PARTICLES SYSTEMS AND NUMERICAL SCHEMES FOR
MEAN REFLECTED STOCHASTIC DIFFERENTIAL EQUATIONS

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Abstract. This paper is devoted to the study of reflected Stochastic Differential Equations when the constraint is not on the paths of the solution but acts on its law. These reflected equations have been introduced recently in a backward form by Briand, Elie and Hu [BEH16] in the context of risk measures. We here focus on the forward version of such reflected equations. Our main objective is to provide an approximation of the solutions with the help of interacting particles systems. This approximation allows to design a numerical scheme for this kind of equations.

1. Introduction.

In this paper, we are concerned with a special type of reflected Stochastic Differentials Equations (SDEs for short in the sequel) in which the constraint is not directly on the paths of the solution to the SDE as in the usual case but on the law of the solution. Typically, the integral of a given function, say $h$, with respect to the law of the solution to the SDE is asked to be nonnegative. We call Mean Reflected Stochastic Differential Equation (MR-SDE) this kind of reflected SDEs which are described by the following system:

\[ \begin{aligned}
X_t &= \xi + \int_0^t b(X_s) \, ds + \int_0^t \sigma(X_s) \, dB_s + K_t, \quad t \geq 0, \\
\mathbb{E}[h(X_t)] &\geq 0, \quad \int_0^t \mathbb{E}[h(X_s)] \, dK_s = 0, \quad t \geq 0,
\end{aligned} \]  

(1.1)

where $b, \sigma$ and $h$ are given Lipschitz functions from $\mathbb{R}$ to $\mathbb{R}$ and where $(B_t, t \geq 0)$ stands for a standard Brownian motion defined on some complete probability space $(\Omega, \mathcal{F}, \mathbb{P})$. We will always assume that $h$ is nondecreasing and that the law of $\xi$ is such that $\mathbb{E}[h(\xi)] \geq 0$. The solution to (1.1) is the couple of continuous processes $(X, K)$, $K$ being needed to ensure that the constraint is satisfied, in a minimal way according to the last condition namely the Skorokhod condition.

Reflected stochastic differential equations have been widely studied in the literature and we refer to the works [Tan79, LS84] for an overview of this theory. As said before, the main particularity comes here from the fact that the constraint acts on the law of the process $X$ rather than on its paths. To the best of our knowledge, Skorokhod problem on the law of type (1.1) have been introduced by Briand, Elie and Hu in their backward forms in [BEH16]. In that work, they show that mean reflected backward stochastic processes exist and are uniquely defined by the associated system of equations of the form of (1.1) under the same assumptions we use below. The main requirement for uniqueness is to ask the process $K$ to be a deterministic function. They then show that such system is useful for super hedging of claims under running risk management constraint.

In this paper, our main objectives are twofold. Due to the fact that the reflection process $K$ depends on the law of the position, it is hence non-linear in the McKean-Vlasov’s terminology.
Putting together all conditions on \( X \) that, here, the terminal value is not fixed. Indeed, in [BEH16], the authors look for the initial portfolio. This financial issue is closed to the one studied in [BEH16] but differs from the fact almost surely, the process \( X \) has a unique strong solution and for the modeling of crowd motion with congestion phenomenon (see [MRCS10]). Diffusion processes with conditioned initial-terminal distribution (see [Bau02], [MT08] and [TT13]) appear in various theoretical and applied situations such as stochastic mechanics (see [CL95]), equation, where the payoff, when the portfolio is also submitted to a risk measure constraint. From a practical point of view, using a particle system (this seems to be a more involved problem in the backward case) to approximate the solution to (1.1) leads to solve numerically a point a view, using a particle system open. Weak localization approach, he builds weak solutions and obtains only partial uniqueness results, leaving the Skorokhod minimality condition and the approximation by particle systems open. Weak dimension remains a difficult problem, to address the difficulties by increasing order, we focus in this paper on mean reflected forward SDEs.

Let us indeed consider an asset manager holding a number of stocks \( S = (S^1, \ldots, S^d) \) in his portfolio and let \( \pi = (\pi^1, \ldots, \pi^d) \) denotes his investment strategy. When the investor is allowed to choose his strategy as he wants, the value of his portfolio at time \( t \), \( X_t = X_0 + \int_0^t \pi_s \cdot dS_s \), can become very negative. For regulation purpose, one can allow only strategies such that \( X_t \) remains non negative or above a certain level. We are interested here in a weaker regulation constraint: the asset manager is allowed to hold its position \( X_t \) at time \( t \) only if it remains acceptable for a given risk measure \( \rho \) \( \text{i.e.} \) it is such that \( \rho(X_t) \leq 0 \). Such a risk measure (see \textit{e.g.} [ADEH99] or [FS02] for partial account on risk measures) could be \textit{e.g.} a utility function \( u : \mathbb{R} \rightarrow \mathbb{R} \) so that \( \rho(X) = \inf \{ m : \mathbb{E}[u(m + X)] \geq p \} \), which means that a minimal profit is guaranteed.

In order to satisfy this constraint, the asset manager thus has to add some cash in the portfolio through the time and the dynamic of its position becomes

\[
dX_t = \pi_t dS_t + dK_t,
\]

where \( K_t \) is the amount of cash added up to time \( t \) in the portfolio to balance the "risk" associated to \( X_t \). Of course, the agent wants to cover the risk in a minimal way, adding cash only when needed: this leads to the Skorokhod condition \( \mathbb{E}[h(X_t)]dK_t = 0 \).

Let us now consider the Black & Scholes model and suppose that the investment strategy depends on the wealth of the portfolio. We end up with the following SDE

\[
dX_t = b(X_t) dt + \sigma(X_t) dB_t + dK_t, \quad t \geq 0,
\]

Putting together all conditions on \( X \), we end up with a dynamic of the form (1.1) for the portfolio. This financial issue is closed to the one studied in [BEH16] but differs from the fact that, here, the terminal value is not fixed. Indeed, in [BEH16], the authors look for the initial amount to invest and for the replicating strategy \( (\pi^1, \ldots, \pi^d) \) for a given terminal value, namely the payoff, when the portfolio is also submitted to a risk measure constraint. From a practical point a view, using a particle system (this seems to be a more involved problem in the backward case) to approximate the solution to (1.1) leads to solve numerically a \( N \)-dimensional stochastic equation, where \( N \) is the number of particles. Since solving numerically backward SDEs in high dimension remains a difficult problem, to address the difficulties by increasing order, we focus in this paper on mean reflected forward SDEs.

Let us eventually point out that, in his work [Jab17], Jabir studies diffusion processes whose time-marginal densities are constrained to belong to a given set at all time. By using a penalization approach, he builds weak solutions and obtains only partial uniqueness results, leaving the Skorokhod minimality condition and the approximation by particle systems open. Weak conditioning involving path-distribution constraints of the form

\[
\text{Law}(X_t; 0 \leq t \leq T) \in \mathcal{K}, \quad \text{for } \mathcal{K} \text{ a given subset of } \mathcal{P}(\mathcal{C}([0, T]; \mathbb{R}^d))
\]

appears in various theoretical and applied situations such as stochastic mechanics (see [CL95]), diffusion processes with conditioned initial-terminal distribution (see [Bau02], [MT08] and [TT13]) and for the modeling of crowd motion with congestion phenomenon (see [MRCS10]).

Organization of this paper. The paper is organized as follows. In Section 2, by letting the coefficients satisfy the usual smoothness assumptions (say Lipschitz continuity) and adding a structural assumption on the function \( h \) (say \( h \) bi-Lipschitz), we show that the system admits a unique strong solution \( \text{i.e.} \) there exists a unique pair of process \( (X, K) \) satisfying system (1.1) almost surely, the process \( K \) being an increasing and deterministic process. Then, we show that,
by adding some regularity on the function $h$, the Stieltjes measure $dK$ is absolutely continuous with respect to the Lebesgue measure and we give the explicit expression of its density.

Having in mind the analogy with McKean-Vlasov processes, we also show in Section 3 that system (1.1) can be seen as the limit of an interacting particles system with oblique reflection of mean field type. This could reflect a system of large number of players whose positions are constrained by the mean of the positions of the other players. If all the players have the same dynamic, and if the interaction between the players is of mean field type, we show that there is a propagation of chaos phenomenon so that when the number of players tends to the infinity, the reflection no more depends on the other positions, but only on their statistical distribution. This obviously comes from the law of large number and is what, in fact, exactly happened in the classical McKean-Vlasov setting.

As an application, this result allows to define in Section 4 an algorithm based on this interacting particle system together with a classical Euler scheme which gives a strong approximation of the solution of (1.1). This leads to an approximation error proportional, up to a log factor, to the number of points of the discretization grid of the time interval (namely of $(\log n/n)^{1/2}$, where $n$ is the number of points of the discretization grid) and on the number of particles (namely $N^{-1/4}$ when the function $h$ is only bi-Lipschitz and $N^{-1/2}$ when the function $h$ is smooth, $N$ standing for the number of particles). Finally, we illustrate in Section 5 these results numerically.

2. Existence, uniqueness and properties of the solution.

Throughout this paper, we consider the following set of assumptions.

**Assumption (A.1).**

(i) The functions $b : \mathbb{R} \mapsto \mathbb{R}$ and $\sigma : \mathbb{R} \mapsto \mathbb{R}$ are Lipschitz continuous;

(ii) The random variable $\xi$ is square integrable.

**Assumption (A.2).**

(i) The function $h : \mathbb{R} \mapsto \mathbb{R}$ is an increasing function and there exist $0 < m \leq M$ such that

$$\forall x \in \mathbb{R}, \quad \forall y \in \mathbb{R}, \quad m|x - y| \leq |h(x) - h(y)| \leq M|x - y|.$$  

(ii) The initial condition $\xi$ satisfies: $\mathbb{E}[h(\xi)] \geq 0$.

**Assumption (A.3).** $\exists p > 4$ such that $\xi$ belongs to $L^p$: $\mathbb{E}[|\xi|^p] < \infty$.

**Assumption (A.4).** The mapping $h$ is a twice continuously differentiable function with bounded derivatives.

In the following, we make an intensive use of this representation formula of the process $K$. Define the function

$$H : \mathbb{R} \times \mathcal{P}_1(\mathbb{R}) \ni (x, \nu) \mapsto H(x, \nu) = \int h(x + z) \nu(dz),$$  

where $\mathcal{P}_1(\mathbb{R})$ denotes the set of probability measures on $\mathbb{R}$ with finite first moment. We will need also the inverse function in space of $H$ evaluated at 0 namely:

$$\tilde{G}_0 : \mathcal{P}_1(\mathbb{R}) \ni \nu \mapsto \inf \{ x \in \mathbb{R} : H(x, \nu) \geq 0 \},$$  

as well as $G_0$, the positive part of $G_0$:

$$G_0 : \mathcal{P}_1(\mathbb{R}) \ni \nu \mapsto \inf \{ x \geq 0 : H(x, \nu) \geq 0 \}.$$  

We start by studying some properties of $H$ and $G_0$.

**Lemma 2.1.** Under (A.2) we have:
(i) For all \( \nu \) in \( \mathcal{P}_1(\mathbb{R}) \), the mapping \( H(\cdot, \nu) : \mathbb{R} \ni x \mapsto H(x, \nu) \) is a bi-Lipschitz function, namely:
\[
\forall x, y \in \mathbb{R}, m |x - y| \leq |H(x, \nu) - H(y, \nu)| \leq M |x - y|.
\] (2.4)

(ii) For all \( x \) in \( \mathbb{R} \), the mapping \( H(x, \cdot) : \mathcal{P}_1(\mathbb{R}) \ni \nu \mapsto H(x, \nu) \) satisfies the following Lipschitz estimate:
\[
\forall \nu, \nu' \in \mathcal{P}_1(\mathbb{R}), |H(x, \nu) - H(x, \nu')| \leq \int h(x + \cdot)(d\nu - d\nu').
\] (2.5)

Proof. The proof is straightforward from the definition of \( H \) see (2.1).

\[\square\]

Note that thanks to Monge-Kantorovitch Theorem, assertion (2.5) implies that for all \( x \in \mathbb{R} \), the function \( H(x, \cdot) \) is Lipschitz continuous w.r.t. the Wasserstein-1 distance. Indeed, for two probability measures \( \nu \) and \( \nu' \), the Wasserstein-1 distance between \( \nu \) and \( \nu' \) is defined by:
\[
W_1(\nu, \nu') = \sup_{\varphi \in 1-Lipschitz} \left| \int \varphi(d\nu - d\nu') \right| = \inf_{X \sim \nu : Y \sim \nu'} \mathbb{E}[|X - Y|].
\]
Therefore
\[
\forall \nu, \nu' \in \mathcal{P}_1(\mathbb{R}), |H(x, \nu) - H(x, \nu')| \leq MW_1(\nu, \nu').
\] (2.6)

Then, we have the following result about the regularity of \( G_0 \):

Lemma 2.2. Under (A.2), the mapping \( G_0 : \mathcal{P}_1(\mathbb{R}) \ni \nu \mapsto G_0(\nu) \) is Lipschitz-continuous in the following sense:
\[
|G_0(\nu) - G_0(\nu')| \leq \frac{1}{m} \int h(G_0(\nu) + \cdot)(d\nu - d\nu'),
\]
where we recall that \( G_0(\nu) \) is the inverse of \( H(\cdot, \nu) \) at point 0. In particular,
\[
|G_0(\nu) - G_0(\nu')| \leq \frac{M}{m} W_1(\nu, \nu').
\] (2.7)

Proof. Let \( \nu \) and \( \nu' \) be two probability measures on \( \mathbb{R} \). From Lipschitz regularity of the positive part, we have
\[
|G_0(\nu) - G_0(\nu')| \leq |\bar{G}_0(\nu) - \bar{G}_0(\nu')|
\]
Next, using the bi-Lipschitz in space property of \( H \), we get that for any \( \eta \) in \( \mathcal{P}(\mathbb{R}) \):
\[
|\bar{G}_0(\nu) - \bar{G}_0(\nu')| \leq \frac{1}{m}|H(\bar{G}_0(\nu), \eta) - H(\bar{G}_0(\nu'), \eta)|.
\]
By definitions of \( H \) and \( G_0 \) we have, for all \( \eta \) in \( \mathcal{P}_1(\mathbb{R}) \): \( H(\bar{G}_0(\eta), \eta) = 0 \). Hence, by choosing \( \eta = \nu' \):
\[
|G_0(\nu) - G_0(\nu')| \leq \frac{1}{m}|H(\bar{G}_0(\nu), \nu') - H(\bar{G}_0(\nu'), \nu')|
= \frac{1}{m}|H(\bar{G}_0(\nu), \nu') - H(\bar{G}_0(\nu), \nu')|
= \frac{1}{m} \int h(\bar{G}_0(\nu) + \cdot)(d\nu - d\nu').
\]
The last assertion immediately follows from (2.6).

\[\square\]

We emphasize that existence and uniqueness results hold only under (A.1) which is the standard assumption for SDEs and (A.2) which is the assumption used in [BEH16]. The convergence of particle systems require only an additional integrability assumption on the initial condition, namely (A.3). We sometimes add the smoothness assumption (A.4) on \( h \) in order to improve some of the results.

We first recall the existence and uniqueness result of [BEH16] in the case of SDEs.
and define the function $reflected \ SDE$ we sketch the proof for the forward case. The proof for the case of backward SDEs is given in [BEH16]. For the ease of the reader, proof.

\[
\text{Proof.} \quad \text{Given this definition, we have the following result.}
\]

**Theorem 2.4** (Briand, Elie and Hu, [BEH16]). Under assumptions (A.1) and (A.2), the mean reflected SDE (1.1) has a unique deterministic flat solution $(X,K)$. Moreover,

\[
\forall t \geq 0, \quad K_t = \sup_{s \leq t} \inf \{x \geq 0 : E[h(x + U_s)] \geq 0\},
\]

where $(U_t)_{0 \leq t \leq T}$ is the process defined by:

\[
U_t = \xi + \int_0^t b(X_s)ds + \int_0^t \sigma(X_s)dB_s.
\]

With these notations, denoting by $(\mu_t)_{0 \leq t \leq T}$ the family of marginal laws of $(U_t)_{0 \leq t \leq T}$ we have

\[
K_t = \sup_{s \leq t} G_0(\mu_s).
\]

**Proof.** The proof for the case of backward SDEs is given in [BEH16]. For the ease of the reader, we sketch the proof for the forward case.

Let $\hat{X}$ be a given continuous process such that, for all $t > 0$, $E\left[\sup_{s \leq t} \left|\hat{X}_s\right|^2\right] < +\infty$. We set

\[
\hat{U}_t = \xi + \int_0^t b(\hat{X}_s)ds + \int_0^t \sigma(\hat{X}_s)dB_s, \quad \text{Law}(\hat{U}_s) =: \tilde{\mu}_s.
\]

and define the function $K$ by setting

\[
K_t = \sup_{s \leq t} \inf \{x \geq 0 : E[h(x + \hat{U}_s)] \geq 0\} = G_0(\tilde{\mu}_s).
\]

The function $K$ being given, let us define the process $\check{X}$ by the formula

\[
\check{X}_t = \xi + \int_0^t b(\hat{X}_s)ds + \int_0^t \sigma(\hat{X}_s)dB_s + K_t,
\]

Let us check that $(X,K)$ is the solution to (1.1). By definition of $K$, $E[h(X_t)] \geq 0$ and we have, $dK$ almost everywhere,

\[
K_t = \sup_{s \leq t} \inf \{x \geq 0 : E[h(x + \hat{U}_s)] \geq 0\} > 0,
\]

so that $E[h(X_t)] = E\left[h\left(\hat{U}_t + K_t\right)\right] = 0$ $dK$-a.e. since $h$ is continuous and nondecreasing.

Next, consider the map $\Xi$ which associates to $\hat{X}$ the solution $X$ of (1.1). Let us show that $\Xi$ is a contraction. Let $\check{X}$ and $\check{X}'$ be given, and define $\hat{U}$, $K$ and $\hat{U}'$, $K'$ as above, using the same Brownian motion. We have from Cauchy-Schwartz and Doob inequality

\[
E\left[\sup_{t \leq T} |X_t - X'_t|^2\right] \leq (T||b||_{\text{Lip}} + 2||\sigma||_{\text{Lip}})E\left[\int_0^T |\check{X}_s - \check{X}'_s|^2 ds\right] + 2 \sup_{t \leq T} |K_t - K'_t|^2.
\]

From the representation (2.10) of the process $K$ we have that

\[
\sup_{t \leq T} |K_t - K'_t|^2 = \sup_{t \leq T} |\sup_{s \leq t} G_0(\tilde{\mu}_s) - \sup_{s \leq t} G_0(\tilde{\mu}'_s)| \leq \sup_{t \leq T} |G_0(\tilde{\mu}_t) - G_0(\tilde{\mu}'_t)|.
\]

Then Lemma 2.2 gives
Proof. We have

\[ \sup_{t \leq T} |K_t - K'_t|^2 \leq \frac{M}{m} \mathbb{E} \left[ \sup_{t \leq T} |\tilde{U}_t - \tilde{U}'_t|^2 \right] \leq C (T||b||_{\text{Lip}} + 2||\sigma||_{\text{Lip}}) \mathbb{E} \left[ \int_0^T |\tilde{X}_s - \tilde{X}'_s|^2 ds \right]. \]

Therefore,

\[ \mathbb{E} \left[ \sup_{t \leq T} |X_t - X'_t|^2 \right] \leq C(1 + T) \mathbb{E} \left[ \int_0^T |\tilde{X}_s - \tilde{X}'_s|^2 ds \right] \leq C(1 + T)T \mathbb{E} \left[ \sup_{t \leq T} |\tilde{X}_t - \tilde{X}'_t|^2 \right]. \]

Hence, there exists a positive \( T \), depending on \( b, \sigma \) and \( h \), such that for all \( T < T \), the map \( \tilde{\Xi} \) is a contraction. We first deduce the existence and uniqueness of the solution on \([0, T]\) and then on \( \mathbb{R}^+ \) by iterating the construction.

\[ \square \]

Remark 2.5. Note that from this construction, we deduce that for all positive \( r \):

\[ K_{t+r} - K_t = \sup_{0 \leq s \leq r} \inf \{ x \geq 0 : \mathbb{E} \left[ h \left( x + X_t + \int_t^{t+s} b(X_u) du + \int_t^{t+s} \sigma(X_u) dB_u \right) \right] \geq 0 \}. \]

It then follows that the unique solution of (1.1) is a Markov process on the space \( \mathbb{R} \times \mathcal{P}(\mathbb{R}) \), where \( \mathcal{P}(\mathbb{R}) \) denotes the space of probability measures on \( \mathbb{R} \).

Proposition 2.6. Suppose that assumptions (A.1) and (A.2) hold. Then, for all \( p \geq 1 \), there exists a positive constant \( C_p \), depending on \( T, b, \sigma \) and \( h \) such that

\[ \mathbb{E} \left[ \sup_{t \leq T} |X_t|^p \right] \leq C_p (1 + \mathbb{E} [|\xi|^p]). \]

Moreover, there exists a positive constant \( C \), depending on \( p, T, b, \sigma \) and \( h \) such that

\[ \forall 0 \leq s \leq t \leq T, \quad |K_t - K_s| \leq C |t - s|^{1/2} \]

and for all \( p \geq 1 \) such that \( \xi \in L^p \) we have

\[ \forall 0 \leq s \leq t \leq T, \quad \mathbb{E} [|X_t - X_s|^p] \leq C |t - s|^{p/2}. \]

Proof. We have

\[ \mathbb{E} \left[ \sup_{t \leq T} |X_t|^p \right] \leq 4^{p-1} \left\{ \mathbb{E} [|\xi|^p] + \mathbb{E} \left[ \sup_{t \leq T} \left( \int_0^t |b(X_s)| ds \right)^p \right] + \mathbb{E} \left[ \sup_{t \leq T} \left( \int_0^t \sigma(X_s) dB_s \right)^p \right] + k_T^p \right\}. \]

Let us first consider the last term \( K_T = \sup_{t \leq T} |G_0(\mu_t)|^p \). From the Lipschitz property of Lemma 2.2 of \( G_0 \), and the definition of the Wasserstein metric we have

\[ \forall t \geq 0, \quad |G_0(\mu_t)| \leq \frac{M}{m} \mathbb{E} [|U_t - U_0|], \]

since \( G_0(\mu_0) = 0 \) as \( \mathbb{E} [h(\xi)] \geq 0 \) and where \( U \) is defined by (2.8). Therefore

\[ |\sup_{t \leq T} G_0(\mu_s)|^p \leq 2^{p-1} \left( \frac{M}{m} \right)^p \left\{ \mathbb{E} \left[ \sup_{t \leq T} \left( \int_0^t |b(X_s)| ds \right)^p \right] + \mathbb{E} \left[ \sup_{t \leq T} \left( \int_0^t \sigma(X_s) dB_s \right)^p \right] \right\}, \]

so that there exists \( C(p, M, m) > 0 \) such that

\[ \mathbb{E} \left[ \sup_{t \leq T} |X_t|^p \right] \leq C(p, M, m) \mathbb{E} \left[ |\xi|^p + \sup_{t \leq T} \left( \int_0^t |b(X_s)| ds \right)^p + \sup_{t \leq T} \left( \int_0^t \sigma(X_s) dB_s \right)^p \right]. \]

The first assertion of the result follows from standard computations since \( b \) and \( \sigma \) are Lipschitz continuous.

For the second assertion, note that from the Lipschitz property of \( \nu \mapsto G_0(\nu) \) (Lemma 2.2) and of the supremum of a Lipschitz function, we have

\[ K_t - K_s = \sup_{r \leq t} G_0(\mu_r) - \sup_{r \leq s} G_0(\mu_r) \leq \frac{M}{m} W_1(\mu_r, \mu_s) \leq \frac{M}{m} \mathbb{E}[|U_r - U_s|]. \]
so that the result follows from standard computations. The third assertion ensues from the following decomposition: \( X_t - X_s = U_t - U_s + K_t - K_s \).

We close this section by giving some additional properties of the solution \((X, K)\) of (1.1) when \(h\) is smooth.

Let \(\mathcal{L}\) be the linear partial operator of second order defined by

\[
\mathcal{L}f(x) := b(x) \frac{\partial}{\partial x} f(x) + \frac{1}{2} \sigma^2 \frac{\partial^2}{\partial x^2} f(x),
\]

for any twice continuously differentiable function \(f\).

**Proposition 2.7.** Suppose that assumptions (A.1), (A.2) and (A.4) hold and let \((X, K)\) denotes the unique deterministic flat solution to (1.1). Then the process \(K\) is Lipschitz continuous and the Stieltjes measure \(dK\) has the following density w.r.t. the Lebesgue measure:

\[
k : t \ni \mathbb{R}^+ \mapsto \left( \mathbb{E}[\mathcal{L}h(X_t)] \right)^- \mathbb{E}[h'(X_t)]^{-1} \mathbb{I}_{[h(X_t)] = 0}.
\]

**Proof.** Let us first prove that \(K\) is Lipschitz continuous. To do so, we prove that \(s \mapsto \bar{G}_0(\mu_s)\) is Lipschitz continuous on \([0, T]\). Indeed, since by definition \(H(\bar{G}_0(\mu_t), \mu_t) = 0\), if \(s < t\), using (2.4),

\[
|\bar{G}_0(\mu_s) - \bar{G}_0(\mu_t)| \leq \frac{1}{m} |H(\bar{G}_0(\mu_s), \mu_t)| \leq \frac{1}{m} \left[ \mathbb{E} \left[ h(\bar{G}_0(\mu_s) + U_t) \right] \right],
\]

\[
= \frac{1}{m} \left[ \mathbb{E} \left[ h \left( \bar{G}_0(\mu_s) + U_s + \int_s^t b(X_r)dr + \int_s^t \sigma(X_r)dB_r \right) \right] \right].
\]

We get from Itô’s formula, setting

\[
\mathcal{E}_y := b(y) \frac{\partial}{\partial x} + \frac{1}{2} \sigma^2 \frac{\partial^2}{\partial x^2},
\]

\[
\mathbb{E} \left[ h \left( \bar{G}_0(\mu_s) + U_t \right) \right] = \mathbb{E} \left[ h \left( \bar{G}_0(\mu_s) + U_s \right) \right] + \int_s^t \mathbb{E} \left[ \mathcal{E}_X, h \left( \bar{G}_0(\mu_s) + U_r \right) \right] dr,
\]

\[
= H \left( \bar{G}_0(\mu_s), \mu_s \right) + \int_s^t \mathbb{E} \left[ \mathcal{E}_X, h \left( \bar{G}_0(\mu_s) + U_r \right) \right] dr,
\]

\[
= \int_s^t \mathbb{E} \left[ \mathcal{E}_X, h \left( \bar{G}_0(\mu_s) + U_r \right) \right] dr.
\]

Since \(h\) has bounded derivatives and \(\sup_{s \leq T} X_s\) is a square integrable random variable for each \(T > 0\) (see Corollary 2.6), the result follows easily.

The same is true for \(s \mapsto G_0(\mu_s) = (\bar{G}_0(\mu_s))^\dagger\); let \(L\) be the Lipschitz constant of this last function. For \(0 \leq s \leq t \leq T\), we have

\[
K_t = \sup_{r \leq s} G_0(\mu_r) = \max \left( \sup_{r \leq s} G_0(\mu_r), \sup_{s \leq r \leq t} G_0(\mu_r) \right) = \max \left( K_s, \sup_{s \leq r \leq t} G_0(\mu_r) \right),
\]

and, for any \(s \leq r \leq t\),

\[
G_0(\mu_r) \leq G_0(\mu_s) + L(r - s) \leq K_s + L(t - s),
\]

\[
\sup_{s \leq r \leq t} G_0(\mu_r) \leq K_s + L(t - s).
\]

It follows, that, for \(0 \leq s \leq t \leq T\),

\[
0 \leq K_s \leq K_t \leq K_s + L(t - s).
\]

Therefore \(K\) is Lipschitz continuous and thus has a bounded density on \([0, T]\) for each \(T > 0\).

Let us fix \(T > 0\) and prove that (2.12) holds almost everywhere on \([0, T]\). Let us consider the compact set

\[
\mathcal{K} := \{ t \in [0, T] : \mathbb{E}[h(X_t)] = 0 \}.
\]
Due to the Skorokhod condition, \( k_t = 0 \) a.e. on \( \mathcal{K}^c = [0, T] \setminus \mathcal{K} \).

Since \( k \) belongs to \( L^1(0, T) \) and \( 0 < m \leq \mathbb{E}[h'(X_t)] \leq M \), Lebesgue's differentiation theorem implies that the function

\[
u(t) = \int_0^t \mathbb{E}[h'(X_s)] \, k_s \, ds
\]

is differentiable almost everywhere on \([0, T] \), say differentiable for every \( t \) in the measurable set \( E \subset [0, T] \) with \( \lambda(E^c) = 0 \) (on which \( k \) is nonnegative). Without loss of generality, we can assume that \( \{0, T\} \subset E^c \) and we have

\[
\forall t \in E, \quad \nu'(t) = \mathbb{E}[h'(X_t)] \, k_t.
\]

Since \( h'' \) is continuous and bounded and \( X \) is a continuous process, the function \( v \) given by

\[
v(t) = \int_0^t \mathbb{E}[\mathcal{L}h(X_s)] \, ds
\]

is \( C^1 \) with \( v'(t) = \mathbb{E}[\mathcal{L}h(X_t)] \).

Let us observe, that if \( \mathbb{E}[\mathcal{L}h(X_t)] > 0 \) for some \( t > 0 \), then \( \mathbb{E}[h(X_t)] > 0 \). Indeed, by continuity, there exists \( 0 < s < t \) such that \( \mathbb{E}[\mathcal{L}h(X_r)] > 0 \) on \([s, t] \) and

\[
\mathbb{E}[h(X_t)] = \mathbb{E}[h(X_s)] + \int_s^t \mathbb{E}[\mathcal{L}h(X_r)] \, dr + \int_s^t \mathbb{E}[h'(X_r)] \, k_r \, dr \geq \int_s^t \mathbb{E}[\mathcal{L}h(X_r)] \, dr > 0.
\]

Thus, \( \mathcal{K} \cap E \) is a subset of the compact set \( F = \{ t \in [0, T] : \mathbb{E}[\mathcal{L}h(X_t)] \leq 0 \} \).

Let \( t \in \mathcal{K} \cap E \). Since \( \mathcal{K} \) is a closed set, \( t \) is either an accumulation point or an isolated point of \( \mathcal{K} \). In the case of an accumulation point, there exists a sequence \( (t_n)_{n \geq 0} \) of points of \( \mathcal{K} \) such that \( t_n \neq t \) and \( \lim_{n \to \infty} t_n = t \). Since \( N = \{ n \in \mathbb{N} : t_n < t \} \cup \{ n \in \mathbb{N} : t_n > t \} \), one at least of the two previous sets of integers is infinite and, as a byproduct, \( (t_n)_{n \geq 0} \) as a subsequence with \( t_n > t \) for all \( n \) or with \( t_n < t \) for all \( n \). We keep the notation \( (t_n)_{n \geq 0} \) for this subsequence and deal with the case \( t_n > t \) for all \( n \) (the other case can be treated in the same way). For each \( n \), the equality

\[
\mathbb{E}[h(X_{t_n})] = \mathbb{E}[h(X_t)] + \int_t^{t_n} \mathbb{E}[\mathcal{L}h(X_r)] \, dr + \int_t^{t_n} \mathbb{E}[h'(X_r)] \, k_r \, dr
\]

rewrites, since \( t \) and \( t_n \) belong to \( \mathcal{K} \),

\[
\int_t^{t_n} \mathbb{E}[\mathcal{L}h(X_r)] \, dr + \int_t^{t_n} \mathbb{E}[h'(X_r)] \, k_r \, dr = 0.
\]

Thus, dividing by \( t_n - t \) and sending \( n \) to \( \infty \) we get, since \( t \in E \) and \( t \in F \),

\[
\mathbb{E}[h'(X_t)] \, k_t = -\mathbb{E}[\mathcal{L}h(X_t)] = \mathbb{E}[\mathcal{L}h(X_t)]^-.
\]

We have proved that, for all \( t \in \mathcal{K} \cap E \) such that \( t \) is an accumulation point of \( \mathcal{K} \),

\[
k_t = \frac{\mathbb{E}[\mathcal{L}h(X_t)]^-}{\mathbb{E}[h'(X_t)]}.
\]

To conclude, let us recall that the set of isolated points of \( \mathcal{K} \) is at most countable and thus of 0 Lebesgue-measure so that, as \( \lambda(E^c) = 0 \),

\[
k_t = \frac{\mathbb{E}[\mathcal{L}h(X_t)]^-}{\mathbb{E}[h'(X_t)]}, \text{ a.e. on } \mathcal{K}.
\]

Remark 2.8. This justifies, at least under the smoothness assumption (A.4) on the constraint function \( h \), the non-negative hypothesis imposed on \( h' \).
3. Mean reflected SDE as the limit of an interacting reflected particles system.

Having in mind the notations defined in the beginning of Section 2 and especially equation (2.9), we can write the unique solution of the SDE (1.1) as:

\[ X_t = \xi + \int_0^t b(X_s)ds + \int_0^t \sigma(X_s)dB_s + \sup_{s \leq t} G_0(\mu_s), \]

where \(\mu_t\) stands for the law of

\[ U_t = \xi + \int_0^t b(X_s)ds + \int_0^t \sigma(X_s)dB_s. \]

We are here interested in the particle approximation of such a system. Our candidates are the particles

\[ X^i_t = \hat{\xi}^i + \int_0^t b(X^i_s)ds + \int_0^t \sigma(X^i_s)dB^i_s + \sup_{s \leq t} G_0(\mu^N_s), \quad 1 \leq i \leq N, \]

where \(B^i\) are independent Brownian motions, \(\hat{\xi}^i = \xi + G_0(\mu^N), (\xi^i)_i\) are independent copies of \(\xi\), \(\mu^N\) denotes the empirical distribution at time \(s\) of the particles

\[ U^i_s = \hat{\xi}^i + \int_0^s b(X^i_s)dr + \int_0^s \sigma(X^i_s)dB^i_s, \quad 1 \leq i \leq N, \quad \mu^N_s = \frac{1}{N} \sum_{i=1}^N \delta_{\xi^i}. \]

It is worth noticing that

\[ G_0(\mu^N) = \inf \left\{ x \geq 0 : \frac{1}{N} \sum_{i=1}^N h(x + U^i_s) \geq 0 \right\}. \]

We also denote, for all \(t \in [0, T]\), \(K^N_t := \sup_{s \leq t} G_0(\mu^N_s).\)

Remark 3.1. At first glance, we can ask why we need to introduce \(\hat{\xi}^i\) in Equation (3.2) instead of using \(\xi^i\). If this had been the case, \(K^N_0\) would not be equal to 0. With this choice of starting point we have

\[ K^N_0 = \inf \{ x \geq 0 : \frac{1}{N} \sum_{i=1}^N h(x + U^i_0) \geq 0 \} = \inf \{ x \geq 0 : \frac{1}{N} \sum_{i=1}^N h(x + \hat{\xi}^i) \geq 0 \}

= \inf \{ x \geq 0 : \frac{1}{N} \sum_{i=1}^N h(x + \xi^i + G_0(\mu^N)) \geq 0 \} = 0, \]

by definition of \(G_0(\mu^N).\)

Remark 3.2. Let us emphasize that the previous system of interacting particles can be seen as a multidimensional reflected SDE with oblique reflection. Indeed, if \(h\) is concave, the set

\[ \mathcal{S} := \{ (x_1, \ldots, x_N) \in \mathbb{R}^N : h(x_1) + \ldots + h(x_N) \geq 0 \} \]

is convex and the system

\[ \begin{cases}
X^i_t = \hat{\xi}^i + \int_0^t b(X^i_s)ds + \int_0^t \sigma(X^i_s)dB^i_s + K^N_t, \quad 1 \leq i \leq N, \\
\frac{1}{N} \sum_{i=1}^N h(X^i_t) \geq 0, \quad \frac{1}{N} \sum_{i=1}^N \int_0^t h(X^i_t) dK^N_s = 0,
\end{cases} \]

is nothing else but the SDE driven by \(b\) and \(\sigma\) reflected in the convex \(\mathcal{S}\) with oblique reflexion in the direction \((1, \ldots, 1)\). We refer to [LS84].
In order to prove that there is indeed a propagation of chaos effect, we introduce the following independent copies of $X$

$$X^i_t = \xi^i + \int_0^t b(X^i_s)ds + \int_0^t \sigma(X^i_s)dB^i_s + \sup_{s \leq t}G_0(\mu_s), \quad 1 \leq i \leq N,$$

and we couple these particles with the previous ones by choosing the same Brownian motion.

We also introduce the decoupled particles $\bar{U}^i_t$, $1 \leq i \leq N$:

$$\bar{U}^i_t = \xi^i + \int_0^t b(X^i_s)ds + \int_0^t \sigma(X^i_s)dB^i_s, \quad t \geq 0.$$

Note for instance that the particles $\bar{U}^i$ are i.i.d. and let us denote by $\bar{\mu}^N_t$ the empirical measure associated with this system of particles.

We have the following result concerning the approximation (1.1) by the interacting particles system (3.2).

**Theorem 3.3.** Let assumptions (A.1) and (A.2) hold and $T > 0$.

(i) Under assumption (A.3), there exists a constant $C$ depending on $b$ and $\sigma$ such that, for each $j \in \{1, \ldots, N\}$,

$$\mathbb{E}\left[\sup_{s \leq T} |X^i_s - \bar{X}^j_s|^2 \right] \leq C \exp\left(C \left(1 + \frac{M^2}{m^2}\right) (1 + T^2)\right) \frac{M^2}{m^2} N^{-1/2}.$$

(ii) If assumption (A.4) is in force, then there exists a constant $C$ depending on $b$ and $\sigma$ such that, for each $j \in \{1, \ldots, N\}$,

$$\mathbb{E}\left[\sup_{s \leq T} |X^i_s - \bar{X}^j_s|^2 \right] \leq C \exp\left(C \left(1 + \frac{M^2}{m^2}\right) (1 + T^2)\right) \frac{1 + T^2}{m^2} \left(1 + \mathbb{E}\left[\sup_{s \leq t} |X^i_s|^2 \right]\right) N^{-1}.$$

**Remark 3.4.** As shown in [FG15], the rate in case (i) is optimal in full generality for the control of the Wasserstein distance of the empirical measure of an i.i.d. sample of random variables towards its own law. It is interesting to note that the supremum over time implies no loss here, as the "propagation of chaos" is mainly herited from the reflection term through $\sup_{s \leq t} W^2_t(\bar{\mu}^N_s, \mu_s)$.

**Proof.** Let $t > 0$. We have, for $r \leq t$,

$$|X^i_r - \bar{X}^j_r| \leq |\xi^i - \xi^j| + \int_0^r |b(X^i_s) - b(\bar{X}^j_s)| \, ds + \int_0^r \left|\sigma(X^i_s) - \sigma(\bar{X}^j_s)\right| \, dB^i_s + \sup_{s \leq r} |G_0(\mu^N_s) - \bar{G}_0(\mu_s)|.$$

Let us study the first term. $|\xi^i - \xi^j| = |G_0(\mu^N) - G_0(\mu)| \leq \sup_{s \leq r} |G_0(\mu^N_s) - \bar{G}_0(\mu_s)|$. Taking into account the fact that

$$\sup_{s \leq r} |G_0(\mu^N_s) - \bar{G}_0(\mu_s)| \leq \sup_{s \leq r} |G_0(\mu^N_s) - G_0(\mu_s)| \leq \sup_{s \leq t} |G_0(\mu^N_s) - G_0(\mu_s)|,$$

we get the inequality

$$\sup_{r \leq t} |X^i_r - \bar{X}^j_r| \leq I^i_1(t) + 2\sup_{s \leq t} |G_0(\mu^N_s) - G_0(\bar{\mu}^N_s)| + 2\sup_{s \leq t} |G_0(\bar{\mu}^N_s) - G_0(\mu_s)|, \quad (3.3)$$

where we have set

$$I^i_1(t) := \int_0^t |b(X^i_s) - b(\bar{X}^j_s)| \, ds + \sup_{r \leq t} \left|\int_0^r \left(\sigma(X^i_s) - \sigma(\bar{X}^j_s)\right) \, dB^i_s\right|.$$
On the one hand we have, using Doob and Cauchy-Schwartz inequalities

\[ \mathbb{E} \left[ |I_1^r(t)|^2 \right] \leq C(1 + t) \int_0^t \mathbb{E} \left[ |X_s^i - \bar{X}_s^j|^2 \right] ds, \]

where \( C \) depends only on \( b \) and \( \sigma \).

On the other hand, by using (2.7),

\[ \sup_{s \leq t} |G_0(\mu_s^N) - G_0(\bar{\mu}_s^N)| \leq \frac{M}{m} \sup_{s \leq t} \frac{1}{N} \sum_{i=1}^N |U_s^i - \bar{U}_s^i| \leq \frac{M}{m} \frac{1}{N} \sum_{i=1}^N \sup_{s \leq t} |U_s^i - \bar{U}_s^i|, \]

and Cauchy-Schwartz inequality gives, since the variables are exchangeable,

\[ \mathbb{E} \left[ \sup_{s \leq t} |G_0(\mu_s^N) - G_0(\bar{\mu}_s^N)|^2 \right] \leq \frac{M^2}{m^2} \frac{1}{N} \sum_{i=1}^N \mathbb{E} \left[ \sup_{s \leq t} |U_s^i - \bar{U}_s^i|^2 \right] = \frac{M^2}{m^2} \mathbb{E} \left[ \sup_{s \leq t} |U_s^j - \bar{U}_s^j|^2 \right]. \]

Since,

\[ U_s^j - \bar{U}_s^j = \int_0^s (b(X_t^j) - b(\bar{X}_t^j)) \, dr + \int_0^s (\sigma(X_t^j) - \sigma(\bar{X}_t^j)) \, dB_t^j \]

the same computations as we did above lead to

\[ \mathbb{E} \left[ \sup_{s \leq t} |G_0(\mu_s^N) - G_0(\bar{\mu}_s^N)|^2 \right] \leq C \frac{M^2}{m^2} (1 + t) \int_0^t \mathbb{E} \left[ |X_s^j - \bar{X}_s^j|^2 \right] ds, \quad C := C(\sigma, b) > 0. \]

Hence, with the previous estimates we get, coming back to (3.3),

\[ \mathbb{E} \left[ \sup_{r \leq t} |X_r^j - \bar{X}_r^j|^2 \right] \leq \bar{C} \int_0^t \mathbb{E} \left[ |X_s^j - \bar{X}_s^j|^2 \right] ds + 6 \mathbb{E} \left[ \sup_{s \leq t} |G_0(\bar{\mu}_s^N) - G_0(\mu_s)|^2 \right], \]

\[ \leq \bar{C} \int_0^t \mathbb{E} \left[ \sup_{r \leq s} |X_r^j - \bar{X}_r^j|^2 \right] ds + 6 \mathbb{E} \left[ \sup_{s \leq t} |G_0(\bar{\mu}_s^N) - G_0(\mu_s)|^2 \right], \]

where \( \bar{C} = C(1 + t) (1 + M^2/m^2) \). Thanks to Gronwall’s lemma

\[ \mathbb{E} \left[ \sup_{r \leq t} |X_r^j - \bar{X}_r^j|^2 \right] \leq C e^{\bar{C}t} \mathbb{E} \left[ \sup_{s \leq t} |G_0(\bar{\mu}_s^N) - G_0(\mu_s)|^2 \right]. \]

By Lemma 2.2 we know that

\[ \mathbb{E} \left[ \sup_{s \leq t} |G_0(\bar{\mu}_s^N) - G_0(\mu_s)|^2 \right] \leq \frac{1}{m^2} \mathbb{E} \left[ \sup_{s \leq t} \left| \int h(\bar{G}_0(\mu_s) + \cdot) (d\bar{\mu}_s^N - d\mu_s) \right|^2 \right], \]

from which we deduce that

\[ \mathbb{E} \left[ \sup_{r \leq t} |X_r^j - \bar{X}_r^j|^2 \right] \leq C e^{\bar{C}t} \frac{1}{m^2} \mathbb{E} \left[ \sup_{s \leq t} \left| \int h(\bar{G}_0(\mu_s) + \cdot) (d\bar{\mu}_s^N - d\mu_s) \right|^2 \right]. \] (3.4)

Since the function \( h \) is, at least, a Lipschitz function, we understand that the rate of convergence follows from the convergence of empirical measure of i.i.d. diffusion processes.

**Proof of (i).** In full generality (i.e. if we only suppose that (A.2) holds) we get that:

\[ \frac{1}{m^2} \mathbb{E} \left[ \sup_{s \leq t} \left| \int h(\bar{G}_0(\mu_s) + \cdot) (d\bar{\mu}_s^N - d\mu_s) \right|^2 \right] \leq \frac{M^2}{m^2} \mathbb{E} \left[ \sup_{s \leq t} W_1^2 (\mu_s^N, \mu_s) \right], \]

The crucial point here is that we consider a uniform (in time) convergence, which may possibly damage the usual rate of convergence. We however succeeded in preserving this optimal rate.
Thanks to the additional assumption (A.3) and to Proposition 2.6, we will adapt and simplify the proof of Theorem 10.2.7 of [RR98] using recent results about the control of Wasserstein distance of empirical measures of i.i.d. sample to the true law by [FG15], to obtain

\[ \mathbb{E} \left[ \sup_{s \leq T} W^2_1(\bar{\mu}_s^N, \mu_s) \right] \leq C N^{-1/2}. \]

Indeed, let \( n \) be a positive integer and set \( t_k = kT/n, 0 \leq k \leq n \). As in [RR98], denote

\[ Z_k = \sup_{t_k \leq s \leq t_{k+1}} \left\{ W^2_1(\bar{\mu}_s^N, \bar{\mu}_{t_k}^N) \wedge W^2_1(\bar{\mu}_s^N, \bar{\mu}_{t_{k+1}}^N) \right\}. \]

Then

\[ \sup_{s \leq T} W^2_1(\bar{\mu}_s^N, \mu_s) \leq 3 \left[ \max_k Z_k + \max_k W^2_1(\bar{\mu}_{t_k}^N, \mu_{t_k}) + \max_k \sup_{t_k \leq t \leq t_{k+1}} W^2_1(\mu_{t_k}, \mu_t) \right]. \]

Now, using the regularity properties of Proposition 2.6 and proceeding exactly as in [RR98, Th. 10.2.7] we have that there exists \( C > 0 \) such that

\[ W^2_1(\mu_{t_k}, \mu_t) \leq \frac{C}{n}, \quad \mathbb{E} \left[ \max_k Z_k \right] \leq \frac{C}{\sqrt{n}}. \]

We are lead to control \( \mathbb{E} \left[ \max_k W^2_1(\bar{\mu}_{t_k}^N, \mu_{t_k}) \right] \): first remark that

\[ \mathbb{E} \left[ \max_k W^2_1(\bar{\mu}_{t_k}^N, \mu_{t_k}) \right] \leq \sqrt{n} \sqrt{\mathbb{E} \left[ W^4_1(\bar{\mu}_{t_k}^N, \mu_{t_k}) \right]}. \]

Use now assumption (A.3) and Theorem 2 (case (3)) in [FG15] to get

\[ \mathbb{E} \left[ W^4_1(\bar{\mu}_{t_k}^N, \mu_{t_k}) \right] \leq \frac{C}{N^2}, \]

from which we deduce that

\[ \mathbb{E} \left[ \sup_{s \leq t} W^2_1(\bar{\mu}_s^N, \mu_s) \right] \leq C \left[ \frac{\sqrt{n}}{N} + \frac{1}{\sqrt{n}} \right] \]

and optimization procedure on \( n \) finishes the proof. Let us emphasize that this result does not care of the fact that \( \bar{\mu}_s^N \) is an empirical measure associated to i.i.d. copies of a diffusion process.

**Proof of (ii).** In the case where \( h \) is a twice continuously differentiable function with bounded derivatives (i.e. under (A.4)), we succeed in taking benefit from the fact that \( \bar{\mu}_s^N \) is an empirical measure associated to i.i.d. copies of diffusion process, in particular we can get rid of the supremum in time. In view of (3.4), we need a sharp estimate of

\[ \mathbb{E} \left[ \sup_{s \leq t} \left| \int h(\bar{G}_0(\mu_s) + \cdot) (d\bar{\mu}_s^N - d\mu_s) \right|^2 \right]. \]

Let us denote by \( \psi \) the Radon-Nikodym derivative of \( \bar{G}_0(\mu) \) (we have proved in Proposition 2.7 that \( s \mapsto \bar{G}_0(\mu_s) \) is Lipschitz continuous). By definition, we have, denoting by \( V^t \) the
semimartingale $s \mapsto \bar{G}_0(\mu_s) + \bar{U}^i_s$, since $\bar{U}^i$ are independent copies of $U$,

$$R_N(s) := \int h(\bar{G}_0(\mu_s) + \cdot) \, d\bar{U}^i_s = \frac{1}{N} \sum_{i=1}^N h(\bar{G}_0(\mu_s) + \bar{U}^i_s) - \mathbb{E} \left[ h(\bar{G}_0(\mu_s) + U_s) \right],$$

$$= \frac{1}{N} \sum_{i=1}^N \left\{ h(\bar{G}_0(\mu_s) + \bar{U}^i_s) - \mathbb{E} \left[ h(\bar{G}_0(\mu_s) + \bar{U}^i_s) \right] \right\},$$

$$= \frac{1}{N} \sum_{i=1}^N \left\{ h(V^i_s) - \mathbb{E} \left[ h(V^i_s) \right] \right\}.$$

From Itô’s formula we have

$$h(V^i_s) = h(V^i_0) + \int_0^s h'(V^i_r) \psi_r \, dr + \int_0^s \bar{\mathcal{L}}_{\bar{X}} \, h(V^i_r) \, dr + \int_0^s h'(V^i_r) \sigma(\bar{X}^i_r) \, dB^i_r,$$

$$= h(V^i_0) + \int_0^s \left\{ h'(V^i_r) \psi_r + \bar{\mathcal{L}}_{\bar{X}} \, h(V^i_r) \right\} \, dr + \int_0^s h'(V^i_r) \sigma(\bar{X}^i_r) \, dB^i_r,$$

so that

$$\mathbb{E} \left[ h(V^i_s) \right] = \mathbb{E} \left[ h(V^i_0) \right] + \int_0^s \mathbb{E} \left[ h'(V^i_r) \psi_r + \bar{\mathcal{L}}_{\bar{X}} \, h(V^i_r) \right] \, dr,$$

$$= 0 + \int_0^s \mathbb{E} \left[ h'(V^i_r) \psi_r + \bar{\mathcal{L}}_{\bar{X}} \, h(V^i_r) \right] \, dr.$$

We thus deduce immediately that

$$R_N(s) = \frac{1}{N} \sum_{i=1}^N h(V^i_0) + \frac{1}{N} \sum_{i=1}^N \int_0^s Y^i(r) \, dr + M_N(s),$$

$$= \frac{1}{N} \sum_{i=1}^N h(V^i_0) + \int_0^s \left( \frac{1}{N} \sum_{i=1}^N Y^i(r) \right) \, dr + M_N(s),$$

where we have set

$$Y^i(r) = h'(V^i_r) \psi_r + \bar{\mathcal{L}}_{\bar{X}} \, h(V^i_r) - \mathbb{E} \left[ h'(V^i_r) \psi_r + \bar{\mathcal{L}}_{\bar{X}} \, h(V^i_r) \right],$$

$$M_N(s) = \frac{1}{N} \sum_{i=1}^N \int_0^s h'(V^i_r) \sigma(\bar{X}^i_r) \, dB^i_r.$$

As a byproduct,

$$\sup_{s \leq t} |R_N(s)| \leq \left| \frac{1}{N} \sum_{i=1}^N h(V^i_0) \right| + \sup_{s \leq t} \left| \int_0^s \left( \frac{1}{N} \sum_{i=1}^N Y^i(r) \right) \, dr + \sup_{s \leq t} |M_N(s)| \right|,$$

$$\leq \left| \frac{1}{N} \sum_{i=1}^N h(V^i_0) \right| + \int_0^t \left| \frac{1}{N} \sum_{i=1}^N Y^i(r) \right| \, dr + \sup_{s \leq t} |M_N(s)|.$$
We get, using Cauchy-Schwartz inequality, since $U^i$ and $X^i$ are i.i.d,

$$
\mathbb{E}\left[ \sup_{s \leq t} |R_N(s)|^2 \right] \leq 3 \left\{ \operatorname{Var} \left[ \frac{1}{N} \sum_{i=1}^{N} h \left( V_0^i \right) \right] + \mathbb{E}\left[ \left( \int_{0}^{t} \left| \frac{1}{N} \sum_{i=1}^{N} Y^i(r) \right| dr \right)^2 \right] + \mathbb{E}\left[ \sup_{s \leq t} |M_N(s)|^2 \right] \right\},
$$

$$= 3 \left\{ \operatorname{Var} \left[ \frac{1}{N} \sum_{i=1}^{N} h \left( V_0^i \right) \right] + 3 t \mathbb{E}\left[ \left( \int_{0}^{t} \left| \frac{1}{N} \sum_{i=1}^{N} Y^i(r) \right| dr \right)^2 \right] + \mathbb{E}\left[ \sup_{s \leq t} |M_N(s)|^2 \right] \right\},
$$

Thus, we obtain defining accordingly to $V^i$ (resp. $C^i$) the semimartingale $V$ (resp. centered r.v. $Y$)

$$
\mathbb{E}\left[ \sup_{s \leq t} |R_N(s)|^2 \right] \leq \frac{3 N}{N} \operatorname{Var} \left[ h \left( V_0 \right) \right] + \frac{3 t}{N} \int_{0}^{t} \operatorname{Var} \left( Y(r) \right) dr + 3 \mathbb{E}\left[ \sup_{s \leq t} |M_N(s)|^2 \right].
$$

Since $M_N$ is a martingale with

$$
\langle M_N \rangle_t = \frac{1}{N^2} \sum_{i=1}^{N} \int_{0}^{t} (h'(V_r^i) \sigma(X_r^i))^2 \, dr,
$$

Doob’s inequality leads to

$$
\mathbb{E}\left[ \sup_{s \leq t} |M_N(s)|^2 \right] \leq 4 \mathbb{E}\left[ |M_N(t)|^2 \right],
$$

$$= 4 \frac{N}{N^2} \sum_{i=1}^{N} \int_{0}^{t} \mathbb{E}\left[ (h'(V_r^i) \sigma(X_r^i))^2 \right] \, dr,
$$

$$= \frac{4}{N} \int_{0}^{t} \mathbb{E}\left[ (h'(V_r) \sigma(X_r))^2 \right] \, dr.
$$

Finally, using the fact that $h$ has bounded derivatives, $b$ and $\sigma$ are Lipschitz, we get

$$
\mathbb{E}\left[ \sup_{s \leq t} |R_N(s)|^2 \right] \leq C(1 + t^2) \left( 1 + \mathbb{E}\left[ \sup_{s \leq t} |X_s|^2 \right] \right) N^{-1}.
$$

This gives the result coming back to (3.4). \hfill \Box

4. A numerical scheme for MRSDE.

We are interested in the numerical approximation of the SDE (1.1) on $[0,T]$. Here are the main steps of the scheme. Let $0 = T_0 < T_1 < \cdots < T_n = T$ be a subdivision of $[0,T]$. Given this subdivision, we denote by “$$” the mapping $s \mapsto s = T_k$ if $s \in [T_k, T_{k+1})$, $k \in \{0, \ldots, n-1\}$. For simplicity, we consider only the case of regular subdivisions: for a given integer $n$, $T_k = k T/n$, $k = 0, \ldots, n$. 


Let us recall that we proved in the previous section that particles system

\[ X^i_t = \hat{\xi}^i + \int_0^t b(X^i_s)ds + \int_0^t \sigma(X^i_s)dB^i_s + \sup_{s \leq t} G_0(\mu^N_s), \quad 1 \leq i \leq N, \]

where we have set

\[ U^i_t = \hat{\xi}^i + \int_0^t b(X^i_s)dr + \int_0^t \sigma(X^i_s)dB^i_r, \quad 1 \leq i \leq N, \quad \mu^N_s = \frac{1}{N} \sum_{i=1}^N \delta_{U^i_t}. \]

\(B^i\) being independent Brownian motions and \(\hat{\xi}^i = \xi^i + G_0(\mu^\xi,\mu^N)\), \((\xi^i)\), being independent copies of \(\xi\), converge toward the solution of (1.1). Thus, the numerical approximation is obtained by an Euler scheme applied to this particles system. We introduce the following discrete version of the particles system

\[ \tilde{X}^i_t = \hat{\xi}^i + \int_0^t b(\tilde{X}^i_s)ds + \int_0^t \sigma(\tilde{X}^i_s)dB^i_s + \sup_{s \leq t} G_0(\tilde{\mu}^N_s), \quad 1 \leq i \leq N, \]

with the notation \(\tilde{K}^N_t = \sup_{s \leq t} G_0(\tilde{\mu}^N_s)\) and

\[ \tilde{U}^i_t = \hat{\xi}^i + \int_0^t b(\tilde{X}^i_s)ds + \int_0^t \sigma(\tilde{X}^i_s)dB^i_s, \quad 1 \leq i \leq N, \quad \tilde{\mu}^N_s = \frac{1}{N} \sum_{i=1}^N \delta_{\tilde{U}^i_s}. \]

### 4.1. Scheme

Using the notations given above, the result on the interacting system of mean reflected particles of the MR-SDE of Section 3 and Remark 2.5, we deduce the following algorithm for the numerical approximation of the MR-SDE:

**Algorithm 1** Particle approximation

1. for \(1 \leq j \leq N\) do
2. Simulate \((\xi^1, \ldots, \xi^N)\), compute \(G_0(\mu^{\xi,N})\) and \((\hat{\xi}^1, \ldots, \hat{\xi}^N)\).
3. \(\tilde{X}^i_0 = \tilde{U}^i_0 = \hat{\xi}^i\), \(\tilde{\mu}^N_0 = \frac{1}{N} \sum_{i=1}^N \delta_{\hat{\xi}^i}\).
4. end for
5. for \(1 \leq k \leq n\) do
6. for \(1 \leq j \leq N\) do
7. \(G^j \sim N(0, 1)\)
8. \(\left(\tilde{U}_{T_{k-1}}\right)^j = \left(\tilde{U}_{T_{k-1}}\right)^j + (T/n)b\left(\left(\tilde{X}_{T_{k-1}}\right)^j\right) + \sqrt{(T/n)}\sigma\left(\left(\tilde{X}_{T_{k-1}}\right)^j\right) G^j\)
9. end for
10. \(\tilde{\mu}^N_{T_k} = N^{-1} \sum_{j=1}^N \delta_{(\tilde{U}_{T_{k}})^j}\)
11. \(\Delta_k\tilde{K}^N = \sup_{l \leq k} G_0(\tilde{\mu}^N_l) - \sup_{l \leq k-1} G_0(\tilde{\mu}^N_l)\)
12. for \(1 \leq j \leq N\) do
13. \(\left(\tilde{X}_{T_{k}}\right)^j = \left(\tilde{X}_{T_{k-1}}\right)^j + (T/n)b\left(\left(\tilde{X}_{T_{k-1}}\right)^j\right) + \sqrt{(T/n)}\sigma\left(\left(\tilde{X}_{T_{k-1}}\right)^j\right) G^j + \Delta_k\tilde{K}^N\)
14. end for
15. end for

**Remark 4.1.** We emphasize that, at each step \(k\) of the algorithm, we approximate the increment of the reflection process \(K\) by the increment of this approximation:

\[ \Delta_k\tilde{K}^N := \sup_{l \leq k} G_0(\tilde{\mu}^N_l) - \sup_{l \leq k-1} G_0(\tilde{\mu}^N_l). \]
As suggested in Remark 2.5, this increment can be approached by:

\[
\Delta_k \tilde{K}_t^N := \inf \left\{ x \geq 0 : \frac{1}{N} \sum_{i=1}^{N} h \left( x + \left( \tilde{X}_{T_{k-1}}^N \right)^i \right) + \frac{T}{n} b \left( \left( \tilde{X}_{T_{k-1}}^N \right)^i \right) + \frac{\sqrt{T}}{\sqrt{n}} \sigma \left( \left( \tilde{X}_{T_{k-1}}^N \right)^i \right) G^i \geq 0 \right\}.
\]

Indeed, using the same kind of arguments as in the sketch of the proof of Theorem 2.4, one can show that the increments of the approximated reflection process are equals to the approximation of the increments:

\[
\forall k \in \{1, \ldots, n\} : \quad \Delta_k \tilde{K}_t^N = \Delta_k \tilde{K}_t^N.
\]

4.2. Scheme error. We recall that \( \tilde{X}^i \) denotes an i.i.d. copy of \( X \):

\[
\tilde{X}_t = \xi + \int_0^t b(\tilde{X})ds + \int_0^t \sigma(\tilde{X})dB_s + K_t,
\]

we have the following result.

**Theorem 4.2.** Let \( T > 0 \), \( N \) and \( n \) be two non-negative integers. Let assumptions (A.1), (A.2) and (A.3) hold.

(i) There exists a constant \( C \) depending on \( T, b, \sigma, h \) and \( \xi \) such that: for all \( i \in \{1, \ldots, N\} \),

\[
\mathbb{E} \left[ \sup_{t \leq T} \left| \tilde{X}_t^i - \tilde{X}_t^i \right|^2 \right] + \mathbb{E} \left[ \sup_{t \leq T} |K_t - \tilde{K}_t^N|^2 \right] \leq C \left( \frac{\log n}{n} + N^{-1/2} \right).
\]

(ii) If in addition (A.4) hold, there exists a positive constant \( C \) depending on \( T, b, \sigma, h \) and \( \xi \) such that: for all \( i \in \{1, \ldots, N\} \),

\[
\mathbb{E} \left[ \sup_{t \leq T} \left| \tilde{X}_t^i - \tilde{X}_t^i \right|^2 \right] + \mathbb{E} \left[ \sup_{t \leq T} |K_t - \tilde{K}_t^N|^2 \right] \leq C \left( \frac{\log n}{n} + N^{-1} \right).
\]

**Proof.** Concerning \( X, \) the proof is straightforward. Write

\[
|\tilde{X}_t^i - \tilde{X}_t^i| \leq |\tilde{X}_t^i - X_t^i| + |X_t^i - \tilde{X}_t^i|.
\]

We bound the first term in the above right hand side by using the proof of Theorem 3.3 and the second term with the following Proposition, which gives the error approximation of the Euler discretization.

**Proposition 4.3.** Let \( T > 0 \), \( N \) and \( n \) be two non-negative integers and let assumptions (A.1), (A.2) and (A.3) hold. There exists a constant \( C \), depending on \( T, b, \sigma, h \) and \( \xi \) but independent of \( N, \) such that: for all \( i = 1, \ldots, N \)

\[
\mathbb{E} \left[ \sup_{s \leq T} \left| X_t^i - \tilde{X}_t^i \right|^2 \right] \leq C \frac{\log n}{n}.
\]

Concerning \( K, \) we write

\[
K_t - \tilde{K}_t^N = \sup_{s \leq t} G_0(\mu_s) - \sup_{s \leq t} G_0(\tilde{\mu}_s^N)
\]

\[
= \sup_{s \leq t} G_0(\mu_s) - \sup_{s \leq t} G_0(\mu_s^N) + \sup_{s \leq t} G_0(\mu_s^N) - \sup_{s \leq t} G_0(\tilde{\mu}_s^N).
\]

Then

\[
\mathbb{E} \left[ \sup_{t \leq T} |K_t - \tilde{K}_t^N|^2 \right] \leq \mathbb{E} \left[ \sup_{t \leq T} |G_0(\mu_t) - G_0(\mu_t^N)|^2 \right] + \mathbb{E} \left[ \sup_{t \leq T} |G_0(\mu_t^N) - G_0(\tilde{\mu}_t^N)|^2 \right].
\]
Since

\[ \text{(proof of Proposition 4.3).} \]

We bound the first term by using the proof of Theorem 3.3 and the second term by using the proof of Proposition 4.3.

Proof of Proposition 4.3. Let us admit for the moment the following result that will be useful for our analysis and whose proof is postponed at the end of the current one.

Lemma 4.4. There exists a constant \( C \) such that

\[
\mathbb{E} \left[ \sup_{s \leq T} |B_s - B_{2s}|^4 \right] \leq C \left( \frac{\log n}{n} \right)^2.
\]

We may now proceed to the proof of Proposition 4.3. Let us fix \( i \in \{1, \ldots, N\} \) and \( T > 0 \). We have, for \( t \leq T \),

\[
|X_i^i - \tilde{X}_i| \leq \int_0^t |b(X_i^i) - b(\tilde{X}_i)| \, ds + \left| \int_0^t \left( \sigma(X_i^i) - \sigma(\tilde{X}_i) \right) dB_s \right| + \sup_{s \leq t} |G_0(\mu^N_s) - G_0(\tilde{\mu}^N_s)|.
\]

Hence, using Cauchy-Schwartz and Doob inequality we get:

\[
\mathbb{E} \left[ \sup_{s \leq t} |X_i^i - \tilde{X}_i|^2 \right] \leq C \int_0^t \mathbb{E} \left[ |X_i^i - \tilde{X}_i|^2 \right] \, ds + \mathbb{E} \left[ \sup_{s \leq t} |G_0(\mu^N_s) - G_0(\tilde{\mu}^N_s)|^2 \right]. \quad (4.1)
\]

We now deal with the last term in the above right hand side: from Lemma 2.2 we have

\[
\mathbb{E} \left[ \sup_{s \leq t} |G_0(\mu^N_s) - G_0(\tilde{\mu}^N_s)|^2 \right] \leq \left( \frac{M}{m} \right)^2 \mathbb{E} \left[ \sup_{s \leq t} \frac{1}{N} \sum_{j=1}^N |U_j^i - \tilde{U}_j|^2 \right],
\]

\[
\leq 2 \left( \frac{M}{m} \right)^2 \mathbb{E} \left[ \sup_{s \leq t} \frac{1}{N} \sum_{j=1}^N \left\{ |U_j^i - \tilde{U}_j|^2 + |\tilde{U}_j - \tilde{\mu}_j|^2 \right\} \right],
\]

and, by exchangeability of the particles,

\[
\mathbb{E} \left[ \sup_{s \leq t} |G_0(\mu^N_s) - G_0(\tilde{\mu}^N_s)|^2 \right] \leq 2 \left( \frac{M}{m} \right)^2 \mathbb{E} \left[ \sup_{s \leq t} |U_j^i - \tilde{U}_j|^2 + \sup_{s \leq t} |\tilde{U}_j - \tilde{\mu}_j|^2 \right]. \quad (4.2)
\]

For the first term of the right hand side, let us observe that, by exchangeability again,

\[
\mathbb{E} \left[ \sup_{s \leq t} |U_j^i - \tilde{U}_j|^2 \right] \leq \mathbb{E} \left[ \sup_{s \leq t} \left\{ \left( \int_0^s |b(X_j^i) - b(\tilde{X}_j)| \, dr \right)^2 + \left| \int_0^s \left( \sigma(X_j^i) - \sigma(\tilde{X}_j) \right) dB_r \right|^2 \right\} \right]
\]

\[
\leq t \|b\|_{\text{Lip}}^2 \int_0^t \mathbb{E} \left[ |X_j^i - \tilde{X}_j|^2 \right] \, ds + 2 |\sigma|_{\text{Lip}}^2 \int_0^t \mathbb{E} \left[ |X_j^i - \tilde{X}_j|^2 \right] \, ds. \quad (4.3)
\]

We have for the second term

\[
\mathbb{E} \left[ \sup_{s \leq t} |\tilde{U}_j - \tilde{\mu}_j|^2 \right] \leq \mathbb{E} \left[ \sup_{s \leq t} \left\{ |b(\tilde{X}_j)| (s - \tilde{g})^2 + |\sigma(\tilde{X}_j)| (B_s - \tilde{B}_s)^2 \right\} \right].
\]

Since

\[
\mathbb{E} \left[ \sup_{s \leq t} |b(\tilde{X}_j)|^2 (s - \tilde{g})^2 \right] \leq C \left( 1 + \mathbb{E} \left[ \sup_{s \leq T} |\tilde{X}_j|^2 \right] \right) \left( \frac{T}{n} \right)^2,
\]

and

\[
\mathbb{E} \left[ \sup_{s \leq t} |\sigma(\tilde{X}_j)| (B_s - \tilde{B}_s)^2 \right] \leq C \left( 1 + \mathbb{E} \left[ \sup_{s \leq T} |\tilde{X}_j|^2 \right] \right) \left( \frac{T}{n} \right)^2,
\]

we get

\[
\mathbb{E} \left[ \sup_{s \leq t} |\tilde{U}_j - \tilde{\mu}_j|^2 \right] \leq C \left( 1 + \mathbb{E} \left[ \sup_{s \leq T} |\tilde{X}_j|^2 \right] \right) \left( \frac{T}{n} \right)^2.
\]

\[ \square \]
and
\[ E \left[ \sup_{s \leq t} |\sigma(\tilde{X}_s^i)(B_s - B_{s \downarrow})|^2 \right] \leq C \left( 1 + E \left[ \sup_{s \leq T} X_s^i \right]^{1/2} \right) E \left[ \sup_{s \leq T} |B_s - B_{s \downarrow}|^4 \right]^{1/2}, \]
\[ \leq C \left( 1 + E \left[ \sup_{s \leq T} X_s^i \right]^{1/2} \right) E \left[ \sup_{s \leq T} |B_s - B_{s \downarrow}|^4 \right]^{1/2}, \]
we thus obtain
\[ E \left[ \sup_{s \leq t} |\tilde{U}_s^i - \tilde{U}_{s \downarrow}|^2 \right] \leq C \frac{2 \log n}{n}. \tag{4.4} \]

Using (4.4) and (4.3) with (4.2) we get
\[ E \left[ \sup_{s \leq t} |G_0(\mu^N_s) - G_0(\tilde{\mu}^N_s)|^2 \right] \leq C \left\{ \left( \frac{\log n}{n} \right) + \int_0^t \frac{1}{n} E \left[ |X_s^i - \tilde{X}_s^i|^2 \right] ds \right\}. \tag{4.5} \]

Plugging this estimate in (4.1) gives
\[ E \left[ |X_t^i - \tilde{X}_t^i|^2 \right] \leq C \left\{ \left( \frac{\log n}{n} \right) + \int_0^t \frac{1}{n} E \left[ |X_s^i - \tilde{X}_s^i|^2 \right] ds \right\}, \tag{4.6} \]

Since
\[ E \left[ |X_s^i - \tilde{X}_s^i|^2 \right] \leq 2 E \left[ |X_s^i - \tilde{X}_s^i|^2 \right] + 2 E \left[ |X_s^i - \tilde{X}_s^i|^2 \right], \]
\[ = 2 E \left[ |X_s^i - \tilde{X}_s^i|^2 \right] + 2 E \left[ |\tilde{U}_s^i - \tilde{U}_{s \downarrow}|^2 \right], \]
it follows from (4.4) and (4.6) that
\[ E \left[ |X_t^i - \tilde{X}_t^i|^2 \right] \leq C \left\{ \left( \frac{\log n}{n} \right) + \int_0^t \frac{1}{n} E \left[ |X_s^i - \tilde{X}_s^i|^2 \right] ds \right\}, \]
and we conclude the proof with Gronwall’s lemma. \hfill \square

**Proof of Lemma 4.4.** Let us start by observing that
\[ \sup_{s \leq T} |B_s - B_{s \downarrow}| = \max_{k=0, \ldots, n-1} \sup_{T_k \leq s \leq T_{k+1}} |B_s - B_{T_k}|, \]
\[ = \max_{k=0, \ldots, n-1} \sup_{T_k \leq s \leq T_{k+1}} \max (B_s - B_{T_k}, -(B_s - B_{T_k})), \]
\[ \leq \max_{k=0, \ldots, n-1} \sup_{T_k \leq s \leq T_{k+1}} (B_s - B_{T_k}) + \max_{k=0, \ldots, n-1} \sup_{T_k \leq s \leq T_{k+1}} (- (B_s - B_{T_k})). \]
Since the random variables \( \sup_{T_k \leq s \leq T_{k+1}} (B_s - B_{T_k}), k = 0, \ldots, n - 1 \), as well as the variables \( \sup_{T_k \leq s \leq T_{k+1}} (- (B_s - B_{T_k})), k = 0, \ldots, n - 1 \), are independent and have the same law as \( |B_T| \),
\[ E \left[ \sup_{s \leq T} |B_s - B_{s \downarrow}|^4 \right] \leq 8 \frac{T^2}{n^2} E \left[ \max (|G_1|^4, \ldots, |G_n|^4) \right], \]
where \( G_k, k = 1, \ldots, n \) are independent normal random variables.

Let \( f \) be the function defined on \( \mathbb{R}_+ \) by \( f(x) = e^{\sqrt{1+x/16}} \); \( f \) is convex, increasing with values in \( [e, +\infty[ \). The inverse of \( f \) is concave on \( [e, +\infty[ \), increasing and \( f^{-1}(y) = 16 \left( (\log y)^2 - 1 \right) \).

We have, by Jensen inequality,
\[ E \left[ \max_{k=1, \ldots, n} |G_k|^4 \right] = E \left[ \max_{k=1, \ldots, n} f^{-1} \circ f \left( |G_k|^4 \right) \right] \leq f^{-1} \left( \max_{k=1, \ldots, n} f \left( |G_k|^4 \right) \right), \]
from which we deduce that
\[ \mathbb{E}\left[ \max_{k=1,\ldots,n} |G_k|^4 \right] \leq f^{-1}\left( \mathbb{E}\left[ \sum_{k=1}^{n} f\left(|G_k|^4\right) \right] \right) = f^{-1}\left( n\mathbb{E}\left[ f\left(|G_1|^4\right) \right] \right) \leq f^{-1}\left( n\mathbb{E}\left[ e^{\left|G_1\right|^2/4}\right] \right). \]

Finally, we have
\[ f^{-1}\left( n\mathbb{E}\left[ e^{\left|G_1\right|^2/4}\right] \right) = f^{-1}\left( n e\sqrt{2} \right) = 16 \left( (1 + \log n + \log(2)/2)^2 - 1 \right). \]

This concludes the proof of the lemma. 

\[\square\]

5. Numerical illustrations.

Throughout this section, we consider, on \([0, T]\), the following type of processes:
\[
\begin{aligned}
X_t &= \xi - \int_0^t (\beta_s + a_s X_s) \, ds + \int_0^t (\sigma_s + \gamma_s X_s) \, dB_s + K_t, \\
\mathbb{E}[h(X_t)] &\geq 0, \quad \int_0^t \mathbb{E}[h(X_s)] \, dK_s = 0,
\end{aligned}
\]

(5.1)

where \((\beta_t)_{t \geq 0}, (a_t)_{t \geq 0}, (\sigma_t)_{t \geq 0}\) and \((\gamma_t)_{t \geq 0}\) are bounded adapted processes. This kind of processes allow us to make some explicit computations which, in turn, allow to illustrate the algorithm. Our results are then presented for different processes of the form of (5.1) and functions \(h\). Associated computations are postponed to Subsection 5.2 below.

5.1. Illustrations. Let \(0 = T_0 < T_1 < \cdots < T_n = T\) be a subdivision of \([0, T]\) of step size \(1/n\), \(n\) being a positive integer. Using Algorithm 1 we draw \(L\) independent copies of \((\tilde{X}_{T_{k}}^{i})_{1 \leq i \leq N}, \tilde{K}_{T_{k}}^{N})_{0 \leq k \leq n,}\) with \(\tilde{K}_{T_{k}}^{N} = \sum_{l=1}^{N} \Delta_{t} \tilde{K}_{l}^{N}\) and \(N\) is the number of path of particles over the time interval \([0, T]\). We denote it by \((\tilde{X}_{T_{k}}^{i}, \tilde{K}_{T_{k}}^{N})_{1 \leq i \leq N, 1 \leq k \leq L}\). We show in the plots below the approximation of the reflection process \(K\) by the empirical mean of the i.i.d. copies of our estimator \(\tilde{K}_{T_{k}}^{N}\) obtained by Algorithm 1. In order to illustrate the variance of the estimation of the reflection process \(K\), we plot the boxplots associated with \((\tilde{K}_{T_{k}}^{N,i})_{1 \leq i \leq L}\) for five arbitrary times \(t\) in \([0, T]\). Indeed, apart from one example (case (iii) below), it appears that the amplitude the empirical 95% confidence interval obtained from the \((\tilde{K}_{T_{k}}^{N,i})_{1 \leq i \leq L}\) is too small to deserve the numerical illustrations.

When possible approximate the \(L^{2}\)-error in Theorem 4.2 by:
\[
\hat{E} = \left( \frac{1}{L} \sum_{l=1}^{L} \max_{0 \leq k \leq n} \left| X_{T_{k}}^{1,l} - \tilde{X}_{T_{k}}^{1,l} \right|^2 \right)^{1/2},
\]

(5.2)

and
\[
\hat{E}^{K} = \left( \frac{1}{L} \sum_{l=1}^{L} \max_{0 \leq k \leq n} \left| K_{T_{k}} - \tilde{K}_{T_{k}}^{N,l} \right|^2 \right)^{1/2}.
\]

(5.3)

Every simulation are launched on Matlab and the minimisation used to compute the increment of the reflection process \(\Delta_{k} \tilde{K}_{N}, k = 1, \cdots, n\) is done through the Matlab function \texttt{fsolve}. 
Linear constraint. We first consider cases where \( h : \mathbb{R} \ni x \mapsto x - p \in \mathbb{R} \).

Case (i) Drifted Brownian motion: \( \beta_t = \beta > 0, a_t = \gamma_t = 0, \sigma_t = \sigma > 0, \xi = x_0 \geq p \). We have

\[
K_t = (p + \beta t - x_0)^+.
\]

Figure 1 represents the evolution of the empirical mean of the \((\tilde{K}^{N,l})_{1 \leq l \leq L}\) (circles) and \(K\) (full line) with respect to time. We notice that the approximation of \(K\) is very close to the exact solution with small variance. Figure 2 represents the evolution of \(\log(\hat{E})\) and \(\log(\hat{E}^K)\) w.r.t. \(\log(N)\). We get a slope of 1/2, which is consistent with Theorem 4.2.

![Figure 1](image1.png)

**Figure 1.** Case (i). Left: value of the empirical mean of \(\tilde{K}^{N,l}\), \(1 \leq l \leq L\) and \(K_t\) w.r.t. time; Right: boxplots of estimated \(K_t\) for five arbitrary times \(t\). Data: \(n = 100, N = 2000, L = 1000, T = 1, \beta = 2, \sigma = 1, x_0 = 1, p = 1/2\).

![Figure 2](image2.png)

**Figure 2.** Case (i). Regression of \(\log(\hat{E})\) and \(\log(\hat{E}^K)\) w.r.t. \(\log(N)\). Data: \(\hat{E}\) when \(N\) varies from 100 to 2200 with step size 300. Parameters: \(n = 100, T = 1, \beta = 2, \sigma = 1, x_0 = 1, p = 1/2, L = 1000\).
Case (ii) Ornstein Uhlenbeck process: \( \beta_t = \beta > 0, a_t = a > 0, \gamma_t = 0, \sigma_t = \sigma > 0, \xi = x_0 \) with \( x_0 \geq p > -\beta/a \). We have

\[
K_t = (a_p + \beta)(t - t^*)_{t \geq t^*}, \text{ where } t^* = \frac{1}{a} (\ln(x_0 + \beta/a) - \ln(p + \beta/a)).
\]

Figure 3 represents the evolution of the empirical mean of \((\tilde{K}_{N,l})_{1 \leq l \leq L}\) (circles) and \(K\) (full line) with respect to time. As in the previous example, the approximation of \(K\) is very close to the exact solution with small variance. Figure 4 represents the evolution of \(\log(\hat{E})\) and \(\log(\hat{E}^K)\) w.r.t. \(\log(N)\). We get a slope of 1/2, which is consistent with Theorem 4.2.

![Figure 3](image1.png)

**Figure 3.** Case (ii). Left: value of the empirical mean of \(\tilde{K}_{N,l}\), \(1 \leq l \leq L\) and \(K\) w.r.t. time; Right: boxplots of estimated \(K_t\) for five arbitrary times \(t\). Data: \(n = 100, N = 2000, L = 1000, T = 1, \beta = 2.1, a = 1, \sigma = 1, p = 3.1, x_0 = p + 1\).

![Figure 4](image2.png)

**Figure 4.** Case (ii). Regression of \(\log(\hat{E})\) and \(\log(\hat{E}^K)\) w.r.t. \(\log(N)\). Data: \(\hat{E}\) when \(N\) varies from 100 to 2200 with step size 300. Parameters: \(n = 100, T = 1, \beta = 2, \sigma = 1, x_0 = 1, p = 3.1, L = 1000\).
Case (iii) Ornstein Uhlenbeck process with stochastic mean parameter: \( \beta_t = \beta > 0, a_t = -\epsilon B_t, \epsilon > 0, \gamma_t = 0, \sigma_t = \sigma > 0, \xi = x_0, x_0 > p. \) When \( \epsilon \to 0^+ \)

\[
K_t = \left( p - x_0 + \beta t - \sigma^2 \epsilon^2 \right) 1_{[t^*, \bar{t}]}(t) + \left( -(x_0 - p) + \frac{\beta^2}{2\epsilon \sigma} \right) 1_{t \geq \bar{t}} + o(\epsilon),
\]

where \( \bar{t} = \beta/(\epsilon \sigma) \) and \( t^* = \left( \beta - \sqrt{\beta^2 - 2(x_0 - p)\epsilon \sigma} \right) / (\epsilon \sigma) \).

Figure 5 represents the evolution of the empirical mean of the \( \tilde{K}^{N,l}_{1 \leq l \leq L} \) (circles) and \( K \) (full line) with respect to time. The times \( t^* \) and \( \bar{t} \) are also plotted. We notice that the approximation of \( K \) is biased on \([\bar{t}, T]\), this may come from the fact that we plot the first order approximation of \( K \) in \( \epsilon \).

**Figure 5.** Case (iii). Value of the empirical mean of \( \tilde{K}^{N,l}_{1 \leq l \leq L} \) and associated 95% approximated centered confidence interval and \( K \) w.r.t. time. Data: \( n = 200, N = 10000, L = 100, T = 5, \beta = 1, \epsilon = 5/100, \sigma = 1/(2\epsilon), x_0 = 1, p = 0.9. \)

**Remark 5.1.** The reader may object that Case (iii) is out of the scope of our theoretical results, which is true. We nevertheless choose to give this example in order to illustrate, numerically, the robustness of the method.

Case (iv) Black and Sholes process: \( \beta_t = \beta > 0, a_t = a > 0, \sigma_t = 0, \gamma_t = \gamma > 0. \) Then

\[
K_t = (ap + \beta)(t - t^*) 1_{t \geq t^*}, \text{ where } t^* = \frac{1}{a} (\ln(x_0 + \beta/a) - \ln(p + \beta/a)).
\]

Figure 6 represents the evolution of the empirical mean of \( \tilde{K}^{N,l}_{1 \leq l \leq L} \) (circles) and \( K \) (full line) with respect to time. We notice that the approximation of \( K \) is quite precise with small variance. As in cases (i) and (ii) the coefficients \( a, \beta, \sigma \) and \( \gamma \) are constants and the constraint is linear, the numerical scheme is closer to the exact solution than in case (iii).
Nonlinear constraint. Secondly, we illustrate the case of non-linear function $h$:

$$h : \mathbb{R} \ni x \mapsto x + \alpha \sin(x) - p \in \mathbb{R}, \quad \alpha > 0.$$ 

Case (v) Ornstein Uhlenbeck process: $a_t = a > 0$, $\beta_t = \beta > 0$, $\gamma_t = 0$, $\sigma_t = \sigma > 0$, $\xi = x_0$ with $x_0 > |\alpha| + p$. We obtain

$$dK_t = e^{-at} d\sup_{s \leq t} (F_s^{-1}(0))^+, \quad \text{where for all } t \in [0, T],$$

$$F_t : \mathbb{R} \ni x \mapsto \left\{ e^{-at} \left( x_0 - \beta \left( \frac{e^{at} - 1}{a} \right) + x \right) + \alpha \exp \left( -e^{-at} \frac{\sigma^2}{2a} \sinh(at) \right) \right. \left. \times \sin \left( e^{-at} \left( x_0 - \beta \left( \frac{e^{at} - 1}{a} \right) + x \right) - p \right) \right\}.$$ 

Figure 7 represents the evolution of the empirical mean of $\tilde{K}_{N,l}^{N,l}$, $1 \leq l \leq L$ and $K_t$ w.r.t. time. Right: boxplots of estimated $K_t$ for five arbitrary times $t$. Data: $n = 100$, $N = 2000$, $L = 1000$, $T = 1$, $a = 1$, $\gamma = 1$, $x_0 = 4$, $p = 1$

5.2. Proofs of the numerical illustrations. In order to have closed, or almost closed, expression for the compensator $K$ we introduce the process $Y$ solution to the non-reflected SDE

$$Y_t = \xi - \int_0^t (\beta_s + a_s Y_s) \, ds + \int_0^t (\sigma_s + \gamma_s Y_s) \, dB_s.$$ 

Letting $A_t = \int_0^t a_s \, ds$ and applying Itô’s formula on $e^{A_t}(X_t - Y_t)$, we get

$$X_t = Y_t + e^{-A_t} \int_0^t e^{As} dK_s + e^{-A_t} \int_0^t e^{As} \gamma_s (X_s - Y_s) \, dB_s.$$ 

Hence, the constraint $\mathbb{E}[h(X_t)] \geq 0$ rewrites

$$\mathbb{E} \left[ h \left( Y_t + e^{-A_t} \int_0^t e^{As} dK_s + e^{-A_t} \int_0^t e^{As} \gamma_s (X_s - Y_s) \, dB_s \right) \right] \geq 0. \quad (5.4)$$
Figure 7. Case (v). Left: value of true and empirical mean of estimated $K_t$ w.r.t. time; Right: Boxplots of estimated $K_t$ for five arbitrary time $t$. Data: $n = 200$, $N = 10000$, $L = 100$, $T = 15$, $\beta = 10^{-2}$, $\sigma = 1$, $p = \pi/2$, $\alpha = 0.9$, $x_0$ is the unique solution of $x + \alpha \sin(x) - p = 0$ plus $10^{-1}$.

Proof of assertions (i), (ii) and (iv). The formula for $K$ comes from the expression of its density given in Corollary 2.7 and the fact that in all these cases

$E[Y_t] - p = e^{-\alpha t} \left( x_0 + \frac{\beta}{a} \right) - \left( p + \frac{\beta}{a} \right).$

□

Proof of (iii). Recall that we supposed $h : \mathbb{R} \ni x \mapsto x - p \in \mathbb{R}$. In that case, since $\gamma \equiv 0$, the constraint (5.4) becomes

$E \left[ e^{-\lambda t} \int_0^t e^{As} dK_s \right] \geq p - E[Y_t], \quad (5.5)$

so that $K$ is nondecreasing with $K_0 = 0$ and, for all $t$ in $[0, T]$,

$E \left[ e^{-\lambda t} \int_0^t e^{As} dK_s \right] \geq p - E[Y_t], \quad \int_0^t (E[X_s] - p) dK_s = 0. \quad (5.6)$

Note first that since

$E[Y_t] = E \left[ e^{-A_s} X_0 \right] - E \left[ \int_0^s e^{-(A_s-A_r)} \beta dr \right] + E \left[ e^{-A_s} \int_0^s e^{Ar} \sigma dB_r \right],$

and using the integration by parts formula we have

$E \left[ e^{-A_s} \int_0^s e^{Ar} \sigma dB_r \right] = \sigma E \left[ \int_0^s D_r (e^{-A_s}) e^{Ar} dr \right] = -\sigma E \left[ \int_0^s \int_r^s (D_u a_u) du e^{-(A_s-A_u)} dr \right].$

Remember that, in this case, we supposed that $T \leq 1$, $\beta_1 = \beta > 0$ and $a_t = -\epsilon B_t$ for $\epsilon > 0$ supposed to be small enough. We here illustrate the dependence of the processes w.r.t. the parameter $\epsilon$ by adding a superscript $\epsilon$ on $Y$ and $K$. Since $\int_s^t B_r dr$ is a centered gaussian random variable with variance $(t - s)^3/3$, we have

$E[Y^\epsilon_t] = x_0 e^{2 \epsilon^3/6} - \beta \int_0^t e^{2(t-s)^3/6} ds + \sigma \epsilon \int_0^t (t-s) e^{2(t-s)^3/6} ds,$

$E[X^\epsilon_t] = E[Y^\epsilon_t] + \int_0^t e^{2(t-s)^3/6} dK^\epsilon_s.$
Therefore, for all \( s \leq t \),
\[
E[X_s] - p = x_0 - p - \beta s + \epsilon \sigma \frac{s^2}{2} + o(\epsilon) + K_t^r (1 + o(\epsilon)).
\]
It follows that, up to \( o(\epsilon) \),
\[
K_t^r = \sup_{s \leq t} \left( - (x_0 - p) + \beta s - \sigma \epsilon \frac{s^2}{2} \right)^+.
\]
Since \( \epsilon \to 0^+ \), we assume that \( \beta^2 > 2 \epsilon \sigma (x_0 - p) \) and we obtain \( K_t^r = 0 \) if \( t < t^* \),
\[
K_t^r = - (x_0 - p) + \beta t - \epsilon \frac{t^2}{2}, \quad \text{if } t^* \leq t < \frac{\beta}{\epsilon \sigma}, \quad K_t^r = - (x_0 - p) + \frac{\beta^2}{2 \epsilon \sigma}, \quad \text{for } t \geq \frac{\beta}{\epsilon \sigma},
\]
where \( t^* = \left( \beta - \sqrt{\beta^2 - 2 \epsilon \sigma (x_0 - p)} \right) / (\epsilon \sigma) \).

**Proof of assertion (v).** In that case, we have
\[
Y_t = e^{-at} \left( x_0 - \beta \left( \frac{e^{-at} - 1}{a} \right) \right) + \sigma e^{-at} \int_0^t e^{as} dB_s := f_t + G_t,
\]
and
\[
X_t = Y_t + e^{-at} \tilde{K}_t, \quad \tilde{K}_t = \int_0^t e^{as} dK_s.
\]
Hence
\[
\begin{align*}
h(X_t) & = Y_t + e^{-at} \tilde{K}_t + \alpha \sin(Y_t + e^{-at} \tilde{K}_t) - p \\
& = Y_t + e^{-at} \tilde{K}_t + \alpha \left( \sin(Y_t) \cos(e^{-at} \tilde{K}_t) + \cos(Y_t) \sin(e^{-at} \tilde{K}_t) \right) - p \\
& = Y_t + e^{-at} \tilde{K}_t + \alpha \left[ \cos(e^{-at} \tilde{K}_t) \sin(f_t) \cos(G_t) + \sin(f_t) \cos(G_t) \right] \\
& \quad + \sin(e^{-at} \tilde{K}_t) \{ \cos(f_t) \cos(G_t) - \sin(f_t) \sin(G_t) \} - p.
\end{align*}
\]
Since \( G_t \) is a centered gaussian random variable with variance \( \sigma^2 \frac{1 - e^{-2at}}{2a} = \sigma^2 e^{-at} \sinh(at) \),
\[
E[\sin(G_t)] = 0, \quad \text{and } \quad E[\cos(G_t)] = \exp \left( -e^{-at} \frac{\sigma^2}{a} \sinh(at) \right) =: g(t),
\]
we obtain that
\[
E[h(X_t)] = f(t) + e^{-at} \tilde{K}_t + \alpha g(t) \sin \left( f_t + e^{-at} \tilde{K}_t \right) - p,
\]
\[
:= F_t(\tilde{K}_t).
\]
Therefore,
\[
\tilde{K}_t = \sup_{s \leq t} \left( F_s^{-1}(0) \right)^+, \quad \text{and } \quad d\tilde{K}_t = e^{-at} d \sup_{s \leq t} \left( F_s^{-1}(0) \right)^+.
\]

**References.**

[ADEH99] Philippe Artzner, Freddy Delbaen, Jean-Marc Eber, and David Heath. Coherent measures of risk. *Math. Finance*, 9(3):203–228, 1999.

[Bau02] Fabrice Baudoin. Conditioned stochastic differential equations : theory, examples and applications in finance. *Stochastic Processes and their applications*, 100:109–145, 2002.

[BEH16] Philippe Briand, Romuald Elie, and Ying Hu. BSDEs with mean reflexion. arXiv:1605.06301, 2016. Ann. Appl. Probab. to appear.

[BPS91] Donald Burkholder, Etienne Pardoux, and Alain-Sol Sznitman. Topics in propagation of chaos. In *Ecole d’Eté de Probabilités de Saint-Flour XIX — 1989*, volume 1464 of *Lecture Notes in Mathematics*, pages 165–251. Springer Berlin / Heidelberg, 1991.
[CL95] Patrick Cattiaux and Christian Léonard. Large deviations and Nelson processes. *Forum Math.*, 7(1):95–115, 1995.

[FG15] Nicolas Fournier and Arnaud Guillin. On the rate of convergence in Wasserstein distance of the empirical measure. *Probab. Theory Related Fields*, 162(3-4):707–738, 2015.

[FS02] Hans Föllmer and Alexander Schied. Convex measures of risk and trading constraints. *Finance Stoch.*, 6(4):429–447, 2002.

[Jab17] Jean-François Jabir. Diffusion processes with weak constraint through penalization approximation. arXiv:1704.01505v2, 2017.

[LS84] Pierre-Louis Lions and Alain-Sol Sznitman. Stochastic Differential Equations with Reflecting Boundary Conditions. *Comm. Pure Appl. Math.*, 37(4):511–537, 1984.

[MRCS10] Bertrand Maury, Aude Roudneff-Chupin, and Filippo Santambrogio. A macroscopic crowd motion model of gradient flow type. *Mathematical Models and Methods in Applied Sciences*, 20(10):1787–1821, 2010.

[MT08] Toshio Mikami and Michèle Thieullen. Optimal transportation problem by stochastic optimal control. *SIAM J. Control Optim.*, 47(3):1127–1139, 2008.

[RR98] Svetlozar T. Rachev and Ludger Rüschendorf. *Mass transportation problems. Vol. I*. Probability and its Applications (New York). Springer-Verlag, New York, 1998. Theory.

[Tan79] Hiroshi Tanaka. Stochastic differential equations with reflecting boundary condition in convex regions. *Hiroshima Mathematical Journal*, 9(1):163–177, 1979.

[TT13] Xiaolu Tan and Nizar Touzi. Optimal transportation under controlled stochastic dynamics. *Annals of Probab.*, 41(5):3201–3240, 2013.

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