A_c$ . Since  $\lambda$  is finite, the set  $A_c$  is either empty or countable, and it follows in particular that both  $A_c$  and  $A_{nc}$  are also Borel spaces.

In the construction of  $\lambda'$  we distinguish the following three cases.

1.  $A_c = \emptyset$ , so that  $A = A_{nc}$  is uncountable. Then, as recalled above, there exists a bijection  $\pi : \mathbb{R} \rightarrow A$  such that  $\pi$  and its inverse are both Borel measurable. We define a measure  $\lambda'$  on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  setting  $\lambda'(B) = \lambda(\pi(B))$  for  $B \in \mathcal{B}(\mathbb{R})$ . Even if we cannot guarantee that  $\lambda'$  has full support, it clearly holds that  $\lambda'(\{r\}) = 0$  for every  $r \in \mathbb{R}$ . Basically, in this case we are identifying  $A$  with  $\mathbb{R}$  and  $\lambda$  with its image measure  $\lambda'$ .
2.  $A_{nc} = \emptyset$ , so that  $A = A_c$  is countable, with the discrete topology. For every  $j \in A$  choose a (nontrivial) interval  $\mathcal{I}_j \subset \mathbb{R}$  in such a way that  $\{\mathcal{I}_j, j \in A\}$  is a partition of  $\mathbb{R}$ . Choose an arbitrary nonatomic finite measure on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  with full support (say, the standard Gaussian measure, denoted by  $\gamma$ ) and denote by  $\lambda'$  the unique positive measure on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  such that

$$\lambda'(B) = \lambda(\{j\})\gamma(B)/\gamma(\mathcal{I}_j), \quad \text{for every } B \subset \mathcal{I}_j, B \in \mathcal{B}(\mathbb{R}), j \in A.$$

Notice that  $\lambda'$  is a finite measure ( $\lambda'(\mathbb{R}) = \lambda(A)$ ), satisfying  $\lambda'(\mathcal{I}_j) = \lambda(\{j\})$  for every  $j \in A$  and  $\lambda'(\{r\}) = 0$  for every  $r \in \mathbb{R}$ . We also define the projection  $\pi : \mathbb{R} \rightarrow A$  given by

$$\pi(r) = j, \quad \text{if } r \in \mathcal{I}_j \text{ for some } j \in A. \quad (4.1)$$

Clearly,  $\lambda = \lambda' \circ \pi^{-1}$ .

3.  $A_c \neq \emptyset$  and  $A_{nc} \neq \emptyset$ . For every  $j \in A_c$  choose a (nontrivial) interval  $\mathcal{I}_j \subset (-\infty, 0]$  in such a way that  $\{\mathcal{I}_j, j \in A_c\}$  is a partition of  $(-\infty, 0]$ . Moreover, there exists a bijection  $\pi_1 : (0, \infty) \rightarrow A_{nc}$  such that  $\pi_1$  and its inverse are both Borel measurable. Denote by  $\lambda'$  the unique positive measure on  $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$  such that

$$\begin{aligned} \lambda'(B) &= \lambda(\{j\})\gamma(B)/\gamma(\mathcal{I}_j), & \text{for every } B \subset \mathcal{I}_j, B \in \mathcal{B}(\mathbb{R}), j \in A_c, \\ \lambda'(B) &= \lambda(\pi_1(B)) & \text{for every } B \subset (0, \infty), B \in \mathcal{B}(\mathbb{R}). \end{aligned}$$

Again,  $\lambda'$  is a finite measure satisfying  $\lambda'(\mathcal{I}_j) = \lambda(\{j\})$  for every  $j \in A_c$  and  $\lambda'(\{r\}) = 0$  for every  $r \in \mathbb{R}$ . We also define the projection  $\pi : \mathbb{R} \rightarrow A$  given by

$$\pi(r) = \begin{cases} j, & \text{if } r \in \mathcal{I}_j \text{ for some } j \in A_c, \\ \pi_1(r), & \text{if } r \in (0, \infty), \end{cases} \quad (4.2)$$

so that in particular  $\lambda = \lambda' \circ \pi^{-1}$ .

Now let  $(\Omega', \mathcal{F}', \mathbb{P}')$  denote the canonical probability space of a non-explosive Poisson point process on  $\mathbb{R}_+ \times \mathbb{R}$  with intensity  $\lambda'$ . Thus,  $\Omega'$  is the set of sequences  $\omega' = (t_n, r_n)_{n \geq 1} \subset (0, \infty) \times \mathbb{R}$  with  $t_n < t_{n+1} \nearrow \infty$ ,  $(T_n, R_n)_{n \geq 1}$  is the canonical marked point process (i.e.  $T_n(\omega') = t_n$ ,  $R_n(\omega') = r_n$ ), and  $\mu' = \sum_{n \geq 1} \delta_{(T_n, R_n)}$  is the corresponding random measure. Let  $\mathcal{F}'$  denote the smallest  $\sigma$ -algebra such that all the maps  $T_n, R_n$  are measurable, and  $\mathbb{P}'$  the unique probability on  $\mathcal{F}'$  such that  $\mu'$  is a Poisson random measure with intensity  $\lambda'$  (since  $\lambda'$  is a finite measure, this probability actually exists). We will also use the completion of the space  $(\Omega', \mathcal{F}', \mathbb{P}')$ , still denoted by the same symbol by abuse of notation. In all the cases considered above, setting

$$A_n = \pi(R_n), \quad \mu = \sum_{n \geq 1} \delta_{(T_n, A_n)},$$

it is easy to verify that  $\mu$  is a Poisson random measure on  $(0, \infty) \times A$  with intensity  $\lambda$ , defined in  $(\Omega', \mathcal{F}', \mathbb{P}')$ . Then, following (3.1), we associate to this Poisson random measure on  $(0, \infty) \times A$ , the  $A$ -valued process

$$I_t = \sum_{n \geq 0} A_n 1_{[T_n, T_{n+1})}(t), \quad t \geq 0,$$

where we use the convention that  $T_0 = 0$  and  $I_0 = a_0$  the point in assumption **(A2)**-(ii). In  $(\Omega', \mathcal{F}')$  we define the natural filtrations  $\mathbb{F}^\mu = (\mathcal{F}_t^\mu)_{t \geq 0}$ ,  $\mathbb{F}^{\mu'} = (\mathcal{F}_t^{\mu'})_{t \geq 0}$  given by

$$\begin{aligned} \mathcal{F}_t^\mu &= \sigma(\mu((0, s] \times C) : s \in [0, t], C \in \mathcal{B}(A)) \vee \mathcal{N}', \\ \mathcal{F}_t^{\mu'} &= \sigma(\mu'((0, s] \times B) : s \in [0, t], B \in \mathcal{B}(\mathbb{R})) \vee \mathcal{N}', \end{aligned}$$

where  $\mathcal{N}'$  denotes the family of  $\mathbb{P}'$ -null sets of  $\mathcal{F}'$ . We denote by  $\mathcal{P}(\mathbb{F}^\mu)$ ,  $\mathcal{P}(\mathbb{F}^{\mu'})$  the corresponding predictable  $\sigma$ -algebras. Note that  $\mathcal{F}_t^\mu \subset \mathcal{F}_t^{\mu'}$  and  $\mathcal{F}_\infty^{\mu'} = \mathcal{F}'$ .

Then we define  $\bar{\Omega} = \Omega \times \Omega'$ , we denote by  $\bar{\mathcal{F}}$  the completion of  $\mathcal{F} \otimes \mathcal{F}'$  with respect to  $\mathbb{P} \otimes \mathbb{P}'$  and by  $\bar{\mathbb{P}}$  the extension of  $\mathbb{P} \otimes \mathbb{P}'$  to  $\bar{\mathcal{F}}$ . The random elements  $V, W, x_0$  in  $\Omega$  and the random measures  $\mu, \mu'$  in  $\Omega'$  have obvious extensions to  $\bar{\Omega}$ , that will be denoted by the same symbols. Then  $(\bar{\Omega}, \bar{\mathcal{F}}, \bar{\mathbb{P}}, V, W, \mu, x_0)$  is a setting for a randomized control problem as formulated in section 3.1. Recall that  $\mathbb{F}^W$  denotes the  $\mathbb{P}$ -completed filtration in  $(\Omega, \mathcal{F})$  generated by the Wiener process  $W$ . All filtrations  $\mathbb{F}^W, \mathbb{F}^\mu, \mathbb{F}^{\mu'}$  can also be lifted to filtrations in  $(\bar{\Omega}, \bar{\mathcal{F}})$ , and  $\bar{\mathbb{P}}$ -completed. In the sequel it should be clear from the context whether they are considered as filtrations in  $(\bar{\Omega}, \bar{\mathcal{F}})$  or in their original spaces. As in Section 3.1 we define the filtration  $\mathbb{F}^{W, \mu} = (\mathcal{F}_t^{W, \mu})_{t \geq 0}$  in  $(\bar{\Omega}, \bar{\mathcal{F}})$  by

$$\mathcal{F}_t^{W, \mu} = \mathcal{F}_t^W \vee \mathcal{F}_t^\mu \vee \mathcal{N},$$

( $\mathcal{N}$  denotes the family of  $\bar{\mathbb{P}}$ -null sets of  $\bar{\mathcal{F}}$ ), we introduce the classes  $\mathcal{V}, \mathcal{V}_{\inf > 0}$  and, for any admissible control  $\nu \in \mathcal{V}$ , the corresponding martingale  $\kappa^\nu$ , the probability  $\mathbb{P}^\nu(dw dw') = \kappa_T^\nu(\omega, \omega') \bar{\mathbb{P}}(dw dw')$  and the gain  $J^{\mathcal{R}}(\nu)$ . For technical purposes, we need to introduce the set  $\mathcal{V}'$  of elements  $\nu' = \nu'_t(\omega', a) : \Omega' \times \mathbb{R}_+ \times A \rightarrow (0, \infty)$ , which are  $\mathcal{P}(\mathbb{F}^{\mu'}) \otimes \mathcal{B}(A)$ -measurable and bounded. We also define another filtration  $\mathbb{F}^{W, \mu'_\infty} = (\mathcal{F}_t^{W, \mu'_\infty})_{t \geq 0}$  in  $(\bar{\Omega}, \bar{\mathcal{F}})$  setting

$$\mathcal{F}_t^{W, \mu'_\infty} = \mathcal{F}_t^W \vee \mathcal{F}' \vee \mathcal{N}$$

(here  $\mathcal{F}'$  denotes a  $\sigma$ -algebra in  $(\bar{\Omega}, \bar{\mathcal{F}})$ , namely  $\{\Omega \times B : B \in \mathcal{F}'\}$ ).

In order to prove the inequality  $\mathcal{V}_0^{\mathcal{R}} \leq \mathcal{V}_0$ , we first prove two technical lemmata. In particular, in Lemma 4.1 we show that the primal problem is equivalent to a new primal problem with  $\mathbb{F}^{W, \mu'_\infty}$ -progressive controls on the enlarged space  $(\bar{\Omega}, \bar{\mathcal{F}})$ .

**Lemma 4.1** We have  $\mathcal{V}_0 = \sup_{\bar{\alpha} \in \mathcal{A}^{W, \mu'}} \bar{J}(\bar{\alpha})$ , where

$$\bar{J}(\bar{\alpha}) = \mathbb{E} \left[ \int_0^T f_t(X^{\bar{\alpha}}, \bar{\alpha}) dt + g(X^{\bar{\alpha}}) \right],$$

and  $\mathcal{A}^{W, \mu'}$  is the set of all  $\mathbb{F}^{W, \mu'}$ -progressive processes  $\bar{\alpha}$  with values in  $A$ . Moreover,  $X^{\bar{\alpha}} = (X_t^{\bar{\alpha}})_{0 \leq t \leq T}$  is the strong solution to (2.5) (with  $\bar{\alpha}$  in place of  $\alpha$ ) satisfying  $X_0^{\bar{\alpha}} = x_0$ , which is unique in the class of continuous processes adapted to the filtration  $(\mathcal{F}_t^B \vee \sigma(x_0) \vee \mathcal{F}' \vee \mathcal{N})_{t \geq 0}$ .

**Proof.** The inequality  $\mathcal{V}_0 \leq \sup_{\bar{\alpha} \in \mathcal{A}^{W, \mu'}} \bar{J}(\bar{\alpha})$  is immediate, since every control  $\alpha \in \mathcal{A}^W$  also lies in  $\mathcal{A}^{W, \mu'}$  and  $J(\alpha) = \bar{J}(\alpha)$ , whence  $J(\alpha) \leq \sup_{\bar{\alpha} \in \mathcal{A}^{W, \mu'}} \bar{J}(\bar{\alpha})$  and so  $\mathcal{V}_0 = \sup_{\alpha \in \mathcal{A}^W} J(\alpha) \leq \sup_{\bar{\alpha} \in \mathcal{A}^{W, \mu'}} \bar{J}(\bar{\alpha})$ .

Let us prove the opposite inequality. Fix  $\tilde{\alpha} \in \mathcal{A}^{W, \mu'}$  and consider the (uncompleted) filtration  $\mathbb{F}'' := (\mathcal{F}_t^W \vee \mathcal{F}')_{t \geq 0}$ . Then we can find an  $A$ -valued  $\mathbb{F}''$ -progressive process  $\bar{\alpha}$  such that  $\bar{\alpha} = \tilde{\alpha} \bar{\mathbb{P}}(d\bar{\omega})dt$ -almost surely, so that in particular  $\bar{J}(\bar{\alpha}) = \bar{J}(\tilde{\alpha})$ . It is easy to verify that, for every  $\omega' \in \Omega'$ , the process  $\alpha^{\omega'}$ , defined by  $\alpha_t^{\omega'}(\omega) := \tilde{\alpha}_t(\omega, \omega')$ , is  $\mathbb{F}^W$ -progressive. Consider now the controlled equation on  $[0, T]$

$$\begin{aligned} X_t &= x_0 + \int_0^t b_s(X, \alpha^{\omega'}) ds + \int_0^t \sigma_s(X, \alpha^{\omega'}) dB_s \\ &= x_0 + \int_0^t b_s(X, \bar{\alpha}(\cdot, \omega')) ds + \int_0^t \sigma_s(X, \bar{\alpha}(\cdot, \omega')) dB_s. \end{aligned} \quad (4.3)$$

From the first line of (4.3) we see that, under Assumption **(A1)**, for every  $\omega'$  there exists a unique (up to indistinguishability) continuous process  $X^{\alpha^{\omega'}} = (X_t^{\alpha^{\omega'}})_{0 \leq t \leq T}$  strong solution to (4.3), adapted to the filtration  $(\mathcal{F}_t^B \vee \sigma(x_0) \vee \mathcal{N})_{t \geq 0}$ . On the other hand, from the second line of (4.3), it follows that the process  $X^{\bar{\alpha}}(\cdot, \omega') = (X_t^{\bar{\alpha}}(\cdot, \omega'))_{0 \leq t \leq T}$  solves the above equation. From the pathwise uniqueness of strong solutions to equation (4.3), it follows that  $X_t^{\alpha^{\omega'}}(\omega) = X_t^{\bar{\alpha}}(\omega, \omega')$ , for all  $t \in [0, T]$ ,  $\mathbb{P}(d\omega)$ -a.s. By the Fubini theorem

$$\bar{J}(\tilde{\alpha}) = \bar{J}(\bar{\alpha}) = \int_{\Omega'} \mathbb{E} \left[ \int_0^T f_t(X^{\alpha^{\omega'}}, \alpha^{\omega'}) dt + g(X^{\alpha^{\omega'}}) \right] \mathbb{P}'(d\omega').$$

Since the inner expectation equals the gain  $J(\alpha^{\omega'})$ , it cannot exceed  $V$  and it follows that  $\bar{J}(\tilde{\alpha}) \leq \mathcal{V}_0$ . The claim follows from the arbitrariness of  $\tilde{\alpha}$ .  $\square$

The next result provides a decomposition of any element  $\nu \in \mathcal{V}$ , i.e.  $\mathcal{P}(\mathbb{F}^{W, \mu}) \otimes \mathcal{B}(A)$ -measurable and bounded.

**Lemma 4.2** (i) Let  $\nu \in \mathcal{V}$ , then there exists a  $\bar{\mathbb{P}}$ -null set  $\bar{N} \in \mathcal{N}$  such that  $\nu$  admits the following representation

$$\begin{aligned} \nu_t(\omega, \omega', a) &= \nu_t^{(0)}(\omega, a) 1_{\{0 < t \leq T_1(\omega')\}} \\ &\quad + \sum_{n=1}^{\infty} \nu_t^{(n)}(\omega, (T_1(\omega'), A_1(\omega')), \dots, (T_n(\omega'), A_n(\omega')), a) 1_{\{T_n(\omega') < t \leq T_{n+1}(\omega')\}}, \end{aligned}$$

for all  $(\omega, \omega', t, A) \in \bar{\Omega} \times \mathbb{R}_+ \times A$ ,  $(\omega, \omega') \notin \bar{N}$ , for some maps  $\nu^{(n)}: \Omega \times \mathbb{R}_+ \times (\mathbb{R}_+ \times A)^n \times A \rightarrow (0, \infty)$ ,  $n \geq 1$ , (resp.  $\nu^{(0)}: \Omega \times \mathbb{R}_+ \times A \rightarrow (0, \infty)$ ), which are  $\mathcal{P}(\mathbb{F}^W) \otimes \mathcal{B}((\mathbb{R}_+ \times A)^n) \otimes \mathcal{B}(A)$ -measurable

(resp.  $\mathcal{P}(\mathbb{F}^W) \otimes \mathcal{B}(A)$ -measurable) and uniformly bounded with respect to  $n$ . Moreover, if  $\nu \in \mathcal{V}_{\inf > 0}$  then  $\inf_{\bar{\Omega} \times [0, T] \times A} \nu^{(n)} > 0$  as well, for every  $n \geq 0$ .

(ii) Let  $\nu \in \mathcal{V}$ , then there exists  $\tilde{N} \in \mathcal{F}$ , with  $\mathbb{P}(\tilde{N}) = 0$ , such that the map  $\nu^\omega = \nu_t^\omega(\omega', a) : \Omega' \times \mathbb{R}_+ \times A \rightarrow (0, \infty)$ , defined by

$$\nu_t^\omega(\omega', a) := \nu_t(\omega, \omega', a), \quad (\omega', t, a) \in \Omega' \times \mathbb{R}_+ \times A,$$

belongs to  $\mathcal{V}'$  whenever  $\omega \notin \tilde{N}$ . Moreover, for every  $\omega \notin \tilde{N}$  there exists  $N_\omega \in \mathcal{N}'$  such that

$$\begin{aligned} \nu_t^\omega(\omega', a) &= \nu_t^{(0)}(\omega, a) 1_{\{0 < t \leq T_1(\omega')\}} \\ &+ \sum_{n=1}^{\infty} \nu_t^{(n)}(\omega, (T_1(\omega'), A_1(\omega')), \dots, (T_n(\omega'), A_n(\omega')), a) 1_{\{T_n(\omega') < t \leq T_{n+1}(\omega')\}}, \end{aligned} \quad (4.4)$$

for all  $(\omega', t, A) \in \Omega' \times \mathbb{R}_+ \times A$ ,  $\omega' \notin N'_\omega$ , where, clearly,  $\nu^{(n)}(\omega, \cdot)$  (resp.  $\nu^{(0)}(\omega, \cdot)$ ) is  $\mathcal{B}(\mathbb{R}_+) \otimes \mathcal{B}((\mathbb{R}_+ \times A)^n) \otimes \mathcal{B}(A)$ -measurable (resp.  $\mathcal{B}(\mathbb{R}_+) \otimes \mathcal{B}(A)$ -measurable).

**Proof.** The proof is an extension of the results in [18] Lemma 3.3, it is based on monotone class arguments and is left to the reader.  $\square$

By Lemma 4.2-(ii), given  $\nu \in \mathcal{V}$ , consider the process  $\nu^\omega \in \mathcal{V}'$ , with corresponding  $\mathbb{P}$ -null set  $\tilde{N} \in \mathcal{F}$ . Define the Doléans exponential process  $\kappa^{\nu^\omega}$  by formula (3.5) with  $\nu^\omega$  in place of  $\nu$ . Notice that by Lemma 4.2-(ii) we have  $\kappa_t^{\nu^\omega}(\omega') = \kappa_t^\nu(\omega, \omega')$ , for all  $(\omega', t) \in \Omega' \times \mathbb{R}_+$ , whenever  $\omega \notin \tilde{N}$ . Moreover, for  $\omega \notin \tilde{N}$ ,  $(\kappa_t^{\nu^\omega})_{t \geq 0}$  is a martingale with respect to  $\mathbb{P}'$  and  $\mathbb{F}^\mu$ . We claim that there exists a unique probability measure  $\mathbb{P}^{\nu^\omega}$  on  $(\Omega', \mathcal{F}_\infty^\mu)$  such that  $\mathbb{P}^{\nu^\omega}(d\omega') = \kappa_t^{\nu^\omega}(\omega') \mathbb{P}'(d\omega')$  on each  $\sigma$ -algebra  $\mathcal{F}_t^\mu$  and, by the Girsanov theorem, the  $\mathbb{F}^\mu$ -compensator of  $\mu$  under  $\mathbb{P}^{\nu^\omega}$  is given by the right-hand side of (4.4).

The verification of the claim is a standard argument: using the boundedness of  $\nu$  one first verifies that

$$\kappa_{t \wedge T_n}^{\nu^\omega}(\omega') \leq a_n e^{b T_n(\omega')}$$

for some constants  $a_n, b$ , which implies that  $(\kappa_{t \wedge T_n}^{\nu^\omega})_{t \geq 0}$  is a uniformly integrable martingale with respect to  $\mathbb{P}'$  and  $\mathbb{F}^\mu$ . Then the probabilities  $\mathbb{P}_n^{\nu^\omega}$  defined on  $\mathcal{F}_{T_n}^\mu$  setting  $\mathbb{P}_n^{\nu^\omega}(d\omega') = \kappa_{T_n}^{\nu^\omega}(\omega') \mathbb{P}'(d\omega')$  satisfy the compatibility condition:  $\mathbb{P}_{n+1}^{\nu^\omega} = \mathbb{P}_n^{\nu^\omega}$  on  $\mathcal{F}_{T_n}^\mu$  for every  $n$ . Arguing as in Theorem 3.6 in [18], by the Kolmogorov extension theorem there exists a unique probability  $\mathbb{P}^{\nu^\omega}$  on  $(\Omega', \mathcal{F}_\infty^\mu)$  such that  $\mathbb{P}^{\nu^\omega} = \mathbb{P}_n^{\nu^\omega}$  on each  $\mathcal{F}_{T_n}^\mu$ , and  $\mathbb{P}^{\nu^\omega}$  has the required properties.

We can now state the following key result (Lemma 4.3) from which the required conclusion of this subsection follows readily (see Proposition 4.1). Recall that  $(\Omega', \mathcal{F}', \mathbb{P}')$  denotes the canonical probability space constructed above.

**Lemma 4.3** *Given  $\nu \in \mathcal{V}_{\inf > 0}$ , there exist a sequence  $(T_n^\nu, A_n^\nu)_{n \geq 1}$  on  $(\bar{\Omega}, \bar{\mathcal{F}}, \bar{\mathbb{P}})$  and a  $\mathbb{P}$ -null set  $N \in \mathcal{F}$ , with  $\tilde{N} \subset N$  ( $\tilde{N}$  is the set appearing in Lemma 4.2-(ii)), such that:*

- (i) for every  $n \geq 1$ ,  $(T_n^\nu, A_n^\nu)$  takes values in  $(0, \infty) \times A$  and  $T_n^\nu < T_{n+1}^\nu$ ;
- (ii) for every  $n \geq 1$ ,  $T_n^\nu$  is an  $\mathbb{F}^{W, \mu'_\infty}$ -stopping time and  $A_n^\nu$  is  $\mathcal{F}_{T_n^\nu}^{W, \mu'_\infty}$ -measurable;
- (iii)  $\lim_{n \rightarrow \infty} T_n^\nu = \infty$ ;

(iv) for every  $\omega \notin N$ , we have

$$\mathcal{L}_{\mathbb{P}^\nu}((T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot))_{n \geq 1}) = \mathcal{L}_{\mathbb{P}^{\nu^\omega}}((T_n, A_n)_{n \geq 1}).$$

Finally, let  $\bar{\alpha}^\nu = a_0 1_{[0, T_1^\nu]} + \sum_{n=1}^\infty A_n^\nu 1_{[T_n^\nu, T_{n+1}^\nu)}(t)$  be the step process associated with  $(T_n^\nu, A_n^\nu)_{n \geq 1}$ . Then,  $\bar{\alpha}^\nu \in \mathcal{A}^{W, \mu'}$  and  $\mathcal{L}_{\mathbb{P}^\nu}(\bar{\alpha}^\nu(\omega, \cdot)) = \mathcal{L}_{\mathbb{P}^{\nu^\omega}}(I)$ ,  $\omega \notin N$ .

**Proof.** Suppose that we have already constructed a multivariate point process  $(T_n^\nu, A_n^\nu)_{n \geq 1}$  satisfying points (i)-(ii)-(iii)-(iv) of the Theorem. Then, by (ii) it follows that  $\bar{\alpha}^\nu$  is càdlàg and  $\mathbb{F}^{W, \mu'}$ -adapted, hence progressive. Moreover, by (iii), for every  $(\bar{\omega}, t) \in \bar{\Omega} \times [0, T]$  the series  $\sum_{n=1}^\infty A_n^\nu(\bar{\omega}) 1_{[T_n^\nu(\bar{\omega}), T_{n+1}^\nu)}(t)$  is a finite sum, and thus  $\bar{\alpha}^\nu \in \mathcal{A}^{W, \mu'}$ . Furthermore, by (iv) we see that  $\mathcal{L}_{\mathbb{P}^\nu}(\bar{\alpha}^\nu(\omega, \cdot)) = \mathcal{L}_{\mathbb{P}^{\nu^\omega}}(I)$ ,  $\omega \notin N$ .

Let us now construct  $(T_n^\nu, A_n^\nu)_{n \geq 1}$  satisfying points (i)-(ii)-(iii)-(iv). Fix  $\nu \in \mathcal{V}_{\inf > 0}$  and let  $\tilde{N} \in \mathcal{F}$  be as in Lemma 4.2. In particular, recall that formula (4.4) holds for some maps  $\nu^{(n)}$ ,  $n \geq 0$ , satisfying  $0 < \inf \nu^{(n)} \leq \sup \nu^{(n)} \leq M^\nu$ , for some constant  $M^\nu > 0$ , independent of  $n$ . Next recall the construction of the map  $\pi : \mathbb{R} \rightarrow A$  and the measure  $\lambda'$ . Accordingly, we split the rest of the proof into two cases.

**Case I:  $A_c = \emptyset$ , so that  $A = A_{nc}$  is uncountable.** In this case  $\pi : \mathbb{R} \rightarrow A$  is a Borel isomorphism, so to shorten notation we identify  $A$  with  $\mathbb{R}$  and use the notations  $A, \lambda, A_n, \mu, \mathbb{F}^{W, \mu_\infty} = (\mathcal{F}_t^{W, \mu_\infty})_{t \geq 0}$  instead of  $\mathbb{R}, \lambda', R_n, \bar{\mu}, \mathbb{F}^{W, \mu'_\infty} = (\mathcal{F}_t^{W, \mu'_\infty})_{t \geq 0}$ . Since we are treating the case  $A_c = \emptyset$ , we have  $\lambda(\{a\}) = 0$  for every  $a \in A$ . We construct by induction on  $n \geq 1$  a sequence  $(T_n^\nu, A_n^\nu)_{n \geq 1}$  and a  $\mathbb{P}$ -null set  $N \in \mathcal{F}$ , with  $\tilde{N} \subset N$ , such that  $(T_n^\nu, A_n^\nu)_{n \geq 1}$  satisfies properties (i) and (ii) of the Theorem, and also the following properties:

(iii)' for every  $n \geq 1$ , we have  $T_n^\nu \geq T_n/M^\nu$ ;

(iv)' for every  $n \geq 1$  and  $\omega \notin N$ , we have

$$\mathcal{L}_{\mathbb{P}^\nu}(T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot)) = \mathcal{L}_{\mathbb{P}^{\nu^\omega}}(T_1, A_1, \dots, T_n, A_n). \quad (4.5)$$

Notice that (iv)' is equivalent to (iv). Moreover, since  $\lim_{n \rightarrow \infty} T_n = \infty$ , we see that (iii)' implies property (iii).

**Step 1: the case  $n = 1$ .** Define

$$\theta_t^{(1)}(\omega) := \frac{1}{\lambda(A)} \int_0^t \int_A \nu_s^{(0)}(\omega, a) \lambda(da) ds. \quad (4.6)$$

Since  $0 < \inf \nu^{(0)} \leq \sup \nu^{(0)} \leq M^\nu$ , we see that, for every  $\omega \in \Omega$ , the map  $t \mapsto \theta_t^{(1)}(\omega)$  is continuous, strictly increasing,  $\theta_0^{(1)}(\omega) = 0$ ,  $\theta_t^{(1)}(\omega) \leq M^\nu t$ , and  $\theta_t^{(1)}(\omega) \nearrow \infty$  as  $t$  goes to infinity. Then there exists a unique  $T_1^\nu : \bar{\Omega} \rightarrow \mathbb{R}_+$  such that

$$\theta_{T_1^\nu(\bar{\omega})}^{(1)}(\omega) = T_1(\omega').$$

Notice that  $T_1^\nu \geq T_1/M_1^\nu$ . Moreover, since  $T_1 > 0$ , we also have  $T_1^\nu > 0$ . Let  $\bar{E}_{T_1} := \{(\bar{\omega}, t) \in \bar{\Omega} \times \mathbb{R}_+ : \theta_t^{(1)}(\omega) = T_1(\omega')\}$ . Since the process  $(\bar{\omega}, t) \mapsto (\theta_t^{(1)}(\omega), T_1(\omega'))$  is  $\mathbb{F}^{W, \mu_\infty}$ -adapted and continuous,  $\bar{E}_{T_1}$  is an  $\mathbb{F}^{W, \mu_\infty}$ -optional set (in fact, predictable). Since  $T_1^\nu(\bar{\omega}) = \inf\{t \in \mathbb{R}_+ : (\bar{\omega}, t) \in \bar{E}_{T_1}\}$  is the début of  $\bar{E}_{T_1}$ , from Theorem 1.14 of [19] it follows that  $T_1^\nu$  is an  $\mathbb{F}^{W, \mu_\infty}$ -stopping time.

In particular,  $T_1^\nu$  is  $\bar{\mathcal{F}}$ -measurable, therefore there exists a  $\mathbb{P}$ -null set  $N_{T_1^\nu} \in \mathcal{F}$  such that  $T_1^\nu(\omega, \cdot)$  is  $\mathcal{F}'$ -measurable, whenever  $\omega \notin N_{T_1^\nu}$ .

Now define

$$F_b := \mathbb{P}'(A_1 \leq b) = \frac{\lambda((-\infty, b])}{\lambda(A)}, \quad F_b^{(1)}(\bar{\omega}) := \frac{\int_{-\infty}^b \nu_{T_1^\nu(\bar{\omega})}^{(0)}(\omega, a) \lambda(da)}{\int_{-\infty}^{+\infty} \nu_{T_1^\nu(\bar{\omega})}^{(0)}(\omega, a) \lambda(da)}.$$

Since  $\inf \nu^{(0)} > 0$  and  $\lambda(\{a\}) = 0$  for any  $a \in A$ , we see that, for every  $\bar{\omega} \in \bar{\Omega}$ , the map  $b \mapsto F_b^{(1)}(\bar{\omega})$  is continuous, strictly increasing, valued in  $(0, 1)$ , and  $\lim_{b \rightarrow -\infty} F_b^{(1)}(\bar{\omega}) = 0$ ,  $\lim_{b \rightarrow +\infty} F_b^{(1)}(\bar{\omega}) = 1$ . Then, there exists a unique  $A_1^\nu: \bar{\Omega} \rightarrow \mathbb{R}$  such that

$$F_{A_1^\nu(\bar{\omega})}^{(1)}(\bar{\omega}) = F_{A_1}(\omega').$$

We note that the process

$$(\bar{\omega}, t) \mapsto \frac{\int_{-\infty}^b \nu_t^{(0)}(\omega, a) \lambda(da)}{\int_{-\infty}^{+\infty} \nu_t^{(0)}(\omega, a) \lambda(da)}$$

is predictable with respect to  $\mathbb{F}^W$ , hence it is also  $\mathbb{F}^{W, \mu_\infty}$ -progressive. Substituting  $t$  with  $T_1^\nu(\bar{\omega})$  we conclude that  $F_b^{(1)}$  is  $(\mathcal{F}_{T_1^\nu}^{W, \mu_\infty})$ -measurable. Since  $A_1$  is clearly  $\mathcal{F}'$ -measurable and  $\mathcal{F}' \subset \mathcal{F}_0^{W, \mu_\infty} \subset \mathcal{F}_{T_1^\nu}^{W, \mu_\infty}$ ,  $A_1$  is also  $(\mathcal{F}_{T_1^\nu}^{W, \mu_\infty})$ -measurable. Recalling the continuity of  $b \mapsto F_b^{(1)}(\bar{\omega})$  it is easy to conclude that  $A_1^\nu$  is  $(\mathcal{F}_{T_1^\nu}^{W, \mu_\infty})$ -measurable. This implies that  $A_1^\nu \vee a$  is also  $\mathcal{F}_{T_1^\nu}^{W, \mu_\infty}$ -measurable. From the arbitrariness of  $a$ , we deduce that  $A_1^\nu$  is  $\mathcal{F}_{T_1^\nu}^{W, \mu_\infty}$ -measurable. In particular,  $A_1^\nu$  is  $\bar{\mathcal{F}}$ -measurable, therefore there exists a  $\mathbb{P}$ -null set  $N_{A_1^\nu} \in \mathcal{F}$  such that  $A_1^\nu(\omega, \cdot)$  is  $\mathcal{F}'$ -measurable, whenever  $\omega \notin N_{A_1^\nu}$ .

In order to conclude the proof of the case  $n = 1$ , let us prove that (4.5) holds for  $n = 1$ , whenever  $\omega \notin N_1 := \tilde{N} \cup N_{T_1^\nu} \cup N_{A_1^\nu}$ . We begin recalling that, for every  $\omega \notin \tilde{N}$ , the  $\mathbb{F}^\mu$ -compensator of  $\mu$  under  $\mathbb{P}^{\nu^\omega}$  is given by the right-hand side of (4.4), so that in particular we have

$$\mathbb{P}^{\nu^\omega}(T_1 > t) = \exp\left(-\int_0^t \int_A \nu_s^{(0)}(\omega, a) \lambda(da) ds\right) = \exp(-\lambda(A)\theta_t^{(1)}(\omega)).$$

Notice that

$$\mathbb{P}'(T_1^\nu(\omega, \cdot) > t) = \mathbb{P}'(\theta_{T_1^\nu(\omega, \cdot)}^{(1)}(\omega) > \theta_t^{(1)}(\omega)) = \mathbb{P}'(T_1 > \theta_t^{(1)}(\omega)) = \exp(-\lambda(A)\theta_t^{(1)}(\omega)),$$

for every  $\omega \notin N_{T_1^\nu}$ , where for the last equality we used the formula  $\mathbb{P}'(T_1 > t) = \exp(-\lambda(A)t)$ . Therefore  $\mathcal{L}_{\mathbb{P}'}(T_1^\nu(\omega, \cdot)) = \mathcal{L}_{\mathbb{P}^{\nu^\omega}}(T_1)$ , for every  $\omega \notin \tilde{N} \cup N_{T_1^\nu}$ . Now, recall that, for every  $\omega \notin \tilde{N}$ , we have,  $\mathbb{P}'$ -a.s.,

$$\mathbb{P}^{\nu^\omega}(A_1 \leq b \mid \sigma(T_1)) = \frac{\int_{-\infty}^b \nu_{T_1}^{(0)}(\omega, a) \lambda(da)}{\int_{-\infty}^{+\infty} \nu_{T_1}^{(0)}(\omega, a) \lambda(da)}.$$

On the other hand, for every  $\omega \notin N_{T_1^\nu} \cup N_{A_1^\nu}$ ,  $\mathbb{P}'$ -a.s.,

$$\begin{aligned} \mathbb{P}'(A_1^\nu(\omega, \cdot) \leq b \mid \sigma(T_1^\nu(\omega, \cdot))) &= \mathbb{P}'(F_{A_1^\nu(\omega, \cdot)}^{(1)}(\omega, \cdot) \leq F_b^{(1)}(\omega, \cdot) \mid \sigma(T_1^\nu(\omega, \cdot))) \\ &= \mathbb{P}'(F_{A_1} \leq F_b^{(1)}(\omega, \cdot) \mid \sigma(T_1^\nu(\omega, \cdot))). \end{aligned}$$



Since  $A_1$  is independent of  $T_1$  under  $\mathbb{P}'$  and  $T_1^\nu(\omega, \cdot)$  is  $\sigma(T_1)$ -measurable, it follows that  $A_1$  is also independent of  $T_1^\nu(\omega, \cdot)$ . Moreover, by definition we see that  $F_b^{(1)}(\omega, \cdot)$  is  $\sigma(T_1^\nu(\omega, \cdot))$ -measurable. Therefore, for every  $\omega \notin N_{T_1^\nu} \cup N_{A_1^\nu}$ , we have,  $\mathbb{P}'$ -a.s.,

$$\mathbb{P}'(F_{A_1} \leq F_b^{(1)}(\omega, \cdot) \mid \sigma(T_1^\nu(\omega, \cdot))) = \mathbb{P}'(F_{A_1} \leq a) \Big|_{a=F_b^{(1)}(\omega, \cdot)} = F_b^{(1)}(\omega, \cdot),$$

where we used the fact that  $F_{A_1}$  is uniformly distributed in  $(0, 1)$  under  $\mathbb{P}'$ . As a consequence, recalling that  $\mathcal{L}_{\mathbb{P}'}(T_1^\nu(\omega, \cdot)) = \mathcal{L}_{\mathbb{P}^\nu}(\omega, T_1)$ , for every  $\omega \notin \tilde{N} \cup N_{T_1^\nu}$ , we deduce that  $\mathcal{L}_{\mathbb{P}'}(T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot)) = \mathcal{L}_{\mathbb{P}^\nu}(\omega, T_1, A_1)$ , whenever  $\omega \notin N_1$ . This concludes the proof of the base case  $n = 1$ .

**Step 2: the inductive step.** Fix  $n \geq 1$  and suppose we are given  $(T_1^\nu, A_1^\nu), \dots, (T_n^\nu, A_n^\nu)$  satisfying points (i) and (ii) of the Theorem. Suppose also that (4.5) holds for the fixed  $n$ , whenever  $\omega \notin N_n$ , for some  $\mathbb{P}$ -null set  $N_n \in \mathcal{F}$  in place of  $N$ , with  $\tilde{N} \subset N_n$ .

Given  $\theta^{(1)}$  as in (4.6), we define recursively, for  $i = 1, \dots, n$ ,

$$\begin{aligned} \theta_t^{(i+1)}(\bar{\omega}) &:= \theta_{T_i^\nu(\bar{\omega}) \wedge t}^{(i)}(\bar{\omega}) \\ &+ \frac{1}{\lambda(A)} \int_{T_i^\nu(\bar{\omega})}^{T_i^\nu(\bar{\omega}) \vee t} \int_A \nu_s^{(i)}(\omega, (T_1^\nu(\bar{\omega}), A_1^\nu(\bar{\omega})), \dots, (T_i^\nu(\bar{\omega}), A_i^\nu(\bar{\omega})), a) \lambda(da) ds. \end{aligned} \quad (4.7)$$

Since  $0 < \inf \nu^{(i)} \leq \sup \nu^{(i)} \leq M^\nu$ , we see that, for every  $\bar{\omega} \in \bar{\Omega}$  and  $i = 1, \dots, n$ , the map  $t \mapsto \theta_t^{(i+1)}(\bar{\omega})$  is continuous, strictly increasing,  $\theta_0^{(i+1)}(\bar{\omega}) = 0$ ,  $\theta_t^{(i+1)}(\bar{\omega}) \leq M^\nu t$ , and  $\theta_t^{(i+1)}(\bar{\omega}) \nearrow \infty$  as  $t$  goes to infinity. Then, there exists a unique  $T_{n+1}^\nu: \bar{\Omega} \rightarrow \mathbb{R}_+$  such that

$$\theta_{T_{n+1}^\nu(\bar{\omega})}^{(n+1)}(\bar{\omega}) = T_{n+1}(\omega').$$

Notice that  $T_{n+1}^\nu \geq T_{n+1}/M^\nu$ . Moreover, since  $T_{n+1} > T_n$ , we also have  $T_{n+1}^\nu > T_n^\nu$ . Indeed, arguing by contradiction, suppose that  $T_{n+1}^\nu(\bar{\omega}) \leq T_n^\nu(\bar{\omega})$  for some  $\bar{\omega} \in \bar{\Omega}$ . Then

$$\theta_{T_n^\nu(\bar{\omega})}^{(n)}(\bar{\omega}) = T_n(\omega') < T_{n+1}(\omega') = \theta_{T_{n+1}^\nu(\bar{\omega})}^{(n+1)}(\bar{\omega}) = \theta_{T_{n+1}^\nu(\bar{\omega})}^{(n)}(\bar{\omega}),$$

where the last equality follows from (4.7). From the monotonicity of  $\theta^{(n)}$ , we get  $T_n^\nu(\bar{\omega}) < T_{n+1}^\nu(\bar{\omega})$ , which yields a contradiction.

Reasoning in the same way as for  $T_1^\nu$ , since  $T_{n+1}^\nu$  is the d ebut of  $\bar{E}_{T_{n+1}^\nu} := \{(\bar{\omega}, t) \in \bar{\Omega} \times \mathbb{R}_+ : \theta_t^{(n+1)}(\bar{\omega}) = T_{n+1}(\omega')\}$ , it is an  $\mathbb{F}^{W, \mu_\infty}$ -stopping time. In particular,  $T_{n+1}^\nu$  is  $\bar{\mathcal{F}}$ -measurable, so that there exists a  $\mathbb{P}$ -null set  $N_{T_{n+1}^\nu} \in \mathcal{F}$  such that  $T_{n+1}^\nu(\omega, \cdot)$  is  $\mathcal{F}'$ -measurable, whenever  $\omega \notin N_{T_{n+1}^\nu}$ .

Now define  $F_b = \mathbb{P}'(A_1 \leq b) = \lambda((-\infty, b])/\lambda(A)$  as before and

$$F_b^{(n+1)}(\bar{\omega}) := \frac{\int_{-\infty}^b \nu_{T_{n+1}^\nu(\bar{\omega})}^{(n)}(\omega, (T_1^\nu(\bar{\omega}), A_1^\nu(\bar{\omega})), \dots, (T_n^\nu(\bar{\omega}), A_n^\nu(\bar{\omega})), a) \lambda(da)}{\int_{-\infty}^{+\infty} \nu_{T_{n+1}^\nu(\bar{\omega})}^{(n)}(\omega, (T_1^\nu(\bar{\omega}), A_1^\nu(\bar{\omega})), \dots, (T_n^\nu(\bar{\omega}), A_n^\nu(\bar{\omega})), a) \lambda(da)}.$$

Since  $\inf \nu^{(n)} > 0$  and  $\lambda(\{a\}) = 0$  for any  $a \in A$ , we see that, for every  $\bar{\omega} \in \bar{\Omega}$ , the map  $b \mapsto F_b^{(n+1)}(\bar{\omega})$  is continuous, strictly increasing, valued in  $(0, 1)$ , and  $\lim_{b \rightarrow -\infty} F_b^{(n+1)}(\bar{\omega}) = 0$ ,  $\lim_{b \rightarrow +\infty} F_b^{(n+1)}(\bar{\omega}) = 1$ . Then, proceeding along the same lines as for the construction of  $A_1^\nu$ , we see that there exists a unique  $\mathcal{F}_{T_{n+1}^\nu}^{W, \mu_\infty}$ -measurable map  $A_{n+1}^\nu: \bar{\Omega} \rightarrow \mathbb{R}$  such that

$$F_{A_{n+1}^\nu(\bar{\omega})}^{(n+1)}(\bar{\omega}) = F_{A_{n+1}}(\omega').$$

In particular,  $A_{n+1}^\nu$  is  $\bar{\mathcal{F}}$ -measurable, therefore there exists a  $\mathbb{P}$ -null set  $N_{A_{n+1}^\nu} \in \mathcal{F}$  such that  $A_{n+1}^\nu(\omega, \cdot)$  is  $\mathcal{F}'$ -measurable, whenever  $\omega \notin N_{A_{n+1}^\nu}$ .

In order to conclude the proof of the inductive step, let us prove that (4.5) holds for  $n+1$ , whenever  $\omega \notin N_{n+1} := N_n \cup N_{T_{n+1}^\nu} \cup N_{A_{n+1}^\nu}$ . Set  $S_{n+1} = T_{n+1} - T_n$  and recall that, for every  $\omega \notin \tilde{N}$ , the  $\mathbb{F}^\mu$ -compensator of  $\mu$  under  $\mathbb{P}^{\nu^\omega}$  is given by the right-hand side of (4.4), so that in particular we have,  $\mathbb{P}'$ -a.s.,

$$\begin{aligned} & \mathbb{P}^{\nu^\omega}(S_{n+1} > t \mid \sigma(T_1, A_1, \dots, T_n, A_n)) \\ &= \exp\left(-\int_{T_n}^{T_n+t} \int_A \nu_s^{(n)}(\omega, (T_1, A_1), \dots, (T_n, A_n), a) \lambda(da) ds\right). \end{aligned} \quad (4.8)$$

Define  $S_{n+1}^\nu := T_{n+1}^\nu - T_n^\nu$  and observe that, whenever  $\omega \notin N_n \cup N_{T_{n+1}^\nu}$ ,  $\mathbb{P}'$ -a.s.,

$$\begin{aligned} & \mathbb{P}'(S_{n+1}^\nu(\omega, \cdot) > t \mid \sigma(T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot))) \\ &= \mathbb{P}'(\theta_{T_{n+1}^\nu(\omega, \cdot)}^{(n+1)}(\omega, \cdot) > \theta_{T_n^\nu(\omega, \cdot)+t}^{(n+1)}(\omega, \cdot) \mid \sigma(T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot))) \\ &= \mathbb{P}'\left(T_{n+1} > \frac{1}{\lambda(A)} \int_{T_n^\nu(\omega, \cdot)}^{T_n^\nu(\omega, \cdot)+t} \int_A \nu_s^{(n)}(\omega, T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot), a) \lambda(da) ds \right. \\ & \quad \left. + \theta_{T_n^\nu(\omega, \cdot)}^{(n)}(\omega, \cdot) \mid \sigma(T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot))\right) \\ &= \mathbb{P}'\left(S_{n+1} > \frac{1}{\lambda(A)} \int_{T_n^\nu(\omega, \cdot)}^{T_n^\nu(\omega, \cdot)+t} \int_A \nu_s^{(n)}(\omega, \dots, a) \lambda(da) ds \mid \sigma(T_1^\nu(\omega, \cdot), \dots, A_n^\nu(\omega, \cdot))\right). \end{aligned}$$

Recall now that  $S_{n+1}$  is independent of  $(T_1, A_1, \dots, T_n, A_n)$  under  $\mathbb{P}'$ , and note that, by construction,  $(T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot))$  is  $\sigma(T_1, A_1, \dots, T_n, A_n)$ -measurable. Therefore,  $S_{n+1}$  is also independent of  $(T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot))$ . As a consequence, for every  $\omega \notin N_n \cup N_{T_{n+1}^\nu}$ ,  $\mathbb{P}'$ -a.s.,

$$\begin{aligned} & \mathbb{P}'\left(S_{n+1} > \frac{1}{\lambda(A)} \int_{T_n^\nu(\omega, \cdot)}^{T_n^\nu(\omega, \cdot)+t} \int_A \nu_s^{(n)}(\omega, \dots, a) \lambda(da) ds \mid \sigma(T_1^\nu(\omega, \cdot), \dots, A_n^\nu(\omega, \cdot))\right) \\ &= \mathbb{P}'(S_{n+1} > r) \Big|_{r=\frac{1}{\lambda(A)} \int_{T_n^\nu(\omega, \cdot)}^{T_n^\nu(\omega, \cdot)+t} \int_A \nu_s^{(n)}(\omega, \dots, a) \lambda(da) ds} \\ &= \exp\left(-\int_{T_n^\nu(\omega, \cdot)}^{T_n^\nu(\omega, \cdot)+t} \int_A \nu_s^{(n)}(\omega, (T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot)), a) \lambda(da) ds\right), \end{aligned}$$

where for the last equality we used the formula  $\mathbb{P}'(S_{n+1} > r) = \exp(-\lambda(A)r)$ . Comparing with (4.8), we see that the conditional distribution of  $S_{n+1}^\nu$  given  $T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot)$  under  $\mathbb{P}'$  is the same as the conditional distribution of  $S_{n+1}$  given  $T_1, A_1, \dots, T_n, A_n$  under  $\mathbb{P}^{\nu^\omega}$ . Together with the inductive assumption (4.5) this proves that

$$\mathcal{L}_{\mathbb{P}'}(T_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot), T_{n+1}^\nu(\omega, \cdot)) = \mathcal{L}_{\mathbb{P}^{\nu^\omega}}(T_1, \dots, T_n, A_n, T_{n+1}), \quad (4.9)$$

for every  $\omega \notin N_n \cup N_{T_{n+1}^\nu}$ . Now, recall that, for every  $\omega \notin \tilde{N}$ ,  $\mathbb{P}'$ -a.s.,

$$\mathbb{P}^{\nu^\omega}(A_{n+1} \leq b \mid \sigma(T_1, \dots, A_n, T_{n+1})) = \frac{\int_{-\infty}^b \nu_{T_{n+1}}^{(n)}(\omega, (T_1, A_1), \dots, (T_n, A_n), a) \lambda(da)}{\int_{-\infty}^{+\infty} \nu_{T_{n+1}}^{(n)}(\omega, (T_1, A_1), \dots, (T_n, A_n), a) \lambda(da)}. \quad (4.10)$$

On the other hand, for every  $\omega \notin N_{n+1}$ , we have,  $\mathbb{P}'$ -a.s.,

$$\begin{aligned} & \mathbb{P}'(A_{n+1}^\nu(\omega, \cdot) \leq b \mid \sigma(T_1^\nu(\omega, \cdot), \dots, A_n^\nu(\omega, \cdot), T_{n+1}^\nu(\omega, \cdot))) \\ &= \mathbb{P}'(F_{A_{n+1}^\nu(\omega, \cdot)}^{(n+1)}(\omega, \cdot) \leq F_b^{(n+1)}(\omega, \cdot) \mid \sigma(T_1^\nu(\omega, \cdot), \dots, A_n^\nu(\omega, \cdot), T_{n+1}^\nu(\omega, \cdot))) \\ &= \mathbb{P}'(F_{A_{n+1}} \leq F_b^{(n+1)}(\omega, \cdot) \mid \sigma(T_1^\nu(\omega, \cdot), \dots, A_n^\nu(\omega, \cdot), T_{n+1}^\nu(\omega, \cdot))). \end{aligned}$$

Since  $A_{n+1}$  is independent of  $(T_1, \dots, A_n, T_{n+1})$  under  $\mathbb{P}'$  and  $(T_1^\nu(\omega, \cdot), \dots, A_n^\nu(\omega, \cdot), T_{n+1}^\nu(\omega, \cdot))$  is  $\sigma(T_1, \dots, A_n, T_{n+1})$ -measurable, it follows that  $A_{n+1}$  is also independent of  $(T_1^\nu(\omega, \cdot), \dots, A_n^\nu(\omega, \cdot), T_{n+1}^\nu(\omega, \cdot))$ . Moreover, by definition we see that  $F_b^{(n+1)}(\omega, \cdot)$  is  $\sigma(T_1^\nu(\omega, \cdot), \dots, A_n^\nu(\omega, \cdot), T_{n+1}^\nu(\omega, \cdot))$ -measurable. Therefore, for every  $\omega \notin N_{n+1}$ , we have,  $\mathbb{P}'$ -a.s.,

$$\begin{aligned} & \mathbb{P}'(F_{A_{n+1}} \leq F_b^{(n+1)}(\omega, \cdot) \mid \sigma(T_1^\nu(\omega, \cdot), \dots, A_n^\nu(\omega, \cdot), T_{n+1}^\nu(\omega, \cdot))) \\ &= \mathbb{P}'(F_{A_{n+1}} \leq a) \Big|_{a=F_b^{(n+1)}(\omega, \cdot)} = F_b^{(n+1)}(\omega, \cdot), \end{aligned}$$

where we used the fact that  $F_{A_{n+1}}$  is uniformly distributed in  $(0, 1)$  under  $\mathbb{P}'$ . Comparing with (4.10), we see that the conditional distribution of  $A_{n+1}^\nu$  given  $T_1^\nu(\omega, \cdot), A_1^\nu(\omega, \cdot), \dots, T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot), T_{n+1}^\nu(\omega, \cdot)$  under  $\mathbb{P}'$  is the same as the conditional distribution of  $A_{n+1}$  given  $T_1, A_1, \dots, T_n, A_n, T_{n+1}$  under  $\mathbb{P}^{\nu\omega}$ . Therefore, by (4.9) we deduce that (4.5) holds for  $n+1$ , whenever  $\omega \notin N_{n+1}$ , which concludes the proof of the inductive step and also the proof of Case I.

**Case II:**  $A_c \neq \emptyset$ . Let  $\pi : \mathbb{R} \rightarrow A$  be the canonical projection (4.1) or (4.2) according whether  $A_{nc} = \emptyset$  or  $A_{nc} \neq \emptyset$ . The idea of the proof is to construct a random sequence with values in  $(0, \infty) \times \mathbb{R}$  using the Case I previously addressed, and obtain the required sequence  $(T_n^\nu, A_n^\nu)_{n \geq 1}$  by projecting the second component onto  $A$ . The detailed construction and proof is presented below in the case  $A_{nc} = \emptyset$ , the other one being simpler and entirely analogous.

Given  $\nu \in \mathcal{V}_{\inf > 0}$ , define  $\bar{\nu} = \bar{\nu}_t(\omega, \omega', r) : \bar{\Omega} \times \mathbb{R}_+ \times \mathbb{R} \rightarrow (0, \infty)$  by

$$\bar{\nu}_t(\omega, \omega', r) := \nu_t(\omega, \omega', \pi(r)).$$

By a monotone class argument we see that  $\bar{\nu}$  is  $\mathcal{P}(\mathbb{F}^{W, \mu'}) \otimes \mathcal{B}(\mathbb{R})$ -measurable. Then we can perform the construction presented in step I, with  $\mathbb{R}, \lambda', \bar{\nu}, R_n, \mu', \mathbb{F}^{W, \mu'_\infty} = (\mathcal{F}_t^{W, \mu'_\infty})_{t \geq 0}$  instead of  $A, \lambda, \nu, A_n, \mu, \mathbb{F}^{W, \mu_\infty} = (\mathcal{F}_t^{W, \mu_\infty})_{t \geq 0}$ , respectively. This way we obtain a  $\mathbb{P}$ -null set  $N \in \mathcal{F}$  and a sequence  $(\bar{T}_n^\nu, \bar{R}_n^\nu)_{n \geq 1}$  with values in  $(0, \infty) \times \mathbb{R}$  such that  $\bar{T}_n^\nu < \bar{T}_{n+1}^\nu \nearrow \infty$ ,  $\bar{T}_n^\nu$  is an  $\mathbb{F}^{W, \bar{\mu}_\infty}$ -stopping time and  $\bar{R}_n^\nu$  is  $\mathcal{F}_{\bar{T}_n^\nu}^{W, \bar{\mu}_\infty}$ -measurable, and

$$\mathcal{L}_{\mathbb{P}'}((\bar{T}_n^\nu(\omega, \cdot), \bar{R}_n^\nu(\omega, \cdot))_{n \geq 1}) = \mathcal{L}_{\mathbb{P}^{\bar{\nu}\omega}}((T_n, R_n)_{n \geq 1}) \quad (4.11)$$

for every  $\omega \notin N$ . We define the required sequence  $(T_n^\nu, A_n^\nu)_{n \geq 1}$  setting

$$T_n^\nu := \bar{T}_n^\nu, \quad A_n^\nu := \pi(\bar{R}_n^\nu).$$

Clearly, conditions (i)-(ii)-(iii) of the Theorem hold true and, recalling the notation  $A_n = \pi(R_n)$ , from (4.11) it follows that

$$\mathcal{L}_{\mathbb{P}'}((T_n^\nu(\omega, \cdot), A_n^\nu(\omega, \cdot))_{n \geq 1}) = \mathcal{L}_{\mathbb{P}^{\bar{\nu}\omega}}((T_n, A_n)_{n \geq 1}). \quad (4.12)$$

Next note that, by the definition of  $\bar{\nu}$ ,

$$\int_{\mathbb{R}} (1 - \bar{\nu}_t(r)) \lambda'(dr) = \int_{(0, \infty)} (1 - \bar{\nu}_t(r)) \lambda'(dr) + \sum_{j \in A_c} \int_{I_j} (1 - \bar{\nu}_t(r)) \lambda'(dr)$$

$$\begin{aligned}
&= \int_{A_{nc}} (1 - \nu_t(s))\lambda(da) + \sum_{j \in A_c} (1 - \nu_t(j))\lambda(\{j\}) \\
&= \int_A (1 - \nu_s(a))\lambda(da)
\end{aligned}$$

and  $\bar{\nu}_{T_n}(R_n) = \nu_{T_n}(\pi(R_n)) = \nu_{T_n}(A_n)$ , so that

$$\begin{aligned}
\kappa_t^{\bar{\nu}} &= \exp\left(\int_0^t \int_{\mathbb{R}} (1 - \bar{\nu}_s(r))\lambda'(dr) ds\right) \prod_{T_n \leq t} \bar{\nu}_{T_n}(R_n) \\
&= \exp\left(\int_0^t \int_A (1 - \nu_s(a))\lambda(da) ds\right) \prod_{T_n \leq t} \nu_{T_n}(A_n) \\
&= \kappa_t^{\nu}.
\end{aligned}$$

Therefore we have, for  $\omega \notin N$ , on every  $\sigma$ -algebra  $\mathcal{F}_t^\mu$ ,

$$\mathbb{P}^{\bar{\nu}^\omega}(d\omega') = \kappa_t^{\bar{\nu}}(\omega, \omega') \mathbb{P}'(d\omega') = \kappa_t^{\nu}(\omega, \omega') \mathbb{P}'(d\omega') = \mathbb{P}^{\nu^\omega}(d\omega')$$

and property (iv) of the Theorem follows from (4.12). The proof is finished.  $\square$

We can now prove the main result of this subsection and conclude the proof of the inequality  $\nu_0^{\mathcal{R}} \leq \nu_0$ .

**Proposition 4.1** *For every  $\nu \in \mathcal{V}_{\text{inf} > 0}$  there exists  $\bar{\alpha}^\nu \in \mathcal{A}^{W, \mu'}$  such that*

$$\mathcal{L}_{\mathbb{P}^\nu}(x_0, B, I) = \mathcal{L}_{\mathbb{P}}(x_0, B, \bar{\alpha}^\nu). \quad (4.13)$$

*In particular,  $V$  and  $W$  are standard Wiener processes,  $V, W, x_0$  are all independent under  $\mathbb{P}^\nu$ , and we have*

$$\mathcal{L}_{\mathbb{P}^\nu}(X, I) = \mathcal{L}_{\mathbb{P}}(X^{\bar{\alpha}^\nu}, \bar{\alpha}^\nu), \quad J^{\mathcal{R}}(\nu) = \bar{J}(\bar{\alpha}^\nu). \quad (4.14)$$

*Finally,  $\nu_0^{\mathcal{R}} := \sup_{\nu \in \mathcal{V}} J^{\mathcal{R}}(\nu) \leq \sup_{\bar{\alpha} \in \mathcal{A}^{W, \mu'}} \bar{J}(\bar{\alpha}) = \sup_{\alpha \in \mathcal{A}^W} J(\alpha) =: \nu_0$ .*

**Proof.** Suppose that (4.13) holds. Then, from equation (2.5) and Assumption **(A1)** it is well-known that the first equality in (4.14) holds as well, and this implies the second equality. From the arbitrariness of  $\nu \in \mathcal{V}_{\text{inf} > 0}$ , we deduce that  $\sup_{\nu \in \mathcal{V}_{\text{inf} > 0}} J^{\mathcal{R}}(\nu) \leq \sup_{\bar{\alpha} \in \mathcal{A}^{W, \mu'}} \bar{J}(\bar{\alpha})$ . Since  $\sup_{\nu \in \mathcal{V}_{\text{inf} > 0}} J^{\mathcal{R}}(\nu) = \sup_{\nu \in \mathcal{V}} J^{\mathcal{R}}(\nu)$  by (3.9), we conclude that  $\sup_{\nu \in \mathcal{V}} J^{\mathcal{R}}(\nu) \leq \sup_{\bar{\alpha} \in \mathcal{A}^{W, \mu'}} \bar{J}(\bar{\alpha}) = \sup_{\alpha \in \mathcal{A}^W} J(\alpha)$ , where the last equality follows from Lemma 4.1.

Let us now prove (4.13). Fix  $\nu \in \mathcal{V}_{\text{inf} > 0}$  and consider the process  $\bar{\alpha}^\nu$  given by Lemma 4.3. In order to prove (4.13), we have to show that

$$\bar{\mathbb{E}}[\kappa_T^\nu \chi(x_0) \psi(B) \phi(I)] = \bar{\mathbb{E}}[\chi(x_0) \psi(B) \phi(\bar{\alpha}^\nu)], \quad (4.15)$$

for any  $\chi \in B_b(\mathbb{R}^n)$  (the space of bounded Borel measurable real functions on  $\mathbb{R}^n$ ), for any  $\psi \in B_b(\mathbf{C}_{m+d})$  (the space of bounded Borel measurable real functions on  $\mathbf{C}_{m+d}$ , which denotes the space of continuous paths from  $[0, T]$  to  $\mathbb{R}^{m+d}$  endowed with the supremum norm) and any  $\phi \in B_b(\mathbf{D}_A)$  (the space of bounded Borel measurable real functions on  $\mathbf{D}_A$ , which denotes the space of càdlàg paths from  $[0, T]$  to  $A$  endowed with the supremum norm). By the Fubini theorem, (4.15) can be rewritten as

$$\int_{\Omega} \chi(x_0(\omega)) \psi(B(\omega)) \left( \int_{\Omega'} \kappa_T^\nu(\omega, \omega') \phi(I(\omega')) \mathbb{P}'(d\omega') \right) \mathbb{P}(d\omega)$$

$$= \int_{\Omega} \chi(x_0(\omega)) \psi(B(\omega)) \left( \int_{\Omega'} \phi(\bar{\alpha}^\nu(\omega, \omega')) \mathbb{P}'(d\omega') \right) \mathbb{P}(d\omega).$$

Let  $\tilde{N} \in \mathcal{F}$  be as in Lemma 4.2. Then we have to prove that  $\mathbb{E}'[\kappa_T^\nu(\omega, \cdot) \phi(I)] = \mathbb{E}'[\phi(\bar{\alpha}^\nu(\omega, \cdot))]$ , whenever  $\omega \notin \tilde{N}$ , or, equivalently by definition of  $\mathbb{P}^{\nu^\omega}$ :

$$\mathbb{E}^{\nu^\omega}[\phi(I)] = \mathbb{E}'[\phi(\bar{\alpha}^\nu(\omega, \cdot))], \quad \text{whenever } \omega \notin \tilde{N}.$$

This is a direct consequence of the last statement of Lemma 4.3.  $\square$

## 4.2 Proof of the inequality $v_0 \leq v_0^{\mathcal{R}}$

In this proof we borrow some constructions from [13] Proposition 4.1, but we need to obtain improved results and we simplify considerably some arguments.

Suppose we are given a setting  $(\Omega, \mathcal{F}, \mathbb{P}, \mathbb{F}, V, W, x_0)$  for the optimal control problem with partial observation, satisfying the conditions in Section 2.2, and consider the controlled equation (2.5) and the gain (2.6). We fix an  $\mathbb{F}^W$ -progressive process  $\alpha$  with values in  $A$ . We will show how to construct a sequence of settings  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}}_k, \hat{V}, \hat{W}, \hat{\mu}_k, \hat{x}_0)_k$  for the randomized control problem of Section 3.1, and a sequence  $(\hat{\nu}^k)_k$  of corresponding admissible controls (both sequences depending on  $\alpha$ ), such that for the corresponding gains, defined by (3.7), we have:

$$J^{\mathcal{R}}(\hat{\nu}^k) \rightarrow J(\alpha), \quad \text{as } k \rightarrow \infty. \quad (4.16)$$

Admitting for a moment that this has been done, the proof is easily concluded by the following arguments. By (4.16), we can find, for any  $\varepsilon > 0$ , some  $k$  such that  $J^{\mathcal{R}}(\hat{\nu}^k) > J(\alpha) - \varepsilon$ . Since  $J^{\mathcal{R}}(\hat{\nu}^k)$  is a gain of a randomized control problem, it can not exceed the value  $v_0^{\mathcal{R}}$  defined in (3.8) which, by Proposition 3.1, does not depend on  $\varepsilon$  nor on  $\alpha$ . It follows that

$$v_0^{\mathcal{R}} > J(\alpha) - \varepsilon$$

and by the arbitrariness of  $\varepsilon$  and  $\alpha$ , we obtain the required inequality  $v_0^{\mathcal{R}} \geq v_0$ .

In order to construct the sequences  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}}_k, \hat{V}, \hat{W}, \hat{\mu}_k, \hat{x}_0)_k$  and  $(\hat{\nu}^k)_k$  satisfying (4.16), we apply Proposition A.1, in the Appendix below, to the probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  of the partially observed control problem and to the filtration  $\mathbb{G} := \mathbb{F}^W$ . In that Proposition a suitable probability space  $(\Omega', \mathcal{F}', \mathbb{P}')$  is introduced and the product space  $(\hat{\Omega}, \hat{\mathcal{F}}, \mathbb{Q})$  is constructed:

$$\hat{\Omega} = \Omega \times \Omega', \quad \hat{\mathcal{F}} = \mathcal{F} \otimes \mathcal{F}', \quad \mathbb{Q} = \mathbb{P} \otimes \mathbb{P}'.$$

Then the random variable  $x_0$  and the processes  $\alpha$  and  $B = (V, W)$  are extended to  $\hat{\Omega}$  in a natural way. We denote  $\hat{x}_0$  and  $\hat{\alpha}$  the extensions of  $x_0$  and  $\alpha$ . The extension of  $B$ , denoted  $\hat{B} = (\hat{V}, \hat{W})$ , remains a Wiener process under  $\mathbb{Q}$ . The filtration  $\mathbb{F}^W$  can also be canonically extended to a filtration in  $(\hat{\Omega}, \hat{\mathcal{F}})$ , which coincides with the filtration  $\mathbb{F}^{\hat{W}}$  generated by  $\hat{W}$ .

Following [24], for any pair  $\alpha^1, \alpha^2 : \hat{\Omega} \times [0, T] \rightarrow \mathbf{A}$  of measurable processes in  $(\hat{\Omega}, \hat{\mathcal{F}}, \mathbb{Q})$  we define a distance  $\tilde{\rho}(\alpha^1, \alpha^2)$  setting

$$\tilde{\rho}(\alpha^1, \alpha^2) = \mathbb{E}^{\mathbb{Q}} \left[ \int_0^T \rho(\alpha_t^1, \alpha_t^2) dt \right], \quad (4.17)$$

where  $\mathbb{E}^{\mathbb{Q}}$  denotes the expectation under  $\mathbb{Q}$ , and  $\rho$  is a metric in  $A$  satisfying  $\rho < 1$ . By Proposition A.1, for any integer  $k \geq 1$  there exists a marked point process  $(\hat{S}_n^k, \hat{\eta}_n^k)_{n \geq 1}$  defined in  $(\hat{\Omega}, \hat{\mathcal{F}}, \mathbb{Q})$  satisfying the following conditions.

1. Setting  $\hat{S}_0^k = 0$ ,  $\hat{\eta}_0^k = a_0$ ,  $\hat{I}_t^k = \sum_{n \geq 0} \hat{\eta}_n^k 1_{[\hat{S}_n^k, \hat{S}_{n+1}^k)}(t)$ , we have  $\tilde{\rho}(\hat{I}^k, \hat{\alpha}) < 1/k$ .
2. Denote  $\hat{\mu}_k = \sum_{n \geq 1} \delta_{(\hat{S}_n^k, \hat{\eta}_n^k)}$  the random measure associated to  $(\hat{S}_n^k, \hat{\eta}_n^k)_{n \geq 1}$  and  $\mathbb{F}^{\hat{\mu}_k} = (\mathcal{F}_t^{\hat{\mu}_k})_{t \geq 0}$  the natural filtration of  $\hat{\mu}_k$ ; then the compensator of  $\hat{\mu}_k$  under  $\mathbb{Q}$  with respect to the filtration  $(\mathcal{F}_t^{\hat{W}} \vee \mathcal{F}_t^{\hat{\mu}_k})_{t \geq 0}$  is absolutely continuous with respect to  $\lambda(da) dt$  and it can be written in the form

$$\hat{\nu}_t^k(\hat{\omega}, a) \lambda(da) dt$$

for some nonnegative  $\mathcal{P}(\mathbb{F}^{\hat{W}, \hat{\mu}}) \otimes \mathcal{B}(A)$ -measurable function  $\hat{\nu}^k$  satisfying  $\inf_{\hat{\Omega} \times [0, T] \times A} \hat{\nu}^k > 0$  and  $\sup_{\hat{\Omega} \times [0, T] \times A} \hat{\nu}^k < \infty$ .

We note that  $\hat{\mu}_k$  (and so also  $\hat{I}^k$  and  $\hat{\nu}^k$ ) depend on  $\alpha$  as well, but we do not make it explicit in the notation. We also observe that  $\hat{\nu}^k$  can be taken identically equal to 1 on  $\hat{\Omega} \times (T, \infty) \times A$ , without loss of generality. Let us now consider the completion of the probability space  $(\hat{\Omega}, \hat{\mathcal{F}}, \mathbb{Q})$ , that will be denoted by the same symbol for simplicity of notation, and let  $\mathcal{N}$  denote the family of  $\mathbb{Q}$ -null sets of the completion. Then the filtration  $(\mathcal{F}_t^{\hat{W}} \vee \mathcal{F}_t^{\hat{\mu}_k} \vee \mathcal{N})_{t \geq 0}$  coincides with the filtration previously denoted by  $\mathbb{F}^{\hat{W}, \hat{\mu}_k} = (\mathcal{F}_t^{\hat{W}, \hat{\mu}_k})_{t \geq 0}$  (compare with formula (3.3) in section 3.1). It is easy to see that  $\hat{\nu}_t^k(\hat{\omega}, a) \lambda(da) dt$  is the compensator of  $\hat{\mu}_k$  with respect to  $\mathbb{F}^{\hat{W}, \hat{\mu}_k}$  and the extended probability  $\mathbb{Q}$  as well.

Using the Girsanov theorem for point processes (see e.g. [18]) we next construct an equivalent probability under which  $\hat{\mu}_k$  becomes a Poisson random measure with intensity  $\lambda$ . Since  $\hat{\nu}^k$  is a strictly positive  $\mathcal{P}(\mathbb{F}^{\hat{W}, \hat{\mu}_k}) \otimes \mathcal{B}(A)$ -measurable random field with bounded inverse, the Doléans exponential process

$$M_t^k := \exp \left( \int_0^t \int_A (1 - \hat{\nu}_s^k(a)^{-1}) \hat{\nu}_s^k(a) \lambda(da) ds \right) \prod_{\hat{S}_n^k \leq t} \hat{\nu}_{\hat{S}_n^k}^k(\hat{\eta}_n^k)^{-1}, \quad t \in [0, T], \quad (4.18)$$

is a strictly positive martingale (with respect to  $\mathbb{F}^{\hat{W}, \hat{\mu}_k}$  and  $\mathbb{Q}$ ), and we can define an equivalent probability  $\hat{\mathbb{P}}_k$  on the space  $(\hat{\Omega}, \hat{\mathcal{F}})$  setting  $\hat{\mathbb{P}}_k(d\hat{\omega}) = M_T^k(\hat{\omega}) \mathbb{Q}(d\hat{\omega})$ . The expectation under  $\hat{\mathbb{P}}_k$  will be denoted  $\hat{\mathbb{E}}_k$ . By the Girsanov theorem, the restriction of  $\hat{\mu}_k$  to  $(0, T] \times A$  has  $(\hat{\mathbb{P}}_k, \mathbb{F}^{\hat{W}, \hat{\mu}_k})$ -compensator  $\lambda(da) dt$ , so that in particular it is a Poisson random measure. It can also be proved by standard arguments (see e.g. [13], page 2155, for detailed verifications in a similar framework) that  $\hat{B}$  is a  $(\hat{\mathbb{P}}_k, \mathbb{F}^{\hat{W}, \hat{\mu}_k})$ -Wiener process and that  $\hat{B}$  and  $\hat{\mu}_k$  are independent under  $\hat{\mathbb{P}}_k$ . We have thus constructed a setting  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}}_k, \hat{V}, \hat{W}, \hat{\mu}_k, \hat{x}_0)$  for a randomized control problem as in Section 3.1. Since  $\hat{\nu}^k$  is a bounded, strictly positive and  $\mathcal{P}(\mathbb{F}^{\hat{W}, \hat{\mu}}) \otimes \mathcal{B}(A)$ -measurable random field it belongs to the class  $\hat{\mathcal{V}}^k$  of admissible controls for the randomized control problem and we now proceed to evaluating its gain  $J^{\mathcal{R}}(\hat{\nu}^k)$  and to comparing it with  $J(\alpha)$ . Our aim is to show that, as a consequence of the fact that  $\tilde{\rho}(\hat{I}^k, \hat{\alpha}) < 1/k$ , we have  $J^{\mathcal{R}}(\hat{\nu}^k) \rightarrow J(\alpha)$  as  $k \rightarrow \infty$ .

We introduce the Doléans exponential process  $\kappa^{\hat{\nu}^k}$  corresponding to  $\hat{\nu}^k$  (compare formula (3.5)):

$$\kappa_t^{\hat{\nu}^k} = \exp \left( \int_0^t \int_A (1 - \hat{\nu}_s^k(a)) \lambda(da) ds \right) \prod_{\hat{S}_n^k \leq t} \hat{\nu}_{\hat{S}_n^k}^k(\hat{\eta}_n^k), \quad t \in [0, T], \quad (4.19)$$

we define the probability  $d\hat{\mathbb{P}}_k^{\hat{\nu}^k} = \kappa_T^{\hat{\nu}^k} d\hat{\mathbb{P}}_k$  and we obtain the gain

$$J^{\mathcal{R}}(\hat{\nu}^k) = \hat{\mathbb{E}}^{\hat{\nu}^k} \left[ \int_0^T f_t(\hat{X}^k, \hat{I}^k) dt + g(\hat{X}^k) \right],$$

where  $\hat{X}^k$  is the solution to the equation

$$d\hat{X}_t^k = b_t(\hat{X}^k, \hat{I}^k) dt + \sigma_t(\hat{X}^k, \hat{I}^k) d\hat{B}_t, \quad \hat{X}_0^k = \hat{x}_0. \quad (4.20)$$

However comparing (4.18) and (4.19) shows that  $\kappa_T^{\hat{\nu}^k} M_T^k \equiv 1$ , so that the Girsanov transformation  $\hat{\mathbb{P}}_k \mapsto \hat{\mathbb{P}}_k^{\hat{\nu}^k}$  is the inverse to the transformation  $\mathbb{Q} \mapsto \hat{\mathbb{P}}_k$  made above, and changes back the probability  $\hat{\mathbb{P}}_k$  into  $\mathbb{Q}$  considered above. Therefore we have  $\hat{\mathbb{P}}_k^{\hat{\nu}^k} = \mathbb{Q}$  and also

$$J^{\mathcal{R}}(\hat{\nu}^k) = \mathbb{E}^{\mathbb{Q}} \left[ \int_0^T f_t(\hat{X}^k, \hat{I}^k) dt + g(\hat{X}^k) \right]. \quad (4.21)$$

On the other hand, the gain  $J(\alpha)$  of the initial control problem with partial observation was defined in (2.6) in terms of the solution  $X^\alpha$  to the controlled equation (2.5). Denoting  $\hat{X}^\alpha$  the extension of  $X^\alpha$  to  $\hat{\Omega}$ , it is easy to verify that it is the solution to

$$d\hat{X}_t^\alpha = b_t(\hat{X}^\alpha, \hat{\alpha}) dt + \sigma_t(\hat{X}^\alpha, \hat{\alpha}) d\hat{B}_t, \quad \hat{X}_0^\alpha = \hat{x}_0, \quad (4.22)$$

and that

$$J(\alpha) = \mathbb{E}^{\mathbb{Q}} \left[ \int_0^T f_t(\hat{X}^\alpha, \hat{\alpha}) dt + g(\hat{X}^\alpha) \right]. \quad (4.23)$$

Equations (4.22) and (4.20) are considered in the same probability space  $(\hat{\Omega}, \hat{\mathcal{F}}, \mathbb{Q})$ . In (4.20) we find a solution adapted to the filtration  $\mathbb{G}^k := \mathbb{F}^{\hat{x}_0, \hat{B}, \hat{\mu}_k}$  (defined as in (3.3)) and in (4.22) we find a solution adapted to the filtration  $\mathbb{G}^0 := \mathbb{F}^{\hat{x}_0, \hat{B}}$  generated by  $\hat{x}_0$  and  $\hat{B}$  (since  $\alpha$  was  $\mathbb{F}^W$ -progressive and so  $\hat{\alpha}$  is progressive with respect to  $\mathbb{F}^{\hat{W}} \subset \mathbb{F}^{\hat{x}_0, \hat{B}}$ ).

In order to conclude, we need the following stability lemma, where the continuity condition **(A1)**-(iii) plays a role.

**Lemma 4.4** *Given a probability space  $(\hat{\Omega}, \hat{\mathcal{F}}, \mathbb{Q})$  with filtrations  $\mathbb{G}^k = (\mathcal{G}_t^k)_{t \geq 0}$  ( $k \geq 0$ ) consider the equations*

$$dY_t^k = b_t(Y^k, \gamma^k) dt + \sigma_t(Y^k, \gamma^k) d\beta_t, \quad \hat{Y}_0^k = y_0,$$

where  $\beta$  is a Wiener process with respect to each  $\mathbb{G}^k$ ,  $\mathbb{E}^{\mathbb{Q}}|y_0|^p < \infty$ ,  $y_0$  is  $\mathcal{G}_t^k$ -measurable and  $\gamma^k$  is  $\mathbb{G}^k$ -progressive for every  $k$ . If  $\tilde{\rho}(\gamma^k, \gamma^0) \rightarrow 0$  as  $k \rightarrow \infty$ , then

$$\mathbb{E}^{\mathbb{Q}} \sup_{t \in [0, T]} |Y_t^k - Y_t^0|^p \rightarrow 0, \quad \mathbb{E}^{\mathbb{Q}} \left[ \int_0^T f_t(Y^k, \gamma^k) dt + g(Y^k) \right] \rightarrow \mathbb{E}^{\mathbb{Q}} \left[ \int_0^T f_t(Y^0, \gamma^0) dt + g(Y^0) \right].$$

**Proof.** This stability result for control problems was first proved in [24] in the standard diffusion case. The extension to the non-Markovian case presented in [13], Lemma 4.1 and Remark 4.1, also holds in our case with the same proof, using the continuity assumption **(A1)**-(iii) and the Lipschitz and growth conditions (2.2)-(2.4).  $\square$

Applying the Lemma to  $\beta = \hat{B}$ ,  $Y^k = \hat{X}^k$ ,  $\gamma^k = \hat{I}^k$  (for  $k \geq 1$ ) and  $Y^0 = \hat{X}^\alpha$ ,  $\gamma^0 = \hat{\alpha}$ , and recalling that  $\tilde{\rho}(\hat{I}^k, \hat{\alpha}) < 1/k \rightarrow 0$  we conclude by (4.21), (4.23) that  $J^{\mathcal{R}}(\hat{\nu}^k) \rightarrow J(\alpha)$  as  $k \rightarrow \infty$ . Therefore relation (4.16) is satisfied for this choice of the sequence  $(\hat{\nu}^k)_k$  and for the corresponding settings  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}}_k, \hat{V}, \hat{W}, \hat{\mu}_k, \hat{x}_0)_k$ . This ends the proof of the inequality  $\mathcal{U}_0 \leq \mathcal{U}_0^{\mathcal{R}}$ .

## 5 The randomized equation

In this section, we show how the randomized formulation of the control problem leads to a randomized equation in terms of a backward SDE. We choose a setting for the randomized control problem (3.8) as in Remark 3.2, i.e. a product extension  $(\bar{\Omega}, \bar{\mathcal{F}}, \bar{\mathbb{P}}, V, W, \mu, x_0)$  of the setting  $(\Omega, \mathcal{F}, \mathbb{P}, V, W, x_0)$  for the initial control problem (2.7). In view of Proposition 3.1, entirely analogous results hold true in any setting  $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{\mathbb{P}}, \hat{V}, \hat{W}, \hat{\mu}, \hat{x}_0)$  for the randomized control problem as described in section 3.1.

### 5.1 The separated randomized control problem

We first consider the (path-dependent) filtering of the randomized process  $X$  solution to (3.2), which consists in the process of conditional distributions  $\rho_t$  of  $X_{\cdot \wedge t}$  given  $\mathcal{F}_t^{W, \mu}$ . More precisely, let  $\mathcal{P}(\mathbf{C}_n)$  be the space of probability measures on  $\mathbf{C}_n$  and let  $B_b(\mathbf{C}_n)$  denote the space of bounded Borel measurable real functions on  $\mathbf{C}_n$ . We define  $\rho = (\rho_t)_{0 \leq t \leq T}$  as an  $\mathbb{F}^{W, \mu}$ -optional process valued in  $\mathcal{P}(\mathbf{C}_n)$  satisfying, for every  $\varphi \in B_b(\mathbf{C}_n)$ , (we use the notation  $\rho_t(\varphi) = \int_{\mathbf{C}_n} \varphi(x) \rho_t(dx)$ )

$$\rho_t(\varphi) = \bar{\mathbb{E}}[\varphi(X_{\cdot \wedge t}) \mid \mathcal{F}_t^{W, \mu}], \quad t \in [0, T], \bar{\mathbb{P}}\text{-a.s.} \quad (5.1)$$

The process  $t \mapsto \bar{\mathbb{E}}[\varphi(X_{\cdot \wedge t}) \mid \mathcal{F}_t^{W, \mu}]$  is understood as an optional projection. The existence of such a process  $\rho$  follows for example from Theorem 2.24 in [1]. While (5.1) is defined for bounded  $\varphi$ , since  $\rho_t$  is constructed as a  $\mathcal{P}(\mathbf{C}_n)$ -valued process, relation (5.1) holds for unbounded  $\varphi$  once the conditional expectation is well-defined, i.e.  $\rho_t(|\varphi|) < \infty$  for all  $t \in [0, T]$ ,  $\bar{\mathbb{P}}$ -a.s. (see e.g. Remark 2.27 in [1]).

We can now express the randomized gain functional in terms of the  $\mathbb{F}^{W, \mu}$ -optional processes  $\rho$  and  $I$ .

**Lemma 5.1** *For any  $\nu \in \mathcal{V}$ , we have*

$$J^{\mathcal{R}}(\nu) = \mathbb{E}^{\nu} \left[ \int_0^T \rho_t(f_t(\cdot, I)) dt + \rho_T(g) \right]$$

and, more generally,

$$\mathbb{E}^{\nu} \left[ \int_t^T f_s(X, I) ds + g(X) \mid \mathcal{F}_t^{W, \mu} \right] = \mathbb{E}^{\nu} \left[ \int_t^T \rho_s(f_s(\cdot, I)) ds + \rho_T(g) \mid \mathcal{F}_t^{W, \mu} \right], \quad (5.2)$$

for all  $0 \leq t \leq T$ .

**Proof.** The result follows from the Bayes formula and the  $(\bar{\mathbb{P}}, \mathbb{F}^{W, \mu})$ -martingale property of the density process  $\kappa^{\nu}$ .  $\square$

The above Lemma 5.1 together with Theorem 3.1 proves that the randomized control problem, and thus the primal control problem under partial observation, can be written in a *separated* form involving  $\mathbb{F}^{W, \mu}$ -optional state processes:

$$v_0 = \sup_{\nu \in \mathcal{V}} \mathbb{E}^{\nu} \left[ \int_0^T \rho_t(f_t(\cdot, I)) dt + \rho_T(g) \right]. \quad (5.3)$$



## 5.2 BSDE representation

The purpose of this paragraph is to show that the separated randomized control problem, described by the right-hand side of (5.3), admits a dual representation in terms of a constrained backward SDE, which then characterizes both the primal control problem and the randomized control problem (as well as the separated randomized control problem). We shall refer to it as the *randomized equation*.

On the space  $(\bar{\Omega}, \bar{\mathcal{F}}, \bar{\mathbb{P}})$  equipped with the filtration  $\mathbb{F}^{W,\mu}$ , let us consider the following constrained BSDE on the time interval  $[0, T]$ :

$$\begin{cases} Y_t = \rho_T(g) + \int_t^T \rho_s(f_s(\cdot, I)) ds + K_T - K_t - \int_t^T Z_s dW_s - \int_t^T \int_A U_s(a) \mu(ds da), \\ U_t(a) \leq 0. \end{cases} \quad (5.4)$$

We look for a (minimal) solution to (5.4) in the sense of the following definition.

**Definition 5.1** *A quadruple  $(Y_t, Z_t, U_t(a), K_t)$  ( $t \in [0, T]$ ,  $a \in A$ ) is called a solution to the BSDE (5.4) if*

1.  $Y \in \mathcal{S}^2(\mathbb{F}^{W,\mu})$ , the set of real-valued càdlàg  $\mathbb{F}^{W,\mu}$ -adapted processes satisfying  $\|Y\|_{\mathcal{S}^2}^2 := \bar{\mathbb{E}}[\sup_{0 \leq t \leq T} |Y_t|^2] < \infty$ ;
2.  $Z \in L_W^2(\mathbb{F}^{W,\mu})$ , the set of  $\mathbb{F}^{W,\mu}$ -predictable processes with values in  $\mathbb{R}^d$  satisfying  $\|Z\|_{L_W^2}^2 := \bar{\mathbb{E}}[\int_0^T |Z_t|^2 dt] < \infty$ ;
3.  $U \in L_\mu^2(\mathbb{F}^{W,\mu})$ , the set of real-valued  $\mathcal{P}(\mathbb{F}^{W,\mu}) \otimes \mathcal{B}(A)$ -measurable processes satisfying  $\|U\|_{L_\mu^2}^2 := \bar{\mathbb{E}}[\int_0^T \int_A |U_t(a)|^2 \lambda(da) dt] < \infty$ ;
4.  $K \in \mathcal{K}^2(\mathbb{F}^{W,\mu})$ , the subset of  $\mathcal{S}^2(\mathbb{F}^{W,\mu})$  consisting of  $\mathbb{F}^{W,\mu}$ -predictable nondecreasing process with  $K_0 = 0$ ;
5.  $\bar{\mathbb{P}}$ -a.s. the equality in (5.4) holds for every  $t \in [0, T]$  and the constraint  $U_t(a) \leq 0$  is understood to hold  $\bar{\mathbb{P}}(d\bar{\omega})\lambda(da)dt$ -almost everywhere.

A minimal solution  $(Y, Z, U, K)$  is a solution to (5.4) such that for any other solution  $(Y', Z', U', K')$ , we have  $\bar{\mathbb{P}}$ -a.s.,  $Y_t \leq Y'_t$  for all  $t \in [0, T]$ .

We now state the main result of this section.

**Theorem 5.1** *There exists a unique minimal solution  $(Y, Z, U, K) \in \mathcal{S}^2(\mathbb{F}^{W,\mu}) \times L_W^2(\mathbb{F}^{W,\mu}) \times L_\mu^2(\mathbb{F}^{W,\mu}) \times \mathcal{K}^2(\mathbb{F}^{W,\mu})$  to the randomized equation (5.4). Moreover, we have  $Y_0 = \sup_{\nu \in \mathcal{V}} J^{\mathcal{R}}(\nu)$ , and, more generally,*

$$Y_t = \operatorname{ess\,sup}_{\nu \in \mathcal{V}} \mathbb{E}^\nu \left[ \int_t^T \rho_s(f_s(\cdot, I)) ds + \rho_T(g) \mid \mathcal{F}_t^{W,\mu} \right]. \quad (5.5)$$

**Remark 5.1** Combining Theorems 3.1 and 5.1 we deduce the BSDE representation for the primal problem

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

We refer sometimes to  $Y_0 = \sup_{\nu \in \mathcal{V}} J^{\mathcal{R}}(\nu)$  as *duality relation*, since  $Y_0$  coincides with the infimum  $\inf\{Y'_0 : (Y', Z', U', K') \in \mathcal{S}^2(\mathbb{F}^{W,\mu}) \times L^2_W(\mathbb{F}^{W,\mu}) \times L^2_{\tilde{\mu}}(\mathbb{F}^{W,\mu}) \times \mathcal{K}^2(\mathbb{F}^{W,\mu}) \text{ solution to (5.4)}\}$ .  $\square$

**Proof (of Theorem 5.1)** Let us introduce for every  $n \in \mathbb{N}$  the following penalized BSDE on  $[0, T]$ :

$$Y_t^n = \rho_T(g) + \int_t^T \rho_s(f_s(\cdot, I)) ds + K_T^n - K_t^n - \int_t^T Z_s^n dW_s - \int_t^T \int_A U_s^n(a) \mu(ds da), \quad (5.6)$$

where

$$K_t^n = n \int_0^t \int_A (U_s^n(a))^+ \lambda(da) ds.$$

Set  $\xi := \rho_T(g)$  and  $F_t := \rho_t(f_t(\cdot, I))$ . By (2.4) and (3.4) (recall that  $p$  in (3.4) is greater than or equal to  $2r$  in (2.4)), we see that

$$\mathbb{E}|\xi|^2 < \infty, \quad \mathbb{E} \left[ \int_0^T |F_t|^2 dt \right] < \infty.$$

Then, from Lemma 2.4 in [30] it follows that, for every  $n \in \mathbb{N}$ , there exists a unique solution  $(Y^n, Z^n, U^n) \in \mathcal{S}^2(\mathbb{F}^{W,\mu}) \times L^2_W(\mathbb{F}^{W,\mu}) \times L^2_{\tilde{\mu}}(\mathbb{F}^{W,\mu})$  to the above penalized BSDE.

Now, proceeding along the same lines as in the proof of Lemma 4.8 in [13], we obtain the formula

$$Y_t^n = \operatorname{ess\,sup}_{\nu \in \mathcal{V}_n} \mathbb{E}^\nu \left[ \int_t^T \rho_s(f_s(\cdot, I)) ds + \rho_T(g) \middle| \mathcal{F}_t^{W,\mu} \right], \quad (5.7)$$

where  $\mathcal{V}_n = \{\nu \in \mathcal{V} : \nu \text{ takes values in } (0, n]\}$ . By (5.2), together with estimates (2.4) and (3.6), we deduce that

$$\sup_n Y_t^n < \infty, \quad \text{for all } 0 \leq t \leq T. \quad (5.8)$$

Notice that equation (5.4) can be written as follows:

$$\begin{cases} Y_t = \rho_T(g) + \int_t^T \left( \rho_s(f_s(\cdot, I)) - \int_A U_s(a) \lambda(da) \right) ds + K_T - K_t \\ \quad - \int_t^T Z_s dW_s - \int_t^T \int_A U_s(a) \tilde{\mu}(ds da), \\ U_t(a) \leq 0. \end{cases} \quad (5.9)$$

Then, we see that the above equation is a particular case of a backward stochastic differential equation studied in a general non-Markovian framework in [23]. In particular, existence and uniqueness of the minimal solution  $(Y, Z, U, K)$  to equation (5.9) (or, equivalently, to equation (5.4)) follow from Theorem 2.1 in [23]. Indeed, Assumption **(H0)** in [23] is clearly satisfied. Concerning Assumption **(H1)**, this is only used in Lemma 2.2 of [23] to prove that the sequence  $(Y^n)_n$  satisfies (5.8), a property that in our setting follows directly from (2.4) and (3.6).

Finally, from Theorem 2.1 in [23] we also have that  $Y_t^n(\bar{\omega})$  converges increasingly to  $Y_t(\bar{\omega})$  as  $n \rightarrow \infty$ ,  $\bar{\mathbb{P}}(d\bar{\omega})$ -a.s. Since  $\mathcal{V} = \cup_n \mathcal{V}_n$ , letting  $n \rightarrow \infty$  in (5.7) we obtain (5.5).  $\square$

**Remark 5.2** Notice that the following generalization of formula (5.5) holds:

$$Y_t = \operatorname{ess\,sup}_{\nu \in \mathcal{V}} \mathbb{E}^\nu \left[ \int_t^s \rho_r(f_r(\cdot, I)) dr + Y_s \middle| \mathcal{F}_t^{W,\mu} \right], \quad (5.10)$$

for all  $0 \leq t \leq s \leq T$ . Indeed, for every  $n$ , considering the penalized BSDE (5.6) on  $[0, s]$  with terminal condition  $Y_s^n$ , and proceeding as in the proof of formula (5.7), we obtain

$$Y_t^n = \operatorname{ess\,sup}_{\nu \in \mathcal{V}_n} \mathbb{E}^\nu \left[ \int_t^s \rho_r(f_r(\cdot, I)) dr + Y_s^n \middle| \mathcal{F}_t^{W, \mu} \right]. \quad (5.11)$$

Recalling that  $\mathcal{V}_n \subset \mathcal{V}$  and  $Y^n \leq Y$ , we get  $Y_t^n \leq \operatorname{ess\,sup}_{\nu \in \mathcal{V}} \mathbb{E}^\nu \left[ \int_t^s \rho_r(f_r(\cdot, I)) dr + Y_s \middle| \mathcal{F}_t^{W, \mu} \right]$ . Since  $Y^n$  converges increasingly to  $Y$ , we end up with

$$Y_t \leq \operatorname{ess\,sup}_{\nu \in \mathcal{V}} \mathbb{E}^\nu \left[ \int_t^s \rho_r(f_r(\cdot, I)) dr + Y_s \middle| \mathcal{F}_t^{W, \mu} \right]. \quad (5.12)$$

To prove the reverse inequality, fix  $m \in \mathbb{N}$  and notice that from (5.11) we have, for every  $n \geq m$ ,

$$Y_t \geq \operatorname{ess\,sup}_{\nu \in \mathcal{V}_n} \mathbb{E}^\nu \left[ \int_t^s \rho_r(f_r(\cdot, I)) dr + Y_s^n \middle| \mathcal{F}_t^{W, \mu} \right] \geq \operatorname{ess\,sup}_{\nu \in \mathcal{V}_n} \mathbb{E}^\nu \left[ \int_t^s \rho_r(f_r(\cdot, I)) dr + Y_s^m \middle| \mathcal{F}_t^{W, \mu} \right],$$

using that  $Y_t \geq Y_t^n$  and  $Y_s^n \geq Y_s^m$  for every  $n \geq m$ . Letting  $n \rightarrow \infty$  in the above right-hand side, we obtain  $Y_t \geq \operatorname{ess\,sup}_{\nu \in \mathcal{V}} \mathbb{E}^\nu \left[ \int_t^s \rho_r(f_r(\cdot, I)) dr + Y_s^m \middle| \mathcal{F}_t^{W, \mu} \right]$ , for all  $m \in \mathbb{N}$ . In particular

$$Y_t \geq \mathbb{E}^\nu \left[ \int_t^s \rho_r(f_r(\cdot, I)) dr + Y_s^m \middle| \mathcal{F}_t^{W, \mu} \right], \quad \text{for all } \nu \in \mathcal{V}, m \in \mathbb{N}.$$

Letting  $m \rightarrow \infty$ , and taking the essential supremum over  $\mathcal{V}$ , we obtain the reverse inequality of (5.12), from which formula (5.10) follows. Equation (5.10) relates the value function of the randomized control problem between two arbitrary dates, and is called *randomized dynamic programming principle*.  $\square$

### 5.3 Verification theorem

In this paragraph we present a *verification theorem* in the context of the randomization method, expressed in terms of the randomized equation (5.4). Firstly, let us fix some notations. We denote by  $\mathbf{D}_{\mathcal{P}(\mathbf{C}_n)}$  the set of càdlàg paths from  $[0, T]$  to  $\mathcal{P}(\mathbf{C}_n)$  (the space of probability measures on  $\mathbf{C}_n$  endowed with the topology of weak convergence). We define the filtration  $(\mathcal{D}_t^{\mathcal{P}(\mathbf{C}_n)})_{t \in [0, T]}$ , where  $\mathcal{D}_t^{\mathcal{P}(\mathbf{C}_n)}$  is the  $\sigma$ -algebra generated by the canonical coordinate maps  $\mathbf{D}_{\mathcal{P}(\mathbf{C}_n)} \rightarrow \mathcal{P}(\mathbf{C}_n)$ ,  $\rho(\cdot) \mapsto \rho(s)$  up to time  $t$ , namely

$$\mathcal{D}_t^{\mathcal{P}(\mathbf{C}_n)} := \sigma\{\rho(\cdot) \mapsto \rho(s) : s \in [0, t]\},$$

and we denote  $\operatorname{Prog}(\mathbf{D}_{\mathcal{P}(\mathbf{C}_n)})$  the progressive  $\sigma$ -algebra on  $[0, T] \times \mathbf{D}_{\mathcal{P}(\mathbf{C}_n)}$  with respect to  $(\mathcal{D}_t^{\mathcal{P}(\mathbf{C}_n)})$ . In this subsection, we suppose that  $\rho = (\rho_t)_{0 \leq t \leq T}$  stands for the càdlàg version of the (path-dependent) filter of  $X_{\cdot \wedge t}$  given  $\mathcal{F}_t^{W, \mu}$ , whose existence is guaranteed by Corollary 2.26 in [1] (notice that  $(X_{\cdot \wedge t})_{0 \leq t \leq T}$  is a  $\mathbf{C}_n$ -valued process with continuous trajectories). We recall from Corollary 2.26 in [1] that in this case there exists a countable set  $Q \subset [0, T]$  such that

$$\rho_t(\varphi) = \bar{\mathbb{E}}[\varphi(X_{\cdot \wedge t}) \mid \mathcal{F}_t^{W, \mu}],$$

for all  $t \in [0, T] \setminus Q$  and  $\varphi \in B_b(\mathbf{C}_n)$ .

**Theorem 5.2** Let  $(Y, Z, U, K)$  be the minimal solution to the randomized equation (5.4).

(1) Suppose that  $U_t(a) = 0$ ,  $\bar{\mathbb{P}}(d\bar{\omega})\lambda(da)dt$ -a.e., and  $K_t = \int_0^t \rho_s(k_s(\cdot, I)) ds$ , for some  $k: [0, T] \times \mathbf{C}_n \times \mathbf{M}_A \rightarrow [0, \infty)$  satisfying:

(i)  $k$  is  $\text{Prog}(\mathbf{C}_n \times \mathbf{M}_A)$ -measurable.

(ii)  $k$  satisfies the following sequential continuity condition analogous to (A1)-(iii): whenever  $x_k, x \in \mathbf{C}_n$ ,  $\alpha_k, \alpha \in \mathbf{M}_A$ ,  $\|x_k - x\|_\infty \rightarrow 0$ ,  $\alpha_k(t) \rightarrow \alpha(t)$  for  $dt$ -a.e.  $t \in [0, T]$  as  $k \rightarrow \infty$  we have

$$k_t(x_k, \alpha_k) \rightarrow k_t(x, \alpha), \quad \text{for } dt\text{-a.e. } t \in [0, T].$$

(iii) There exist nonnegative constants  $K$  and  $r$  such that

$$|k_t(x, a)| \leq K(1 + \|x\|_\infty^r),$$

for all  $(t, x, a) \in [0, T] \times \mathbf{C}_n \times \mathbf{M}_A$ . To simplify the presentation we assume, without loss of generality, that  $K$  and  $r$  are the same constants appearing in (2.4).

(2) Suppose further that there exists a  $\text{Prog}(\mathbf{D}_{\mathcal{D}(\mathbf{C}_n)})$ -measurable map  $\hat{\alpha}_t(\rho)$ ,  $(t, \rho) \in [0, T] \times \mathbf{D}_{\mathcal{D}(\mathbf{C}_n)}$ , valued in  $A$  such that:

(i)  $\rho_t(k_t(\cdot, \hat{\alpha}_t(\rho))) := \int_{\mathbf{C}_n} k_t(x, \hat{\alpha}_t(\rho)) \rho_t(dx) = 0$  for all  $(t, \rho) \in [0, T] \times \mathbf{D}_{\mathcal{D}(\mathbf{C}_n)}$ .

(ii) The stochastic differential equation

$$dX_t = b_t(X, \hat{\alpha}_t(\rho)) dt + \sigma_t(X, \hat{\alpha}_t(\rho)) dB_t, \quad X_0 = x_0,$$

with  $\rho$  satisfying (5.1), admits a unique continuous  $\mathbb{F}$ -adapted strong solution  $\hat{X} = (\hat{X}_t)_{0 \leq t \leq T}$ . We denote by  $\hat{\rho} = (\hat{\rho}_t)_{0 \leq t \leq T}$  the càdlàg version of the corresponding (path-dependent) filter.

(iii)  $(\hat{\alpha}_t(\hat{\rho}))_{0 \leq t \leq T}$  lies in  $\mathcal{A}^W$ .

Then  $\hat{\alpha}$  is an optimal feedback control. If  $k_t(x, a) = k(t, x(t), a)$  is not path-dependent, then  $\hat{\alpha} = \hat{\alpha}(t, \rho_t)$  is an optimal Markovian control.

**Remark 5.3** We conjecture that the equality  $U_t(a) = 0$ ,  $\bar{\mathbb{P}}(d\bar{\omega})\lambda(da)dt$ -a.e., holds. More precisely, we conjecture that  $Y$  does not jump at a jump time  $\hat{S}_n$  of  $\hat{\mu}$  (recall that  $(\hat{S}_n, \hat{\eta}_n)_{n \geq 1}$  is the marked point process associated to  $\hat{\mu}$ ). Indeed, if this latter property holds, then, noting that  $\Delta Y_{\hat{S}_n} 1_{\{\hat{S}_n \leq T\}} = U_{\hat{S}_n}(\hat{\eta}_n) 1_{\{\hat{S}_n \leq T\}}$  for every  $n \geq 1$ , we obtain  $0 = \hat{\mathbb{E}}[\sum_{n \geq 1} \Delta Y_{\hat{S}_n} 1_{\{\hat{S}_n \leq T\}}] = \hat{\mathbb{E}}[\int_0^T \int_A U_t(a) \mu(dt da)] = \hat{\mathbb{E}}[\int_0^T \int_A U_t(a) \lambda(da) dt]$ . Since  $U$  is nonpositive, we conclude that  $U_t(a) = 0$ ,  $\bar{\mathbb{P}}(d\bar{\omega})\lambda(da)dt$ -a.e., holds.

The conjecture that  $Y$  does not jump at a jump time  $\hat{S}_n$  of  $\hat{\mu}$  is motivated by control-theoretic reasons, and, more precisely, by the property that the value of the randomized problem  $v_0^{\mathcal{R}}$  does not depend on  $a_0$ , the initial value of  $\hat{I}$  (see Theorem 3.1). It is worth mentioning that this conjecture holds true for the class of backward stochastic differential equations introduced in [23], section 3, where the classical Markovian model in (1.1) is studied by means of the randomization method. In [23] the authors formulate the primal problem for every  $(t, x) \in [0, T] \times \mathbb{R}^n$  and define the corresponding primal value  $v(t, x)$ . Similarly, they define the value  $v^{\mathcal{R}}(t, x, a)$  of the randomized control problem for every  $(t, x, a) \in [0, T] \times \mathbb{R}^n \times A$ . Then, the authors identify  $Y$  with the value

function  $v^{\mathcal{R}}$  of the randomized problem:  $Y_t = v^{\mathcal{R}}(t, X_t, I_t)$ . As a consequence, they deduce the identification for the component  $U$ :  $U_t(a) = v^{\mathcal{R}}(t, X_t, a) - v^{\mathcal{R}}(t, X_t, I_{t-})$  (see the beginning of section 3.3 in [23]). Since  $v^{\mathcal{R}}$  coincides with the value function of the primal problem, namely  $v^{\mathcal{R}}(t, x, a) = v(t, x)$ , then  $v^{\mathcal{R}}$  does not depend on the variable  $a$ , so that  $U_t(a) = 0$ .  $\square$

**Proof (of Theorem 5.2).** Set  $\tilde{f}_t(x, a) = f_t(x, a) + k_t(x, a)$  and

$$\tilde{J}(\alpha) = \mathbb{E} \left[ \int_0^T \tilde{f}_t(X^\alpha, \alpha) dt + g(X^\alpha) \right], \quad \tilde{J}^{\mathcal{R}}(\nu) = \mathbb{E}^\nu \left[ \int_0^T \tilde{f}_t(X, I) dt + g(X) \right].$$

Notice that  $\tilde{f}$  satisfies the same assumptions of  $f$  as stated in **(A1)**(ii)-(iii)-(iv). Then, proceeding as in (4.16) for the proof of Theorem 3.1, we see that, for every  $\varepsilon > 0$ , there exists  $\nu^\varepsilon \in \mathcal{V}$  such that

$$\tilde{J}^{\mathcal{R}}(\nu^\varepsilon) \leq \tilde{J}(\hat{\alpha}(\hat{\rho})) + \varepsilon = J(\hat{\alpha}(\hat{\rho})) + \varepsilon, \quad (5.13)$$

where the last equality follows from condition (2)-(i). Now, as  $U_t(a) = 0$ ,  $\bar{\mathbb{P}}(d\bar{\omega})\lambda(da)dt$ -a.e., equation (5.4) becomes

$$Y_t = \rho_T(g) + \int_t^T \rho_s(\tilde{f}_s(\cdot, I)) ds - \int_t^T Z_s dW_s, \quad 0 \leq t \leq T.$$

In particular, when  $t = 0$ , taking the expectation  $\mathbb{E}^{\nu^\varepsilon}$ , and proceeding as in the proof of Lemma 5.1, we obtain  $Y_0 = \tilde{J}^{\mathcal{R}}(\nu^\varepsilon)$ . Therefore, by Theorems 3.1 and 5.1, together with inequality (5.13), we find

$$\sup_{\alpha \in \mathcal{A}^W} J(\alpha) = \sup_{\nu \in \mathcal{V}} J^{\mathcal{R}}(\nu) = Y_0 = \tilde{J}^{\mathcal{R}}(\nu^\varepsilon) \leq J(\hat{\alpha}(\hat{X})) + \varepsilon.$$

The claim follows from the arbitrariness of  $\varepsilon$ .  $\square$

As the statement of Theorem 5.2 is quite involved, especially due to the partial observation feature, it is worth presenting the verification theorem for the full observation problem, where we also suppose that there is no delay in the control.

**Theorem 5.3** *Let  $(Y, Z, U, K)$  be the minimal solution to the randomized equation (5.4).*

(1) *Consider a full observation problem ( $W$  coincides with  $B$  and  $m = 0$ ) with no delay in the control (i.e.  $b_t(x, a) = b_t(x, a(t))$  with  $b_t$  continuous on  $\mathbf{C}_n \times A$  for every  $t$ , and similarly for the coefficients  $\sigma$  and  $f$ ). Also suppose  $U_t(a) = 0$ ,  $\bar{\mathbb{P}}(d\bar{\omega})\lambda(da)dt$ -a.e., and  $K_t = \int_0^t k_s(X, I_s) ds$ , for some  $k: [0, T] \times \mathbf{C}_n \times A \rightarrow [0, \infty)$  satisfying:*

- (i)  *$k$  is  $\text{Prog}(\mathbf{C}_n) \otimes \mathcal{B}(A)$ -measurable.*
- (ii) *For all  $t \in [0, T]$  the function  $k_t(x, a)$  is continuous in  $(x, a) \in \mathbf{C}_n \times A$ .*
- (iii) *There exist nonnegative constants  $K$  and  $r$  such that*

$$|k_t(x, a)| \leq K(1 + \|x\|_\infty^r),$$

*for all  $(t, x, a) \in [0, T] \times \mathbf{C}_n \times A$ . To simplify the presentation we assume, without loss of generality, that  $K$  and  $r$  are the same constants appearing in (2.4).*

(2) *Suppose further that there exists a  $\text{Prog}(\mathbf{C}_n)$ -measurable map  $\hat{\alpha}_t(x)$ ,  $(t, x) \in [0, T] \times \mathbf{C}_n$ , valued in  $A$  such that:*

(i)  $\inf_{a \in A} k_t(x, a) = k_t(x, \hat{\alpha}_t(x)) = 0$  for all  $(t, x) \in [0, T] \times \mathbf{C}_n$ .

(ii) The stochastic differential equation

$$dX_t = b_t(X, \hat{\alpha}_t(X)) dt + \sigma_t(X, \hat{\alpha}_t(X)) dW_t, \quad X_0 = x_0,$$

admits a unique continuous  $\mathbb{F}^W$ -adapted strong solution  $\hat{X} = (\hat{X}_t)_{0 \leq t \leq T}$ .

(iii)  $(\hat{\alpha}_t(\hat{X}))_{0 \leq t \leq T}$  lies in  $\mathcal{A}^W$ .

Then  $\hat{\alpha}$  is an optimal feedback control. If  $k_t(x, a) = k(t, x(t), a)$  is not path-dependent, then  $\hat{\alpha} = \hat{\alpha}(t, x(t))$  is an optimal Markovian control.

**Proof.** The proof can be done proceeding along the same lines as in Theorem 5.2.  $\square$

**Remark 5.4** As a particular case of the verification Theorem 5.3, consider the problem without path-dependence, i.e.  $b_t(x, a) = b(t, x(t), a)$  and similarly for the other coefficients  $\sigma, f, g$ . Suppose that  $Y_t = w(t, X_t)$  for some function  $w \in C^{1,2}([0, T] \times \mathbb{R}^n) \cap C^0([0, T] \times \mathbb{R}^n)$ , satisfying a polynomial growth condition in its second argument  $x$ , uniformly with respect to  $t \in [0, T]$ , with  $w(T, x) = g(x)$  for all  $x \in \mathbb{R}^n$ . Then Theorem 5.3 reduces to the classical verification theorem, for which we refer e.g. to Theorem 3.5.2 in [28]. Indeed, applying Itô's formula to  $w(t, X_t)$ , we see that in this case the function  $k$  can be computed explicitly and takes the following form:

$$k(t, x, a) = - \left\{ \frac{\partial w}{\partial t}(t, x) + b(t, x, a) \cdot D_x w(t, x) + \frac{1}{2} \text{tr}[\sigma \sigma^\top(t, x, a) D_x^2 w(t, x)] + f(t, x, a) \right\} 1_{[0, T]}(t),$$

for all  $(t, x, a) \in [0, T] \times \mathbb{R}^n \times A$ . Then, condition (2)-(i) in Theorem 5.3 becomes

$$-\frac{\partial w}{\partial t}(t, x) - \sup_{a \in A} \{ \mathcal{L}^a w(t, x) + f(t, x, a) \} = -\frac{\partial w}{\partial t}(t, x) - \mathcal{L}^{\hat{\alpha}(t, x)} w(t, x) - f(t, x, \hat{\alpha}(t, x)) = 0,$$

for all  $(t, x) \in [0, T] \times \mathbb{R}^n$ , which is the classical sufficient condition for an optimal control by dynamic programming method. In general, verification theorem is difficult to use in practice, and a nice feature of the randomization method is that it leads to some probabilistic numerical scheme which provides an approximation not only of the value function but also of the optimal control. This is studied in [20] for Markovian control problem under full observation, and will be the focus of future investigation in the case of partial observation control problem.  $\square$

## A Appendix: proof of Proposition A.1

This section is devoted to the proof of Proposition A.1 below, which was used in the proof of Theorem 3.1. We assume that  $A, b, \sigma, f, g, \Delta, \rho_0, \lambda, a_0$  are given and satisfy the assumptions **(A1)**-**(A2)**. Our starting point is also a probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ , with a filtration  $\mathbb{G} = (\mathcal{G}_t)_{t \geq 0}$ .

Following [24], for any pair  $\alpha^1, \alpha^2 : \Omega \times [0, T] \rightarrow A$  of  $\mathbb{G}$ -progressive processes we define a distance  $\tilde{\rho}(\alpha^1, \alpha^2)$  setting

$$\tilde{\rho}(\alpha^1, \alpha^2) = \mathbb{E} \left[ \int_0^T \rho(\alpha_t^1, \alpha_t^2) dt \right].$$

where  $\rho$  is an arbitrary metric in  $A$  satisfying  $\rho < 1$ .

Below we will use an auxiliary probability space denoted  $(\Omega', \mathcal{F}', \mathbb{P}')$ . This can be taken as an arbitrary probability space where appropriate random objects are defined. For integers  $m, n, k \geq 1$ , we assume that real random variables  $U_n^m, V_n^m$  and random measures  $\pi^k$  are defined on  $(\Omega', \mathcal{F}', \mathbb{P}')$  and satisfy the following conditions:

1. every  $U_n^m$  is uniformly distributed on  $(0, 1)$ ;
2. each  $V_n^m$  has exponential distribution with parameter  $\lambda_{nm}$  and  $\sum_{n=1}^{\infty} \lambda_{nm}^{-1} = 1/m$  for every  $m \geq 1$ ;
3. every  $\pi^k$  is a Poisson random measure on  $(0, \infty) \times A$ , admitting compensator  $k^{-1}\lambda(da) dt$  with respect to its natural filtration;
4. the random elements  $U_n^m, V_j^h, \pi^k$  are all independent.

The role of these random elements will become clear in the constructions that follow. Notice that for the construction of the space  $(\Omega', \mathcal{F}', \mathbb{P}')$  only the knowledge of the measure  $\lambda$  is required. Next we define

$$\hat{\Omega} = \Omega \times \Omega', \quad \hat{\mathcal{F}} = \mathcal{F} \otimes \mathcal{F}', \quad \mathbb{Q} = \mathbb{P} \otimes \mathbb{P}'$$

and note that the filtration  $\mathbb{G}$  can be canonically extended to a filtration  $\hat{\mathbb{G}} = (\hat{\mathcal{G}}_t)_{t \geq 0}$  in  $(\hat{\Omega}, \hat{\mathcal{F}})$  setting  $\hat{\mathcal{G}}_t = \{A \times \Omega' : A \in \mathcal{G}_t\}$ . Similarly, any process  $\alpha$  in  $(\Omega, \mathcal{F})$  admits an extension  $\hat{\alpha}$  to  $(\hat{\Omega}, \hat{\mathcal{F}})$  given by  $\hat{\alpha}_t(\hat{\omega}) = \alpha_t(\omega)$ , where  $\hat{\omega} = (\omega, \omega')$ . The metric  $\tilde{\rho}$  can also be extended to any pair  $\beta^1, \beta^2 : \hat{\Omega} \times [0, T] \rightarrow A$  of  $\hat{\mathbb{G}}$ -progressive processes setting

$$\tilde{\rho}(\beta^1, \beta^2) = \mathbb{E}^{\mathbb{Q}} \left[ \int_0^T \rho(\beta_t^1, \beta_t^2) dt \right].$$

We use the same symbol  $\tilde{\rho}$  to denote the extended metric as well.

Our aim in this section is to prove the following result.

**Proposition A.1** *Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be any probability space with a filtration  $\mathbb{G} = (\mathcal{G}_t)_{t \geq 0}$  and let  $(\hat{\Omega}, \hat{\mathcal{F}}, \mathbb{Q})$  be the product space defined above. Then for any  $\mathbb{G}$ -progressive  $A$ -valued process  $\alpha$ , and for any  $\delta > 0$ , there exists a marked point process  $(\hat{S}_n, \hat{\eta}_n)_{n \geq 1}$  defined in  $(\hat{\Omega}, \hat{\mathcal{F}}, \mathbb{Q})$  satisfying the following conditions:*

1. *setting*

$$\hat{S}_0 = 0, \quad \hat{\eta}_0 = a_0, \quad \hat{I}_t = \sum_{n \geq 0} \hat{\eta}_n 1_{[\hat{S}_n, \hat{S}_{n+1})}(t),$$

*the process  $\hat{I}$  satisfies*

$$\tilde{\rho}(\hat{I}, \hat{\alpha}) = \mathbb{E}_{\mathbb{Q}} \left[ \int_0^T \rho(\hat{I}_t, \hat{\alpha}_t) dt \right] < \delta; \tag{A.1}$$

2. *denoting  $\hat{\mu} = \sum_{n \geq 1} \delta_{(\hat{S}_n, \hat{\eta}_n)}$  the random measure associated to  $(\hat{S}_n, \hat{\eta}_n)_{n \geq 1}$ ,  $\mathbb{F}^{\hat{\mu}} = (\mathcal{F}_t^{\hat{\mu}})_{t \geq 0}$  the natural filtration of  $\hat{\mu}$  and  $\hat{\mathbb{G}} \vee \mathbb{F}^{\hat{\mu}} = (\hat{\mathcal{G}}_t \vee \mathcal{F}_t^{\hat{\mu}})_{t \geq 0}$ , then the  $\hat{\mathbb{G}} \vee \mathbb{F}^{\hat{\mu}}$ -compensator of  $\hat{\mu}$  under  $\mathbb{Q}$  is absolutely continuous with respect to  $\lambda(da) dt$  and it can be written in the form*

$$\hat{\nu}_t(\hat{\omega}, a) \lambda(da) dt \tag{A.2}$$

for some nonnegative  $\mathcal{P}(\hat{\mathbb{G}} \vee \mathbb{F}^{\hat{\mu}}) \otimes \mathcal{B}(A)$ -measurable function  $\hat{\nu}$  satisfying

$$\inf_{\hat{\Omega} \times [0, T] \times A} \hat{\nu} > 0, \quad \sup_{\hat{\Omega} \times [0, T] \times A} \hat{\nu} < \infty. \quad (\text{A.3})$$

**Proof.** Fix  $\alpha$  and  $\delta$  as in the statement of the Proposition. It can be proved that there exists an  $A$ -valued process  $\bar{\alpha}$  such that  $\tilde{\rho}(\alpha, \bar{\alpha}) < \delta$  and  $\bar{\alpha}$  has the form  $\bar{\alpha}_t = \sum_{n=0}^{N-1} \alpha_n 1_{[t_n, t_{n+1})}(t)$ , where  $0 = t_0 < t_1 < \dots < t_N = T$  is a deterministic subdivision of  $[0, T]$ ,  $\alpha_0, \dots, \alpha_{N-1}$  are  $A$ -valued random variables that take only a finite number of values, and each  $\alpha_n$  is  $\mathcal{G}_{t_n}$ -measurable: this is an immediate consequence of Lemma 3.2.6 in [24], where it is proved that the set of admissible controls  $\bar{\alpha}$  having the form specified in the lemma are dense in the set of all  $\mathbb{G}$ -progressive  $A$ -valued processes with respect to the metric  $\tilde{\rho}$ .

We can (and will) choose  $\bar{\alpha}$  satisfying  $\alpha_0 = a_0$  ( $a_0$  is the same as in **(A2)**). Indeed this additional requirement can be fulfilled by adding, if necessary, another point  $t'$  close to 0 to the subdivision and modifying  $\bar{\alpha}$  setting  $\bar{\alpha}_t = a_0$  for  $t \in [0, t')$ . This modification is as close as we wish to the original process with respect to the metric  $\tilde{\rho}$ , provided  $t'$  is chosen sufficiently small.

Finally, we further extend  $\bar{\alpha}$  to a function defined on  $\Omega \times [0, \infty)$  in a trivial way setting  $\bar{\alpha}_t = \sum_{n=0}^{\infty} \alpha_n 1_{[t_n, t_{n+1})}(t)$  where  $\alpha_n = \alpha_{N-1}$  for  $n \geq N$  and  $t_n = t + n - N$  for  $n > N$ . This way  $\bar{\alpha}$  is associated to the marked point process  $(t_n, \alpha_n)_{n \geq 1}$  and  $\bar{\alpha}_0 = a_0$ .

Next recall the spaces  $(\Omega', \mathcal{F}', \mathbb{P}')$  and  $(\hat{\Omega}, \hat{\mathcal{F}}, \mathbb{Q})$  and the filtration  $\hat{\mathbb{G}}$  introduced before the statement of Proposition A.1. We extend the processes  $\alpha$  and  $\bar{\alpha}$  to  $\hat{\Omega} \times [0, \infty)$  and denote  $\hat{\alpha}$  and  $\hat{\bar{\alpha}}$  the corresponding extensions. We note that clearly

$$\tilde{\rho}(\hat{\alpha}, \hat{\bar{\alpha}}) = \tilde{\rho}(\alpha, \bar{\alpha}) < \delta/3. \quad (\text{A.4})$$

The next step of the proof consists in constructing a sequence of random measures  $\kappa^m$  whose associated piecewise trajectories, denoted  $\hat{\alpha}_t^m$ , approximate  $\hat{\alpha}$  in the sense of the metric  $\tilde{\rho}$ . The construction will be carried out in such a way that  $\kappa^m$  admits a compensator absolutely continuous with respect to the measure  $\lambda(da) dt$ .

For every  $m \geq 1$ , let  $\mathbf{B}(b, 1/m)$  denote the open ball of radius  $1/m$ , with respect to the metric  $\rho$ , centered at  $b \in A$ . Since  $\lambda(da)$  has full support, we have  $\lambda(\mathbf{B}(b, 1/m)) > 0$  and we can define a transition kernel  $q^m(b, da)$  in  $A$  setting

$$q^m(b, da) = \frac{1}{\lambda(\mathbf{B}(b, 1/m))} 1_{\mathbf{B}(b, 1/m)}(a) \lambda(da).$$

We recall that we require  $A$  to be a Borel space, and we denote by  $\mathcal{B}(A)$  its Borel  $\sigma$ -algebra. There exists a Borel measurable function  $q^m : A \times [0, 1] \rightarrow A$  such that for every  $b \in A$  the measure  $B \mapsto q^m(b, B)$  ( $B \in \mathcal{B}(A)$ ) is the image of the Lebesgue measure on  $[0, 1]$  under the mapping  $u \mapsto q^m(b, u)$ ; equivalently,

$$\int_A k(a) q^m(b, da) = \int_0^1 k(q^m(b, u)) du,$$

for every nonnegative measurable function  $k$  on  $A$ . Thus, if  $U$  is a random variable defined on some probability space and having uniform law on  $[0, 1]$  then, for fixed  $b \in A$ , the  $A$ -valued random variable  $q^m(b, U)$  has law  $q^m(b, da)$ . The use of the same symbol  $q^m$  should not generate confusion. The existence of the function  $q^m$  (even for a general transition kernel on  $A$ ) is well known when  $A$



is a separable complete metric space, in particular, when  $A$  is the unit interval  $[0, 1]$ , (see e.g. [32], Theorem 3.1.1) and the general case reduces to this one, since it is known that any Borel space is either finite or countable (with the discrete topology) or isomorphic, as a measurable space, to the interval  $[0, 1]$ : see e.g. [4], Corollary 7.16.1.

For fixed  $m \geq 1$ , define  $V_0^m = R_0^m = S_0^m = 0$  and

$$R_n^m = t_n + V_1^m + \dots + V_n^m, \quad S_n^m = t_n + V_1^m + \dots + V_{n-1}^m, \quad \beta_n^m = q^m(\alpha_n, U_n^m), \quad n \geq 1.$$

Since we assume  $t_n < t_{n+1}$  and since  $V_n^m > 0$  we see that  $(R_n^m, \beta_n^m)_{n \geq 1}$  is a marked point process in  $A$ . Also note that  $R_{n-1}^m < S_n^m < R_n^m$  for  $n \geq 1$ . Let

$$\kappa^m = \sum_{n \geq 1} \delta_{(R_n^m, \beta_n^m)}, \quad \hat{\alpha}_t^m = \sum_{n \geq 0} \beta_n^m 1_{[R_n^m, R_{n+1}^m)}(t),$$

(with the convention  $\beta_0^m = a_0$ ) denote the corresponding random measure and the associated trajectory. We claim that

$$\tilde{\rho}(\hat{\alpha}, \hat{\alpha}^m) \rightarrow 0 \tag{A.5}$$

as  $m \rightarrow \infty$ . Indeed, since  $0 = t_0 < t_1 < \dots < t_N = T$  we have

$$\tilde{\rho}(\hat{\alpha}, \hat{\alpha}^m) = \sum_{n=0}^{N-1} \mathbb{E}_{\mathbb{Q}} \int_{t_n}^{t_{n+1}} \rho(\hat{\alpha}_t, \hat{\alpha}_t^m) dt. \tag{A.6}$$

Note that  $t_n < R_n^m$ , and whenever  $R_n^m \leq t < t_{n+1} < R_{n+1}^m$  we have  $\hat{\alpha}_t = \alpha_n$ ,  $\hat{\alpha}_t^m = \beta_n^m$  and so  $\rho(\hat{\alpha}_t, \hat{\alpha}_t^m) = \rho(\alpha_n, \beta_n^m) < 1/m$  since, for every  $b \in A$ ,  $q^m(b, da)$  is supported in  $\mathbf{B}(b, 1/m)$ . If  $R_n^m < t_{n+1}$  then, recalling that  $\rho < 1$ ,

$$\begin{aligned} \int_{t_n}^{t_{n+1}} \rho(\hat{\alpha}_t, \hat{\alpha}_t^m) dt &= \int_{t_n}^{R_n^m} \rho(\hat{\alpha}_t, \hat{\alpha}_t^m) dt + \int_{R_n^m}^{t_{n+1}} \rho(\hat{\alpha}_t, \hat{\alpha}_t^m) dt \\ &\leq (R_n^m - t_n) + \frac{1}{m}(t_{n+1} - R_n^m) \\ &\leq V_1^m + \dots + V_n^m + \frac{1}{m}(t_{n+1} - t_n). \end{aligned}$$

If  $R_n^m \geq t_{n+1}$  then the same inequality still holds since we even have

$$\int_{t_n}^{t_{n+1}} \rho(\hat{\alpha}_t, \hat{\alpha}_t^m) dt \leq t_{n+1} - t_n \leq R_n^m - t_n = V_1^m + \dots + V_n^m.$$

Substituting in (A.6) and computing the expectation of the exponential random variables  $V_n^m$  we arrive at

$$\tilde{\rho}(\hat{\alpha}, \hat{\alpha}^m) = \sum_{n=0}^{N-1} \left( \lambda_{1^m}^{-1} + \dots + \lambda_{nm}^{-1} + \frac{1}{m}(t_{n+1} - t_n) \right) \leq \sum_{n=1}^{\infty} \lambda_{nm}^{-1} + \frac{T}{m} \leq \frac{1}{m} + \frac{T}{m}$$

which proves the claim (A.5). From now on we fix a value of  $m$  so large that

$$\tilde{\rho}(\hat{\alpha}, \hat{\alpha}^m) < \delta/3. \tag{A.7}$$

Let  $\mathbb{F}^{\kappa^m} = (\mathcal{F}_t^{\kappa^m})$  denote the natural filtration of  $\kappa^m$  and set

$$\mathbb{H}^m = (\mathcal{H}_t^m)_{t \geq 0} = (\hat{\mathcal{G}}_t \vee \mathcal{F}_t^{\kappa^m})_{t \geq 0}.$$

We have the following technical result that describes the compensator  $\tilde{\kappa}^m$  of  $\kappa^m$  with respect to the filtration  $\mathbb{H}^m$ .

**Lemma A.1** *With the previous assumptions and notations, the compensator of the random measure  $\kappa^m$  with respect to  $\mathbb{H}^m$  and  $\mathbb{Q}$  is given by the formula*

$$\tilde{\kappa}^m(dt, da) = \sum_{n \geq 1} 1_{(S_n^m, R_n^m]}(t) q^m(\alpha_n, da) \lambda_{nm}.$$

**Proof of Lemma A.1.** To shorten notation, we drop all the sub- and superscripts  $m$  and write  $\tilde{\kappa}$ ,  $S_n$ ,  $R_n$ ,  $q$ ,  $\lambda_n$ ,  $\mathbb{F}^\kappa$ ,  $\mathbb{H} = (\mathcal{H}_t) = (\hat{\mathcal{G}}_t \vee \mathcal{F}_t^\kappa)$  instead of  $\tilde{\kappa}^m$ ,  $S_n^m$ ,  $R_n^m$ ,  $q^m$ ,  $\lambda_{nm}$ ,  $\mathbb{F}^{\kappa^m}$ ,  $\mathbb{H}^m = (\mathcal{H}_t^m) = (\hat{\mathcal{G}}_t \vee \mathcal{F}_t^{\kappa^m})$ .

Let us first check that  $\tilde{\kappa}(dt, da)$ , defined by the formula above, is an  $\mathbb{H}$ -predictable random measure. The variables  $R_n$  are clearly  $\mathbb{F}^\kappa$ -stopping times and hence  $\mathbb{H}$ -stopping times and therefore  $S_n = R_{n-1} + t_n - t_{n-1}$  are also  $\mathbb{H}$ -stopping times. Since  $\alpha_n$  are  $\mathcal{F}_{t_n}$ -measurable and  $\mathcal{F}_{t_n} \subset \mathcal{H}_{t_n} \subset \mathcal{H}_{S_n}$ ,  $\alpha_n$  are also  $\mathcal{H}_{S_n}$ -measurable. It follows that for every  $C \in \mathcal{B}(A)$  the process  $1_{(S_n, R_n]}(t) q(\alpha_n, C) \lambda_n$  is  $\mathbb{H}$ -predictable and finally that  $\tilde{\kappa}(dt, da)$  is an  $\mathbb{H}$ -predictable random measure.

To finish the proof we need now to verify that for every positive  $\mathcal{P}(\mathbb{H}) \otimes \mathcal{B}(A)$ -measurable random field  $H_t(\omega, a)$  we have

$$\mathbb{E} \left[ \int_0^\infty \int_A H_t(a) \kappa(dt da) \right] = \mathbb{E} \left[ \int_0^\infty \int_A H_t(a) \tilde{\kappa}(dt da) \right].$$

Since  $\mathcal{H}_t = \mathcal{F}_t \vee \mathcal{F}_t^\kappa$ , by a monotone class argument it is enough to consider  $H$  of the form

$$H_t(\omega, a) = H_t^1(\omega) H_t^2(\omega) k(a),$$

where  $H^1$  is a positive  $\hat{\mathbb{G}}$ -predictable random process,  $H^2$  is a positive  $\mathbb{F}^\kappa$ -predictable random process and  $k$  is a positive  $\mathcal{B}(A)$ -measurable function. Since  $\mathbb{F}^\kappa$  is the natural filtration of  $\kappa$ , by a known result (see e.g. [18] Lemma (3.3))  $H^2$  has the following form:

$$\begin{aligned} H_t^2 &= b_1(t) 1_{(0, R_1]}(t) + b_2(\beta_1, R_1, t) 1_{(R_1, R_2]}(t) \\ &\quad + b_3(\beta_1, \beta_2, R_1, R_2, t) 1_{(R_2, R_3]}(t) + \dots \\ &\quad + b_n(\beta_1, \dots, \beta_{n-1}, R_1, \dots, R_{n-1}, t) 1_{(R_{n-1}, R_n]}(t) + \dots, \end{aligned}$$

where each  $b_n$  is a positive measurable deterministic function of  $2n - 1$  real variables. Since

$$\mathbb{E} \left[ \int_0^\infty \int_A H_t(a) \kappa(dt da) \right] = \mathbb{E} \left[ \sum_{n \geq 1} H_{R_n}(\beta_n) \right]$$

to prove the thesis it is enough to check that for every  $n \geq 1$  we have the equality

$$\mathbb{E} [H_{R_n}(\beta_n)] = \mathbb{E} \left[ \int_0^\infty \int_A H_t(a) q(\alpha_n, da) \lambda_n 1_{S_n < t \leq R_n} dt \right]$$

which can also be written

$$\begin{aligned} &\mathbb{E} [H_{R_n}^1 b_n(\beta_1, \dots, \beta_{n-1}, R_1, \dots, R_{n-1}, R_n) k(\beta_n)] = \\ &\mathbb{E} \left[ \int_0^\infty \int_A H_t^1 b_n(\beta_1, \dots, \beta_{n-1}, R_1, \dots, R_{n-1}, t) k(a) q(\alpha_n, da) \lambda_n 1_{S_n < t \leq R_n} dt \right]. \end{aligned}$$

We use the notation

$$K_n(t) = H_t^1 b_n(\beta_1, \dots, \beta_{n-1}, R_1, \dots, R_{n-1}, t)$$

to reduce the last equality to

$$\mathbb{E}[K_n(R_n)k(\beta_n)] = \mathbb{E}\left[\int_0^\infty \int_A K_n(t) k(a) q(\alpha_n, da) \lambda_n 1_{S_n < t \leq R_n} dt\right]. \quad (\text{A.8})$$

By the definition of  $R_n$  and  $\beta_n$ , we have  $\mathbb{E}[K_n(R_n)k(\beta_n)] = \mathbb{E}[K_n(S_n + V_n)k(q(\alpha_n, U_n))]$ . As noted above, since  $U_n$  has uniform law on  $(0, 1)$ , the random variable  $q(b, U_n)$  has law  $q(b, da)$  on  $A$ , for any fixed  $b \in A$ . We note that  $R_1, \dots, R_{n-1}, S_n$  are measurable with respect to  $\sigma(V_1, \dots, V_{n-1})$ , that  $\beta_1, \dots, \beta_{n-1}$  are measurable with respect to  $\hat{\mathcal{G}}_\infty \vee \sigma(U_1, \dots, U_{n-1})$  and therefore that the random elements  $U_n, S_n$  and  $(\hat{\mathcal{G}}_\infty, \beta_1, \dots, \beta_{n-1}, R_1, \dots, R_{n-1}, S_n)$  are all independent. Recalling that  $V_n$  is exponentially distributed with parameter  $\lambda_n$  we obtain

$$\mathbb{E}[K_n(R_n)k(\beta_n)] = \mathbb{E}\left[\int_0^\infty \int_A K_n(S_n + s) k(a) q(\alpha_n, da) \lambda_n e^{-\lambda_n s} ds\right]. \quad (\text{A.9})$$

Using again the independence of  $V_n$  and  $(\hat{\mathcal{G}}_\infty, \beta_1, \dots, \beta_{n-1}, R_1, \dots, R_{n-1}, S_n)$  we also have

$$\begin{aligned} & \mathbb{E}\left[\int_0^\infty \int_A K_n(S_n + s) k(a) q(\alpha_n, da) \lambda_n 1_{V_n \geq s} ds\right] \\ &= \mathbb{E}\left[\int_0^\infty \int_A K_n(S_n + s) k(a) q(\alpha_n, da) \lambda_n \mathbb{P}(V_n \geq s) ds\right] \end{aligned}$$

and since  $\mathbb{P}(V_n \geq s) = e^{-\lambda_n s}$ , this coincides with the right-hand side of (A.9). By a change of variable we arrive at equality (A.8):

$$\begin{aligned} \mathbb{E}[K_n(R_n)k(\beta_n)] &= \mathbb{E}\left[\int_{S_n}^\infty \int_A K_n(t) k(a) q(\alpha_n, da) \lambda_n 1_{V_n \geq t - S_n} dt\right] \\ &= \mathbb{E}\left[\int_0^\infty \int_A K_n(t) k(a) q(\alpha_n, da) \lambda_n 1_{S_n < t \leq R_n} dt\right]. \end{aligned}$$

This concludes the proof of Lemma A.1.  $\square$

It follows from this lemma that the  $\mathbb{H}^m$ -compensator of  $\kappa^m$  under  $\mathbb{Q}$  is absolutely continuous with respect to  $\lambda(da) dt$  and it can be written in the form

$$\tilde{\kappa}^m(dt, da) = \phi_t^m(a) \lambda(da) dt$$

for a suitable nonnegative  $\mathcal{P}(\mathbb{H}^m) \otimes \mathcal{B}(A)$ -measurable function  $\phi^m$  which is bounded on  $\hat{\Omega} \times [0, T] \times A$ . Indeed, from the choice of the kernel  $q^m(b, da)$  we obtain

$$\phi_t^m(a) = \sum_{n \geq 1} 1_{(S_n^m, R_n^m)}(t) \frac{1}{\lambda(\mathbf{B}(\alpha_n, 1/m))} 1_{\mathbf{B}(\alpha_n, 1/m)}(a) \lambda_{nm}.$$

which is bounded on  $\hat{\Omega} \times [0, T] \times A$  since each  $\alpha_n$  takes only a finite number of values and  $S_N^m > t_N = T$ , so that the values of  $\phi_t^m$  on  $[0, T]$  only depend on the first  $N - 1$  summands.

In the final step of the proof we will modify the random measure  $\kappa^m$  by adding an independent Poisson process  $\pi^k$  with “small” intensity. This will not affect too much the  $\tilde{\rho}$ -distance between the corresponding trajectories and will produce a random measure whose compensator remains absolutely continuous with respect to the measure  $\lambda(da) dt$  and has a bounded density which, in addition, is bounded away from zero.

Recall that on the space  $(\Omega', \mathcal{F}', \mathbb{P}')$  we assumed that for every integer  $k \geq 1$  there existed a Poisson random measure  $\pi^k$  on  $(0, \infty) \times A$ , admitting compensator  $k^{-1}\lambda(da) dt$  with respect to its natural filtration. We will consider  $\pi^k$  as defined in  $(\hat{\Omega}, \hat{\mathcal{F}})$ . Each  $\pi^k$  has the form

$$\pi^k = \sum_{n \geq 1} \delta_{(T_n^k, \xi_n^k)},$$

for a marked point process  $(T_n^k, \xi_n^k)_{n \geq 1}$  on  $(0, \infty) \times A$ , and we denote  $\mathbb{F}^{\pi^k} = (\mathcal{F}_t^{\pi^k})$  its natural filtration. Let us define another random measure setting

$$\mu^{km} = \kappa^m + \pi^k.$$

Note that the jumps times  $(R_n^m)_{n \geq 1}$  are independent of the jump times  $(T_n^k)_{n \geq 1}$ , and the latter have absolutely continuous laws. It follows that, except possibly on a set of  $\mathbb{Q}$  probability zero, their graphs are disjoint, i.e.  $\kappa^m$  and  $\pi^k$  have no common jumps. Therefore, the random measure  $\mu^{km}$  and its associated pure jump process (denoted  $I^{km}$ ) admit a representation

$$\mu^{km} = \sum_{n \geq 1} \delta_{(S_n^{km}, \eta_n^{km})}, \quad I_t^{km} = \sum_{n \geq 0} \eta_n^{km} 1_{[S_n^{km}, S_{n+1}^{km})}(t), \quad t \geq 0,$$

where  $\eta_0^{km} = a_0$ ,  $(S_n^{km}, \eta_n^{km})_{n \geq 1}$  is a marked point process, each  $S_n^{km}$  coincides with one of the times  $R_n^m$  or one of the times  $T_n^k$ , and each  $\eta_n^{km}$  coincides with one of the random variables  $\xi_n^k$  or one of the random variables  $\beta_n^m$ . We claim that, for large  $k$ ,  $I^{km}$  is close to  $\hat{\alpha}^m$  with respect to the metric  $\tilde{\rho}$ , namely that

$$\tilde{\rho}(I^{km}, \hat{\alpha}^m) \rightarrow 0 \tag{A.10}$$

as  $k \rightarrow \infty$ . To prove this claim it suffices to prove that  $I^{km} \rightarrow \hat{\alpha}^m$  in  $dt \otimes d\mathbb{Q}$ -measure. Recall that the jump times of  $\pi^k$  are denoted  $T_n^k$ . Since  $T_1^k$  has exponential law with parameter  $\lambda(A)/k$  the event  $B_k = \{T_1^k > T\}$  has probability  $e^{-\lambda(A)T/k}$ , so that  $\mathbb{Q}(B_k) \rightarrow 1$  as  $k \rightarrow \infty$ . Noting that on the set  $B_k$ , we have  $\hat{\alpha}_t^m = \alpha_0 = a_0 = \eta_0^{km} = I_t^{km}$  for all  $t \in [0, T]$ , the claim (A.10) follows immediately. We will fix from now on an integer  $k$  so large that

$$\tilde{\rho}(\hat{\alpha}^m, I^{km}) < \delta/3. \tag{A.11}$$

Having fixed both  $m$  and  $k$  we now define, for  $n \geq 0$ ,

$$\hat{S}_n = S_n^{km}, \quad \hat{\eta}_n = \hat{\eta}_n^{km}, \quad \hat{\mu} = \sum_{n \geq 1} \delta_{(\hat{S}_n, \hat{\eta}_n)}, \quad \hat{I}_t = \sum_{n \geq 0} \hat{\eta}_n 1_{[\hat{S}_n, \hat{S}_{n+1})}(t),$$

so that the random measure  $\hat{\mu}$  and the associated process  $\hat{I}$  coincide with  $\mu^{km}$  and  $I^{km}$  respectively. The inequalities (A.4), (A.7), (A.11) imply that  $\tilde{\rho}(\hat{\alpha}, \hat{I}) < \delta$ , which gives (A.1).

To finish the proof it remains to prove (A.2)-(A.3). We first note that, since  $\kappa^m$  and  $\pi^k$  are independent, it is easy to prove that  $\hat{\mu} = \mu^{km}$  has compensator  $(\phi_t^m(a) + k^{-1})\lambda(da) dt$  with respect to the filtration  $\mathbb{H}^m \vee \mathbb{F}^{\pi^k} := (\mathcal{H}_t^m \vee \mathcal{F}_t^{\pi^k})_{t \geq 0} = (\hat{\mathcal{G}}_t \vee \mathcal{F}_t^{\kappa^m} \vee \mathcal{F}_t^{\pi^k})_{t \geq 0}$ . Let  $\mathbb{F}^{\hat{\mu}} = (\mathcal{F}_t^{\hat{\mu}})_{t \geq 0}$  denote the natural filtration of  $\hat{\mu}$  and let  $\hat{\mathbb{G}} \vee \mathbb{F}^{\hat{\mu}}$  be the filtration  $(\hat{\mathcal{G}}_t \vee \mathcal{F}_t^{\hat{\mu}})_{t \geq 0}$ , which is smaller than  $\mathbb{H}^m \vee \mathbb{F}^{\pi^k}$ . We wish to compute the compensator of  $\hat{\mu}$  with respect to  $\hat{\mathbb{G}} \vee \mathbb{F}^{\hat{\mu}}$  under  $\mathbb{Q}$ . To this end, consider the measure space  $([0, \infty) \times \Omega \times A, \mathcal{B}([0, \infty)) \otimes \mathcal{F} \otimes \mathcal{B}(A), dt \otimes \mathbb{Q}(d\omega) \otimes \lambda(da))$ . Although this is not a probability space, one can define in a standard way the conditional expectation of any positive measurable function, given an arbitrary sub- $\sigma$ -algebra. Let us denote by  $\hat{\nu}_t(\hat{\omega}, a)$  the conditional

expectation of the random field  $\phi_t^m(\hat{\omega}, a) + k^{-1}$  with respect to the  $\sigma$ -algebra  $\mathcal{P}(\hat{\mathbb{G}} \vee \mathbb{F}^{\hat{\mu}}) \otimes \mathcal{B}(A)$ . It is then easy to verify that the compensator of  $\hat{\mu}$  with respect to  $\hat{\mathbb{G}} \vee \mathbb{F}^{\hat{\mu}}$  coincides with  $\hat{\nu}$ . Moreover, since  $\phi_t^m(\hat{\omega}, a)$  is nonnegative and bounded on  $\hat{\Omega} \times [0, T] \times A$ , we can take a version of  $\hat{\nu}$  satisfying

$$k^{-1} \leq \inf_{\hat{\Omega} \times [0, T] \times A} \hat{\nu} \leq \sup_{\hat{\Omega} \times [0, T] \times A} \hat{\nu} < \infty.$$

Now (A.2)-(A.3) are proved and the proof of Proposition A.1 is finished.  $\square$

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