

# Uncertain Darcy's problem and the stochastic particle transport

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# 1 Expected exit time from a domain

We aim to estimate the exit time of a particle driven by a deterministic transport field and a stochastic diffusion from a domain  $D \subset \mathbb{R}^d$ . Given a vector  $W(t)$  of  $m$  independent Brownian motions and two functions  $f: \mathbb{R}^d \rightarrow \mathbb{R}^d, g: \mathbb{R}^d \rightarrow \mathbb{R}^{d \times m}$ , we consider the following stochastic differential equation (SDE)

$$\begin{cases} dX(t) = f(X(t))dt + g(X(t))dW(t), & 0 < t \leq T, \\ X(0) = X_0, & X_0 \in D. \end{cases} \quad (1)$$

The problem is completed with two different types of boundary conditions, namely

- i. *killing boundaries*: if the particle exits  $D$  the process is stopped,
- ii. *reflecting boundaries*: the particle trajectory is reflected normally inside  $D$  when it touches the boundary  $\partial D$ .

Our aim is to estimate numerically the first exit time of the solution  $X(t)$  from  $D$ , *i.e.*, the quantity

$$\tau = \min\{\min\{t: X(t) \notin D\}, T\}. \quad (2)$$

Let us remark that the parameter  $\tau$  is meaningful only if there exists a portion of the boundary  $\Gamma_k \subset \partial D$  that is endowed with killing boundary conditions. Otherwise, the process  $X(t)$  will stay in  $D$  for the whole time interval, giving as a result  $\tau = T$  for each realisation of  $X(t)$ . Another quantity of interest is defined as follows

$$\phi = \phi(T, X_0, F) = \mathbb{1}_{\{\tau < T\}} F(X(T)), \quad (3)$$

where  $F: \mathbb{R}^d \rightarrow \mathbb{R}$  is a smooth function. An interesting choice of  $F$  could be the function mapping every  $x$  of  $\mathbb{R}^d$  to the value 1. In this case, the expectation of  $\phi$  is equal to the probability for  $X(t)$  to exit the domain before the final time  $T$ . Let us choose the notation  $F = 1$  in this case, getting

$$\Phi(T, X_0) = \mathbb{E}(\phi(T, X_0, 1)) = \Pr(\tau < T | X(0) = X_0) \quad (4)$$

In the case of general  $f, g$  and for a  $d$ -dimensional SDE, there is no closed form for  $\tau$  and  $\phi$ . Therefore, we approximate the value of  $\tau$  by means of two numerical schemes, briefly presented in the following.

## 1.1 Numerical Methods

### 1.1.1 Discrete Euler-Maruyama

Given  $N \in \mathbb{N}$  let us define a partition of  $[0, T]$  as  $P_h = \{t_i\}_{i=0}^N, t_i = ih, h = T/N$ . The Discrete Euler-Maruyama method (DEM) for problem (1) is defined as follows

$$\begin{cases} X_h^d(t_{i+1}) = f(X_h^d(t_i))h + g(X_h^d(t_i))(W(t_{i+1}) - W(t_i)), \\ X_h^d(0) = X_0. \end{cases} \quad (5)$$

The exit time  $\tau$  is approximated with the quantity  $\tau_h^d$  defined as

$$\tau_h^d = \min\{\min\{t_i: X_h^d(t_i) \notin D\}, T\}. \quad (6)$$

We approximate analogously  $\phi$  as

$$\phi_h^d = \mathbb{1}_{\{\tau_h^d < T\}} F(X_h^d(T)). \quad (7)$$

Let us state two results concerning the weak error of this method.

**Proposition 1.1.** *Under appropriate assumptions of smoothness of  $f, g, D, \partial D, F$ ,*

$$|\mathbb{E}(\tau_h^d) - \mathbb{E}(\tau)| = O(\sqrt{h}). \quad (8)$$

**Proposition 1.2.** *Under appropriate assumptions of smoothness of  $f, g, D, \partial D, F$ ,*

$$|\mathbb{E}(\phi_h^d) - \mathbb{E}(\phi)| = O(\sqrt{h}). \quad (9)$$

An discussion of result 1.1 can be found in [5], its proof in [3]. A proof of 1.2 can be found in [1].

**Algorithm 1:** Continuous Euler-Maruyama

```

for  $t_i \in P_h$  do
   $X(t_{i+1}) = f(X(t_i))h + g(X(t_i))(W(t_{i+1}) - W(t_i))$  ;
  if  $X(t_{i+1}) \notin D$  then
     $\tau_h^c = t_{i+1}$  ;
     $\phi_h^c = F(X_h^c(t_{i+1}))$  ;
    return;
  else
    compute  $p = p(x_i, x_{i+1}, h)$  ;
    simulate  $u \sim \text{Unif}(0, 1)$  ;
    if  $u < p$  then
       $\tau_h^c = t_{i+1}$  ;
       $\phi_h^c = F(X_h^c(t_{i+1}))$  ;
      return;
    end
  end
end

```

**1.1.2 Continuous Euler-Maruyama.**

Let us consider the partition  $P_h$  of  $[0, T]$  as above. The Continuous Euler-Maruyama (CEM) method is defined as

$$\begin{cases} X_h^c(t) = f(X(t_i))(t - t_i) + g(X(t_i))(W(t) - W(t_i)), & t_i < t \leq t_{i+1}, \\ X_h^c(0) = X_0. \end{cases} \quad (10)$$

Let us remark that in case the particle does not exit the domain,  $X_h^c(t_i) = X_h^d(t_i)$  for all  $t_i \in P_h$ . It is possible to compute the probability that a particle has exited the domain at a time  $t$  between two consecutive timesteps  $t_i, t_{i+1}$  when  $D$  is an half-space with the following formula [2]

$$\Pr(\exists t \in [t_i, t_{i+1}] \quad X_h^d(t) \notin D | X_h^d(t_i) = x_i, X_h^d(t_{i+1}) = x_{i+1}) = p(x_i, x_{i+1}, h), \quad (11)$$

with  $p(x_i, x_{i+1}, h)$  given by

$$p(x_i, x_{i+1}, h) = \exp\left(-2 \frac{[n \cdot (x_i - z_i)][n \cdot (x_{i+1} - z_i)]}{hn \cdot (gg^T(x_i)n)}\right), \quad (12)$$

where  $z_i$  is the projection of  $x_i$  on  $\partial D$  and  $n$  is the normal to  $\partial D$  in  $z_i$ . At each timestep  $t_{i+1}$  we compute the probability  $p(x_i, x_{i+1}, h)$ , and then simulate a variable  $U$  distributed uniformly in the interval  $[0, 1]$ , thus obtaining a realization  $u$ . Hence, we conclude that the particle has left the domain for a time  $t$  in  $(t_i, t_{i+1})$  if  $u$  is smaller than  $p$ . Therefore, we approximate the exit time as

$$\tau_h^c = \min\{T, \min\{t_i = hi : X_h(t_i) \notin D\}, \min\{t_i = hi : u < p(x_{i-1}, x_i, h)\}\}, \quad (13)$$

In the same way as in DEM, we can approximate  $\phi$  as

$$\phi_h^c = \mathbb{1}_{\{\tau_h^c < T\}} F(X_h^c(T)). \quad (14)$$

We show the pseudocode for the implementation of CEM in Algorithm 1. The weak error of this method has been studied exhaustively in previous work.

**Proposition 1.3.** *Under appropriate smoothness assumptions,*

$$|\mathbb{E}(\phi_h^c) - \mathbb{E}(\phi)| = O(h). \quad (15)$$

A proof of result 1.3 can be found in [2].

### 1.1.3 Reflecting boundaries

The reflecting boundaries are treated in the same way for both DEM and CEM. Let us denote by  $\Gamma_k$  and  $\Gamma_r$  the killing and reflecting subsets of  $\partial D$ , *i.e.*

$$\Gamma_r \cup \Gamma_k = \partial D, \quad \Gamma_r \cap \Gamma_k = \emptyset \quad (16)$$

In case the particle approaches  $\Gamma_k$  the exit is treated as above. If for a timestep of  $t_i \in P_h$ ,  $X(t_i)$  is not in  $D$  and has crossed  $\Gamma_r$  at a time  $t_{i-1} < t < t_i$ , we update the solution to be the normal reflection inside  $D$  of  $X(t_i)$ .

### 1.1.4 An adaptive procedure

Let us consider the function  $g$  in (1) to be fixed to a real constant  $\sigma$ . The numerical methods we presented can be completed with an adaptive procedure for the step size  $h$ . In this frame, adaptivity is performed with respect to the position of the numerical solution  $X_h(t_i)$ , *i.e.*, the step size is reduced if the solution is near to the boundary of the domain  $D$ . If we denote by  $d_i$  the distance between  $X_h(t_i)$  and its normal projection on  $\partial D$ , by  $l \in \mathbb{N}$  a fixed parameter and by  $h_0$  a maximum bound for  $h$ , the step size is chosen using the following formula

$$h = \max \left\{ 2^{-2l} h_0, \min \left\{ 2^{-l} h_0, \left( \frac{d}{(l+3)\sigma} \right)^2 \right\} \right\}. \quad (17)$$

This formula is equivalent to dividing the domain  $D$  in three zones, in particular

- an interior zone where  $h = h_{int} = 2^{-l} h_0$ ,
- a boundary zone where  $h = h_{bound} = 2^{-2l} h_0$ ,
- an intermediate zone where  $h = \left( \frac{d}{(l+3)\sigma} \right)^2$ .

Since the loss of 0.5 in the weak order of convergence of Euler-Maruyama is due to the non-detected exits from the domain  $D$ , refining the step size only near to the boundary could lead to an error equal to the one obtained using  $h_{bound}$  on the whole domain.

## 1.2 A PDE approach

It is possible to express the mean exit time and the probability of exit from a domain in terms of the solution of partial differential equations (PDE's). Let us denote by  $\Gamma_k, \Gamma_r$  the killing and reflecting subsets of  $\partial D$ . We consider then the expectation of the exit time from the domain  $D$  for a trajectory that at  $t = 0$  is at position  $x$ , *i.e.*,

$$\bar{\tau}(x) = \mathbb{E}(\tau | X(0) = x). \quad (18)$$

Let us define the operator  $\mathcal{L}$  induced by (1) acts on a function  $u: \mathbb{R}^d \rightarrow \mathbb{R}$  as follows

$$\mathcal{L}u = f \cdot \nabla u + \frac{1}{2} g g^T : \nabla \nabla u, \quad (19)$$

where the  $:$  operator between two matrices  $A, B$  in  $\mathbb{R}^{d \times d}$  is defined as follows

$$A : B = \sum_{i,j=1}^d \{A\}_{ij} \{B\}_{ij} = \text{tr}(A^T B). \quad (20)$$

The following result allows computing the mean exit time as the solution of an appropriate PDE.

**Proposition 1.4.** *Let  $\mathcal{L}$  be the differential operator defined as (19). Then, if  $\Gamma_k$  and  $\Gamma_r$  are respectively the killing and reflecting subsets of  $\partial D$ , such that  $\Gamma_k \cup \Gamma_r = \partial D, \Gamma_k \cap \Gamma_r = \emptyset$ , the mean*

exit time  $\bar{\tau}(x)$  for the solution  $X(t)$  of (1) with  $X_0 = x$  is the solution of the following boundary value problem

$$\begin{cases} \mathcal{L}\bar{\tau}(x) = -1, & \text{in } D, \\ \bar{\tau}(x) = 0, & \text{on } \Gamma_k, \\ \nabla\bar{\tau}(x) \cdot n = 0, & \text{on } \Gamma_r, \end{cases} \quad (21)$$

where  $n$  is the normal to  $\Gamma_r$ .

Further analytical treatment of the mean exit time can be found in [6, 8]. We now consider the probability of exit from  $D$  for a solution  $X(t)$  that is equal to  $x$  for  $t = s < T$ . This probability is the solution of a boundary value problem.

**Proposition 1.5.** *Let  $\mathcal{L}$  be the differential operator defined as (19). Then, if  $\Gamma_k$  and  $\Gamma_r$  are respectively the killing and reflecting subsets of  $\partial D$ , such that  $\Gamma_k \cup \Gamma_r = \partial D$ ,  $\Gamma_k \cap \Gamma_r = \emptyset$*

$$\Pr(\tau < T | X(s) = x) = \Phi(x, s, T) \quad (22)$$

where  $\Phi(x, t, T)$  is the solution of the following backwards PDE

$$\begin{cases} \frac{\partial}{\partial t}\Phi(x, t, T) + \mathcal{L}\Phi(x, t, T) = 0 & \text{in } D, s \leq t < T, \\ \Phi(x, t, T) = 1 & \text{on } \Gamma_k, s \leq t \leq T, \\ \nabla\Phi(x, t, T) \cdot n = 0, & \text{on } \Gamma_r, s \leq t \leq T, \\ \Phi(x, T, T) = 0 & \text{in } D, \end{cases} \quad (23)$$

where  $n$  is the normal to  $\Gamma_r$ .

The proof in case  $\Gamma_k = \partial D$  of this result can be found in [10]. Further treatment in case of mixed boundary conditions and the closed form of the solution for some particular geometries of  $D \subset \mathbb{R}^2$  can be found in [4]. It is therefore possible to approximate  $\bar{\tau}$  and  $\Phi$  by means of classical methods for solving PDE's numerically, such as finite differences or the Finite Elements Method.

### 1.3 One-Dimensional Case

We consider problem (1) in case  $d = 1$ . Given  $f, g: \mathbb{R} \rightarrow \mathbb{R}$ , an interval  $D = [l, r]$  and a Brownian motion  $W(t)$ , let us consider the following one dimensional SDE

$$\begin{cases} dX(t) = f(X(t))dt + g(X(t))dW(t), & 0 < t \leq T, \\ X(0) = X_0, & X_0 \in D. \end{cases} \quad (24)$$

In this case, the boundary of  $D$  consists of the two points  $\{l, r\}$ . In order for the problem of the determination of  $\tau$  to be meaningful, at least one of the two points should be endowed with a killing boundary condition.

#### 1.3.1 Analytical expression of the mean exit time

In this simple frame, it is possible to deduce an analytical solution  $\bar{\tau}$  of (21). Let us consider the boundary condition at  $x = l$  fixed as *killing* and vary the boundary condition at  $x = r$ . Since the scope is deducing the exit time of a particle from  $D$ , this assumption is plausible. In this frame, it is possible to rewrite (21) as

$$\begin{cases} f(x)\bar{\tau}'(x) + \frac{1}{2}g^2(x)\bar{\tau}''(x) = -1, & l < x < r, \\ \bar{\tau}(l) = 0, \\ \bar{\tau}(r) = 0, & \text{if for } x = r \text{ the boundary is } \textit{killing}, \\ \bar{\tau}'(r) = 0, & \text{if for } x = r \text{ the boundary is } \textit{reflecting}. \end{cases} \quad (25)$$

It is possible to show [6, 8] that  $\bar{\tau}$  is in the one-dimensional case given by

$$\bar{\tau}(x) = -2 \int_l^x \exp(-\psi(z)) \int_l^z \frac{\exp(\psi(y))}{g^2(y)} dy + c_1 \int_l^x \exp(-\psi(y)) dy + c_2, \quad (26)$$

where the function  $\psi$  is defined as

$$\psi(x) = \int_l^x \frac{2f(y)}{g^2(y)} dy, \quad (27)$$

and the constants  $c_1, c_2 \in \mathbb{R}$  depend on the boundary conditions as follows

$$\begin{aligned} c_1 &= 2 \frac{\int_l^r \exp(-\psi(z)) \int_l^z \frac{\exp(\psi(y))}{g^2(y)} dy}{\int_l^r \exp(-\psi(y)) dy}, \text{ if for } x = r \text{ the boundary is } \textit{killing}, \\ c_1 &= 2 \int_l^r \frac{\exp(-\psi(y))}{g(y)^2} dy, \text{ if for } x = r \text{ the boundary is } \textit{reflecting}, \\ c_2 &= 0. \end{aligned} \quad (28)$$

Let us remark that in case  $f = -V'$  for some smooth function  $V$  and  $g = \sigma \in \mathbb{R}$ , the expression of  $\psi$  simplifies to

$$\psi(x) = 2 \frac{V(l) - V(x)}{\sigma^2}. \quad (29)$$

The value for the expected exit time given by (26) will be used as a reference for verifying the order of convergence of the numerical methods.

### 1.3.2 Numerical experiments - Estimation of $\tau$

**Smooth case.** We consider as a domain for (24) the interval  $D = [-1, 1]$ , final time  $T = 5$  and the following functions

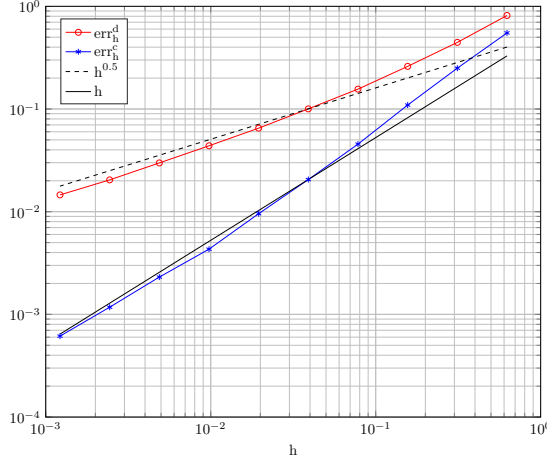
$$\begin{aligned} f(x) &= -V'(x), \text{ where } V(x) = 0.1(8x^4 - 8x^2 + x + 2), \\ g(x) &= \sigma = 3. \end{aligned} \quad (30)$$

We approximate the value of  $\tau$  with a Montecarlo simulation of  $\tau_h^d$  and  $\tau_h^c$  computed as in (6) and (13) from the solutions provided by DEM and CEM respectively. In order to verify the order of convergence of the methods, we let  $N$  vary in the set  $2^i, i = 3, \dots, 12$  and we fix the number of trajectories  $M$  to 10000. In this way, the error caused by the Montecarlo estimation should not spoil the order of convergence. In Figure 1 we show the errors obtained fixing  $X_0 = 0$  in both the cases of killing and reflecting boundary conditions in  $x = 1$ . Moreover, in Figure 2 we show an approximation of  $\tau$  obtained with the two methods with  $h = T/128$  and  $M = 1000$  for a set of 10 initial values equispaced along  $D$ . It is possible to remark that computing the probability of exit between two consecutive timesteps as in (12) allows correcting the overestimation of  $\tau$  obtained simply using DEM. We want to estimate the computational time for both the method. We consider  $M = 10000$ , killing boundary conditions and  $N = 2^i, i = 3, \dots, 12$ . We remark that the computational time required by CEM is higher than for DEM if the same value of  $h$  is employed. On the other hand, fixing the error, CEM is faster than DEM in this case.

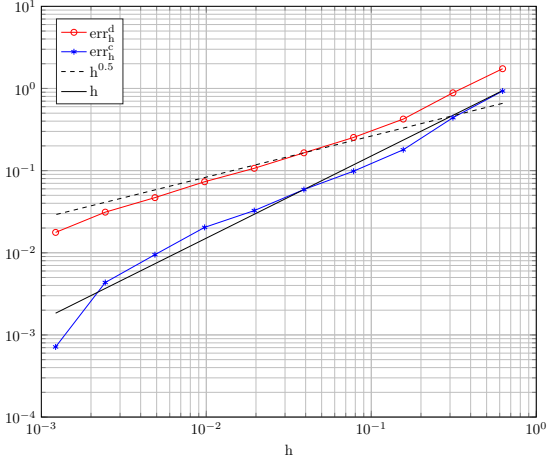
**Rough case.** We consider the same domain  $D$  as above,  $T = 5$  and  $g = \sigma = 3$ . We consider  $V$  to be piecewise linear, so that  $f = -dV$  is piecewise constant. In particular, we choose the following form for  $V$

$$V = 0.1 \begin{cases} -2x - 1, & x < -0.5, \\ 4x + 2, & -0.5 \leq x < 0, \\ -2x + 2, & 0 \leq x < 0.5, \\ 4x - 1, & x \geq 0.5. \end{cases} \quad (31)$$

This is a linear interpolation of the function  $V$  we used in the smooth case above in the points  $\{-1, -0.5, 0, 0.5, 1\}$ . This case is of particular interest, since if the function  $f$  is the result of a

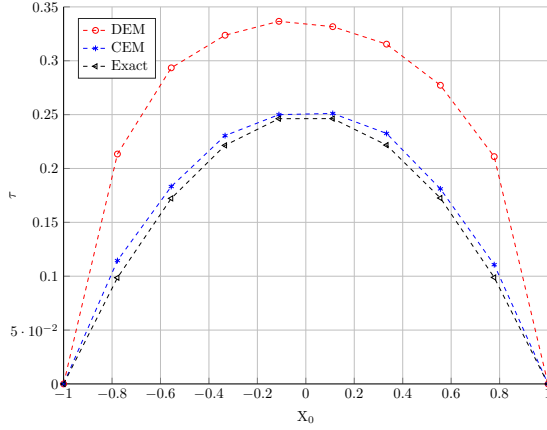


(a) Killing boundary in  $x = 1$

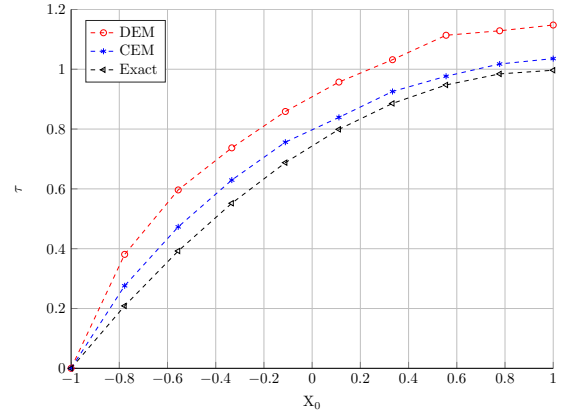


(b) Reflecting boundary in  $x = 1$

Figure 1: Approximation of  $\tau$ . Orders of convergence for DEM and CEM in the one-dimensional case.



(a) Killing boundary in  $x = 1$



(b) Reflecting boundary in  $x = 1$

Figure 2: Approximation of  $\tau$  as a function of the initial value  $X_0$ .

numerical method on a *PDE*, it could not be smooth as in the previous case. We perform DEM and CEM with the same parameters as before, *i.e.*,  $M = 10000, N = 2^i, i = 3, \dots, 12$ . In Figure 3 it is possible to remark that the rate of convergence of DEM is unvaried with respect to the previous case. The CEM method experiences a slight decrease in the order of convergence with respect to the smooth case.

### 1.3.3 Numerical approximation of $\Phi$ with the PDE approach

Let us consider  $D$  as the interval  $[l, r]$ , the boundary condition in  $l$  to be fixed to killing and in  $r$  to be either killing or reflecting. In this case and for  $f$  independent of  $t$  and  $g = \sigma \in \mathbb{R}$  (23) can

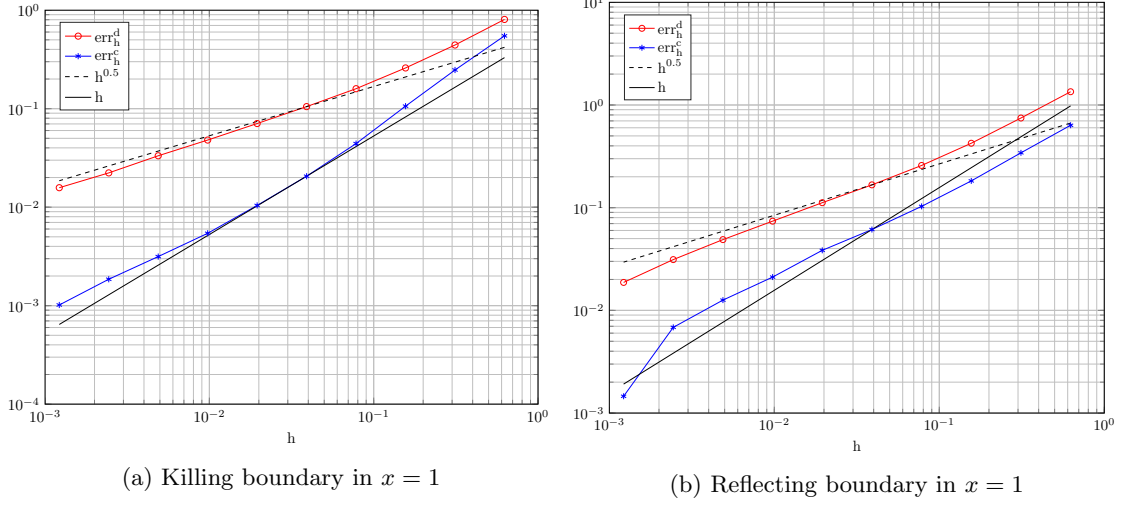


Figure 3: Approximation of  $\tau$ . Orders of convergence for DEM and CEM in the one-dimensional case with  $f$  piecewise constant.

be written as the following initial value PDE

$$\left\{ \begin{array}{l} -\frac{\partial}{\partial t}\Phi(t, x) + f \frac{\partial}{\partial x}\Phi(t, x) + \frac{1}{2}\sigma^2 \frac{\partial^2}{\partial x^2}\Phi(t, x) = 0, \quad l < x < r \\ \Phi(t, l) = 1, \\ \Phi(t, r) = 1, \quad \text{if for } x = r \text{ the boundary is } \textit{killing} \\ \frac{\partial}{\partial x}\Phi(t, r) = 0, \quad \text{if for } x = r \text{ the boundary is } \textit{reflecting} \\ \Phi(0, x) = 0. \end{array} \right. \quad (32)$$

This equation can be solved, *e.g.*, using finite differences. We employ the theta method for solving (32). Let us consider the case in which  $r$  is a killing boundary, *i.e.*, the PDE is endowed with Dirichlet boundary conditions. Given a step size  $\Delta_t$  for time integration and an uniform grid  $x_i = l + i\Delta_x, i = 0, \dots, N+1, x_{N+1} = r$ , at each timestep  $k$  one has to find the solution of the linear system

$$(I - \Delta_t \theta A)u^{k+1} = (I + \Delta_t(1 - \theta)A)u^k + hF, \quad 0 \leq \theta \leq 1, \quad (33)$$

where  $I$  is the identity matrix of  $\mathbb{R}^{N \times N}$ . The matrix  $A$  of  $\mathbb{R}^{N \times N}$  and the vector  $F$  of  $\mathbb{R}^N$  define the space discretization and the boundary conditions and are defined by

$$A = \frac{1}{2\Delta_x} \begin{pmatrix} \alpha_1 & \beta_1 & & \\ \gamma_1 & \alpha_2 & \beta_2 & \\ & \ddots & \ddots & \ddots \end{pmatrix}, \quad F = \frac{1}{2\Delta_x} (F_1 \dots F_N)^T \quad (34)$$

and the coefficients are given by

$$\begin{aligned} \alpha_i &= -\frac{2\sigma^2}{\Delta_x}, \quad i = 1, \dots, N, \\ \beta_i &= \frac{\sigma^2}{\Delta_x} + f(x_i), \quad i = 1, \dots, N-1, \\ \gamma_i &= \frac{\sigma^2}{\Delta_x} - f(x_{i+1}), \quad i = 1, \dots, N-1, \\ F_1 &= \frac{\sigma^2}{\Delta_x} - f(x_1), \\ F_N &= \frac{\sigma^2}{\Delta_x} - f(x_{N-1}). \end{aligned} \quad (35)$$



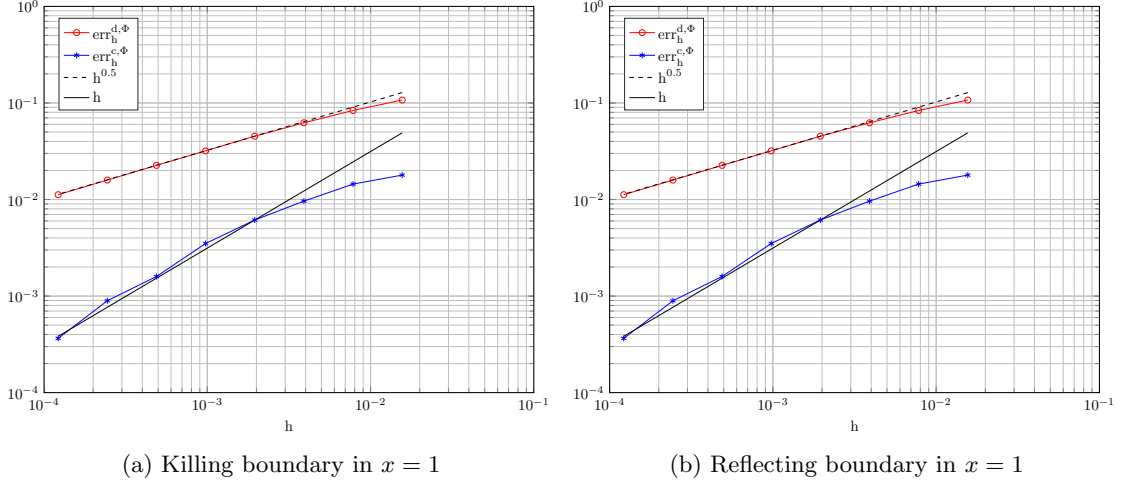


Figure 4: Approximation of  $\Phi$ . Orders of convergence of DEM and CEM in the one-dimensional case.

The case of reflecting boundary condition in  $x = r$  is similar and affects only the computation of the matrix  $A$  and the vector  $F$ . In particular, we introduce a *ghost node* at position  $x = r + \Delta_x$ , compute the derivative using a centrate approximation and impose that it is equal to 0, which leads to the condition that the value in the node in  $x = r$  is equal to the value in  $x = r - \Delta_x$ . Since the matrix defining the system (33) is tridiagonal, one can choose  $\Delta_t, \Delta_x$  to be small and obtain a precise solution of (32) in a reasonable computational time. In the following, we will compare the values given by Montecarlo simulations using DEM and CEM with the solution of the theta method with  $\theta = 0.5$ .

#### 1.3.4 Numerical experiments - Estimation of $\Phi$

**Smooth case.** We consider (24) with  $D = [-1, 1]$ , the final time  $T = 0.5$  and we define

$$\begin{aligned} f(x) &= -V'(x), \text{ where } V(x) = 8x^4 - 8x^2 + x + 2, \\ g(x) &= \sigma = 2. \end{aligned} \quad (36)$$

In order to approximate  $\Phi$ , we perform a Montecarlo simulation using both DEM and CEM, with  $M = 6 \cdot 10^5$  trajectories in order to kill the statistical error. We consider the number of timesteps for the time integration to be  $N = 2^i, i = 5, \dots, 12$ . Numerical results (Figure 4a) confirm that the weak error for DEM is of order 0.5, while for CEM the order of convergence is 1.

### 1.4 Two-dimensional case

We are interested in estimating the exit time of a particle from a domain  $D \subset \mathbb{R}^2$ . Given  $W(t)$  a vector of two independent Brownian motions, we consider the equation (1). In this case,  $f: \mathbb{R}^2 \rightarrow \mathbb{R}^2, g: \mathbb{R}^2 \rightarrow \mathbb{R}^{2 \times 2}$ . We compute the mean exit time and the exit probability using DEM and CEM and compare results with the numerical solution of the PDE's presented in 1.2.

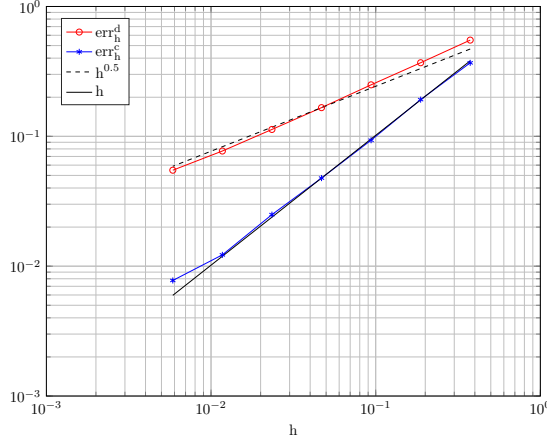
#### 1.4.1 Numerical experiments - Estimation of $\tau$

**Killing boundary conditions.** We consider a simple case of (1) in  $D = [-1, 1] \times [-1, 1]$ , where

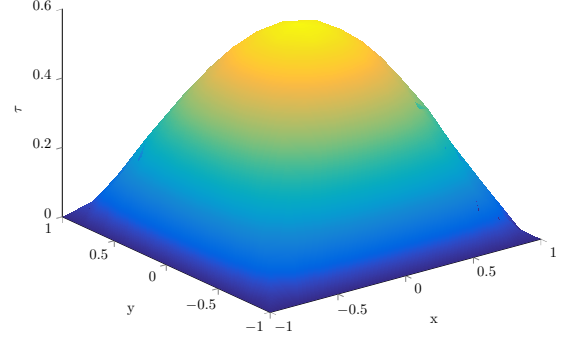
$$f = 0 \in \mathbb{R}^2, g = \sigma I \in \mathbb{R}^{2 \times 2}, \sigma \in \mathbb{R}.$$

Moreover, we consider  $\partial D$  to be a killing boundary. The solution in this case is a Brownian motion. In this case, the partial differential equation (21) reduces to

$$\begin{cases} -\sigma^2 \Delta \bar{\tau} = 2, & \text{in } D, \\ \bar{\tau} = 0, & \text{on } \partial D. \end{cases} \quad (37)$$



(a) Convergence of CEM and DEM.



(b) Expectation of exit time.

Figure 5: Summary of the results for  $\tau$  in the two-dimensional case with pure killing boundary conditions.

This is the Poisson equation, hence it is possible to solve it numerically with the Finite Elements Method or the finite differences avoiding a high computational cost. We use the Finite Elements Method adopting a regular mesh with equal constant spacing in the  $x$  and  $y$  directions, obtaining a solution as in Figure 5b. In order to verify the orders of convergence of DEM and CEM, we set  $T = 3$ ,  $\sigma = 1$ ,  $X_0 = (0,0)^T$ , with  $M = 10000$  and  $N = 2^i, i = 3, \dots, 9$ . We then compare the Montecarlo estimation we obtain with the value of  $\bar{\tau}$  in  $(0,0)$ , obtained by interpolation on the Finite Elements solution. The orders of convergence for this numerical experiment are shown in Figure 5a. The results confirm the theoretical orders of convergence for DEM and CEM, with an average order of 0.55 for DEM and 0.93 for CEM, which corrects to 0.98 if the last point is not taken into account.

**Mixed boundary conditions.** We consider the same problem as above with mixed killing and reflecting boundary conditions.  $f$  and  $g$  are the same as above, so the SDE model does not change, but we consider the two left and right boundaries of  $D$ , defined by  $x = \pm 1$ , to be reflecting. We denote this portion of the boundary as  $\Gamma_r$ , and the rest as  $\Gamma_k$ . In this case, the equation for  $\bar{\tau}$  becomes

$$\begin{cases} -\sigma^2 \Delta \bar{\tau} = 2, & \text{in } D, \\ \bar{\tau} = 0, & \text{on } \Gamma_k, \\ \partial \bar{\tau} \cdot n = 0, & \text{on } \Gamma_r. \end{cases} \quad (38)$$

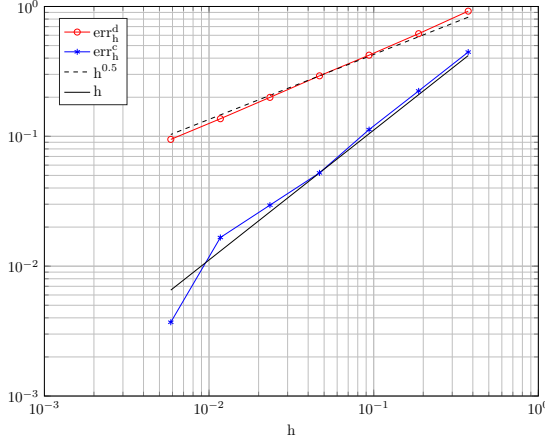
The solution of this equation is shown in Figure 6b. We compute the expectation of  $\tau$  with DEM and CEM with the same parameters as above. The results (Figure 6a), show that the theoretical orders of convergence are not spoiled by this choice of boundary conditions. The mean order for DEM in this case is 0.55, while for CEM it is 1.15.

#### 1.4.2 Numerical experiments - Estimation of $\Phi$

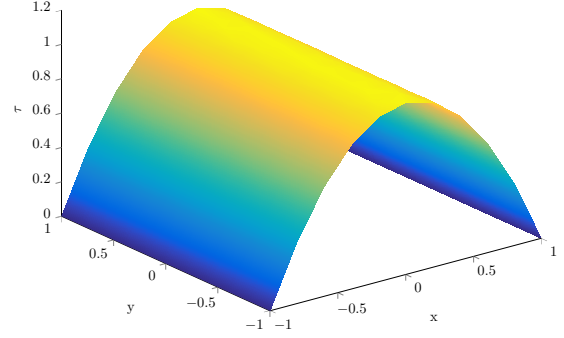
**Killing boundary conditions.** We consider the same simple case as in section 1.4.1 We consider  $\partial D$  to be a killing boundary. The solution of (1) is in this case a Brownian motion. In this case, the partial differential equation (23) reduces to

$$\begin{cases} \frac{\partial}{\partial t} \Phi(x, t, T) + \frac{1}{2} \sigma^2 \Delta \Phi(x, t, T) = 0, & \text{in } D, 0 \leq t < T, \\ \Phi(x, t, T) = 1, & \text{on } \partial D, 0 \leq t < T, \\ \Phi(x, T, T) = 0, & \text{in } D. \end{cases} \quad (39)$$

We solve this problem numerically with the Finite Elements Method as for (38). The solution at  $t = 0$  is shown in Figure 7b. We verify the orders of convergence of DEM and CEM setting

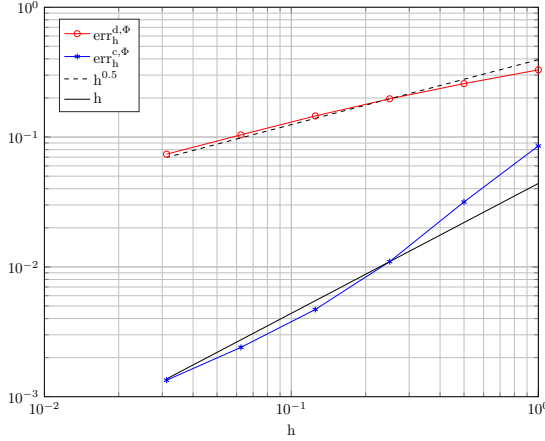


(a) Convergence of CEM and DEM.

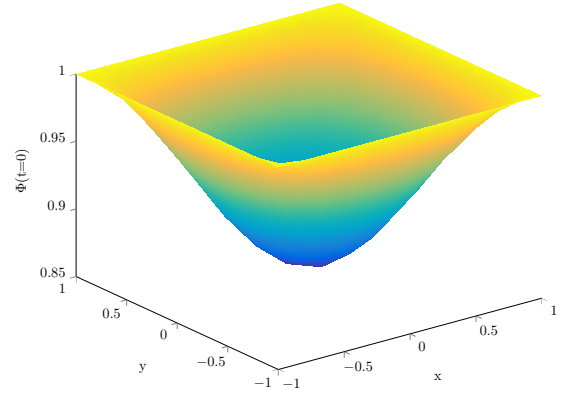


(b) Expectation of exit time.

Figure 6: Summary of the results for  $\tau$  in the two-dimensional case with mixed boundary conditions.



(a) Convergence of CEM and DEM.



(b) Probability of exit.

Figure 7: Summary of the results for  $\Phi$  in the two-dimensional case with pure killing boundary conditions.

$X_0 = (0, 0)^T, \sigma = 1, T = 1$ . We consider  $M = 100000$  trajectories and  $N = 2^i, i = 0, \dots, 5$ . We then compare the Montecarlo estimation with the value of  $\Phi$  in  $(0, 0)$ , obtained by interpolation on the Finite Elements solution. The orders of convergence for this numerical experiment are shown in Figure 7a. The theoretical orders of convergence are confirmed in this case as well, with an average order of 0.43 for DEM and 1.19 for CEM.

**Mixed boundary conditions.** We consider the same values for the parameters, the time integration and the Montecarlo estimation as in the pure killing case. In this case, we set the boundary conditions to be reflecting on the subset of the boundary of  $D$  defined by  $x = \pm 1$  and killing for the other boundaries. Therefore, in this case the exit probability  $\Phi$  is the solution of the following PDE

$$\left\{ \begin{array}{l} \frac{\partial}{\partial t} \Phi(x, t, T) + \frac{1}{2} \sigma^2 \Delta \Phi(x, t, T) = 0, \quad \text{in } D, 0 \leq t < T, \\ \Phi(x, t, T) = 1, \quad \text{on } \Gamma_k, 0 \leq t < T, \\ \nabla \Phi(x, t, T) \cdot n = 0, \quad \text{on } \Gamma_r, 0 \leq t < T, \\ \Phi(x, T, T) = 0, \quad \text{in } D. \end{array} \right. \quad (40)$$

The solution of this equation computed with Finite Elements is shown in Figure 8b. The convergence results for DEM and CEM are shown in Figure 8a. The mean orders in this case are 0.37

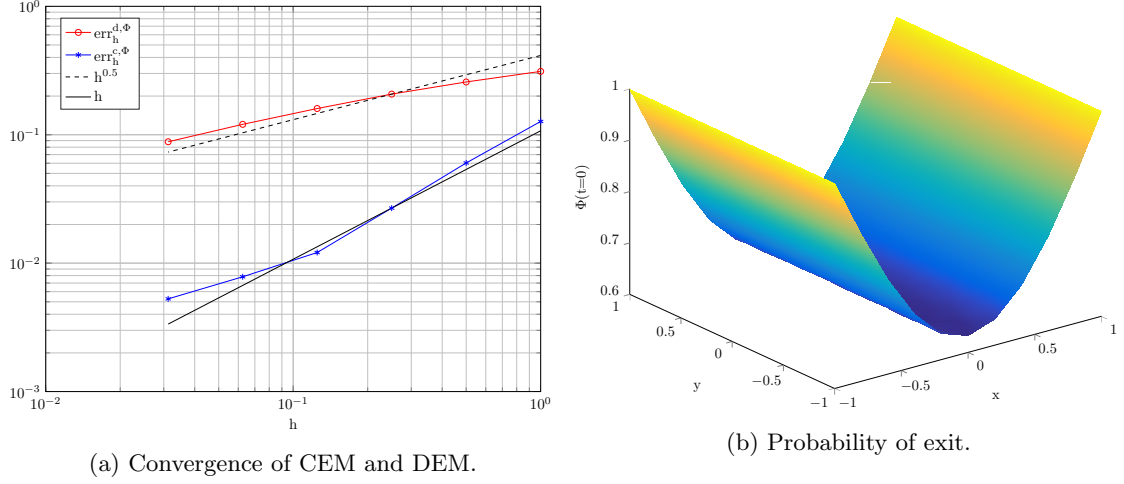


Figure 8: Summary of the results for  $\Phi$  in the two-dimensional case with mixed boundary conditions.

for DEM and 0.87 for CEM, which is less than the prediction given by theoretical results. This decrease in the convergence rate is remarkable for small values of  $h$ . This could mean that the error caused by the Finite Element approximation of the solution of (40) is not negligible with respect to the error of CEM.

#### 1.4.3 Numerical experiments - Adaptivity

We apply to a test case the adaptivity procedure explained in section 1.1.4. In particular, we fix  $f = 0, g = \sigma = 1, T = 3$  and  $X_0 = (0, 0)^T$  in the square domain  $D = [0, 1]^2$  with pure killing boundary conditions. We vary  $l$  in (17) in the range  $l = 0, \dots, 7$  and we run three methods

1. Adaptive method with  $h_0 = T$
2. DEM with  $h = h_{bound}$  for each timestep
3. CEM with  $h = h_{int}$  for each timestep

We expect the three methods to have an error of order  $O(h_{int})$  when estimating the mean exit time. In Figure 9a it is possible to remark that the error is of the same order for the three methods. Moreover, the methods have approximately the same error, *i.e.*, the constant multiplying  $h_{int}$  is the same for the three methods. In order to choose which method performs better from the point of view of computational cost, we compute the mean number of timesteps that they perform in order to estimate the exit time. From Figure 9b it is clear that CEM with  $h_{int}$  for every timestep performs better than the other two methods, with the adaptive procedure applied to DEM which implies lower computational time than DEM with constant timestep equal to  $h_{bound}$ . We can conclude that the approach based on Brownian bridge proposed in [2] has better performances when estimating the mean exit time from a domain.

## 2 The uncertain Darcy problem

The two methods for approximating the mean exit time have been investigated in a general frame. In the following we will consider (1) with  $f: \mathbb{R}^2 \rightarrow \mathbb{R}^2$  given by the solution of the uncertain Darcy problem.

### 2.1 Problem statement

Let us consider a domain  $D \subset \mathbb{R}^2$ . Let us define the Neumann boundaries of  $D$  as  $\Gamma_N$ , its inlet boundary as  $\Gamma_{in}$  and its outlet boundary as  $\Gamma_{out}$ . Then, we search the solution of the following

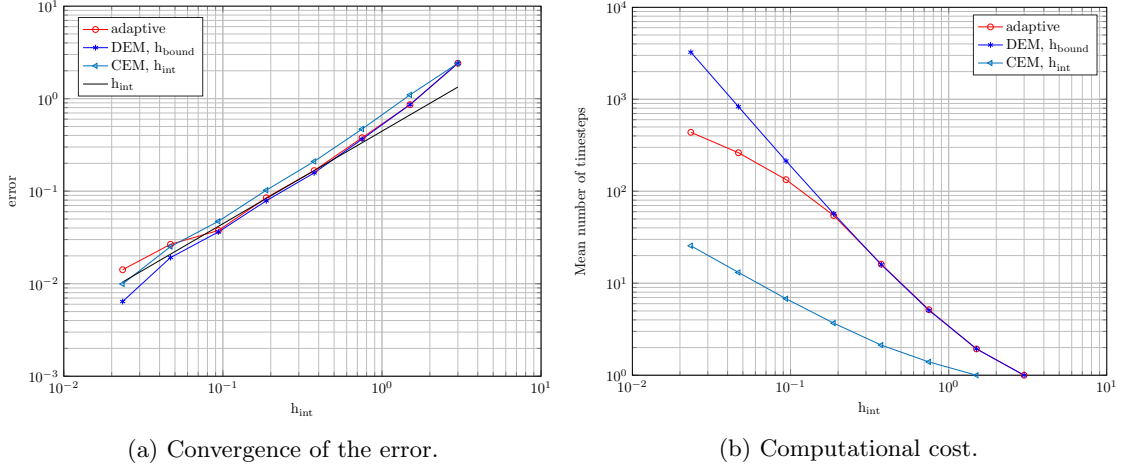


Figure 9: Estimation of  $\tau$  in the square domain with mixed boundary conditions. Comparison between DEM with fixed or adaptive step size.

problem

$$\begin{cases} u = -A\nabla p, & \text{in } D, \\ \nabla \cdot u = 0, & \text{in } D, \\ p = p_0, & \text{on } \Gamma_{\text{in}}, \\ p = 0, & \text{on } \Gamma_{\text{out}}, \\ \nabla p = 0, & \text{on } \Gamma_N, \end{cases} \quad (41)$$

where  $A$  is a random field. The solution  $u$  of this equation is used as transport field in equation (1), which can be therefore written as

$$\begin{cases} dX(t) = u(X)dt + \sigma dW(t), & 0 < t \leq T, \\ X(0) = X_0, & X_0 \in D, \end{cases} \quad (42)$$

where we set the boundary conditions to be reflecting on  $\Gamma_N$  and killing on both  $\Gamma_{\text{in}}, \Gamma_{\text{out}}$ .

## 2.2 Finite Elements solution of the Darcy problem

Let us consider the domain  $D = [-1, 1] \times [-1, 1]$ . The random field  $A$  in (41) is chosen to be lognormal, *i.e.*,

$$A = e^\gamma, \quad (43)$$

where  $\gamma$  is a normal random field defined by its covariance function  $\text{cov}_\gamma(x_1, x_2)$  for any couple of points  $x_1, x_2$  in the domain  $D$ . The covariance function is of the Matern family, thus having the following form

$$\text{cov}_\gamma(x_1, x_2) = \frac{\sigma_A^2}{\Gamma(\nu)2^{\nu-1}} \left( \sqrt{2\nu} \frac{|x_1 - x_2|}{L_c} \right)^\nu K_\nu \left( \sqrt{2\nu} \frac{|x_1 - x_2|}{L_c} \right), \quad \nu \geq 0.5, \quad (44)$$

where  $\sigma_A^2$  is the variance,  $L_c$  is the correlation length,  $\Gamma$  is the gamma function,  $K_\nu$  is the modified Bessel function of the second kind and  $\nu$  is a parameter. Let us remark that the covariance function does not depend on  $x_1, x_2$  but only on their euclidean distance  $|x_1 - x_2|$ . The regularity of the covariance function and of the realizations of  $A$  depend on  $\nu$ . In particular, for  $\nu$  equal to 0.5, the covariance is Lipschitz continuous and the field is  $\alpha$ -Hölder continuous for  $\alpha < 0.5$ . Results concerning further regularity properties of  $A$  can be found in [7]. The realizations of  $A$  are computed using a discrete Fourier transformation on the vertices of a grid of  $D$ , equispaced on both the  $x$  and  $y$  directions with the same spacing  $\Delta_A$ . Then, the numerical solution  $\hat{p}$  of (41) is obtained with linear Finite Elements on a regular mesh  $T_p$  with maximum element size  $\Delta_p$ . Since the vertices of

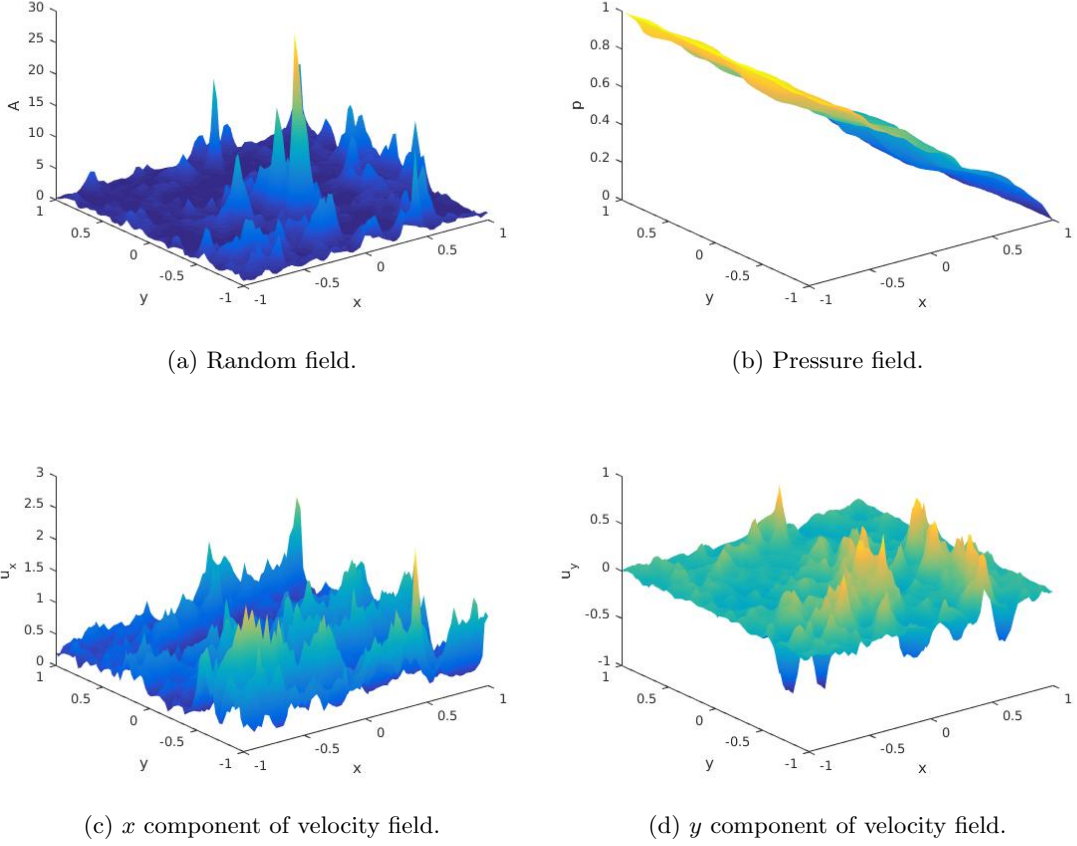


Figure 10: Approximate solution of the uncertain Darcy problem.

the grid on which we compute  $A$  do not coincide with the vertices of  $T_p$ , we interpolate  $A$  on  $T_p$  to obtain  $\hat{p}$ . Then, the velocity field  $\hat{u}$  is retrieved computing the gradient of  $\hat{p}$ . The results for a realization of  $A$  are shown in Figure 10, where the value of the inlet pressure  $p_0$  is equal to 1, and the parameters for the random field are  $\nu = 0.5, L_c = 0.05$ .

### 2.3 Solution of the SDE

Once the Finite Element approximation  $\hat{u}$  of the velocity field is available, it is possible to approximate by means of DEM and CEM the solution of (42). The values of the numerical solution  $X_h$  can take any value in  $D$ , therefore it is necessary that the velocity field is defined in any point in  $D$ . If an interpolation of  $\hat{u}$  is performed at each step, both DEM and CEM lose in computational efficiency. Hence, an interpolation of  $\hat{u}$  has to be performed before the numerical integration of the SDE. Therefore, we define a grid with spacing  $\Delta_u$ , interpolating the values of  $\hat{u}$  in the center of each square defined by the grid (Figure 11). Let us denote by  $Q$  the set of the interpolation points, whose elements are defined by

$$\{Q\}_{ij} = (-1 + (i - 0.5)\Delta_u, -1 + (j - 0.5)\Delta_u)^T, \quad i, j = 1, \dots, \frac{2}{\Delta_u} =: N_u. \quad (45)$$

We compute two matrices  $U_x, U_y$  of  $\mathbb{R}^{N_u \times N_u}$  containing the values of the two components of  $\hat{u}$  interpolated on the points of  $Q$ . Then, the velocity field is considered to be piecewise constant in each square of the grid defined by  $\Delta_u$ . Therefore, if we denote by  $\tilde{u}$  the transport field for the

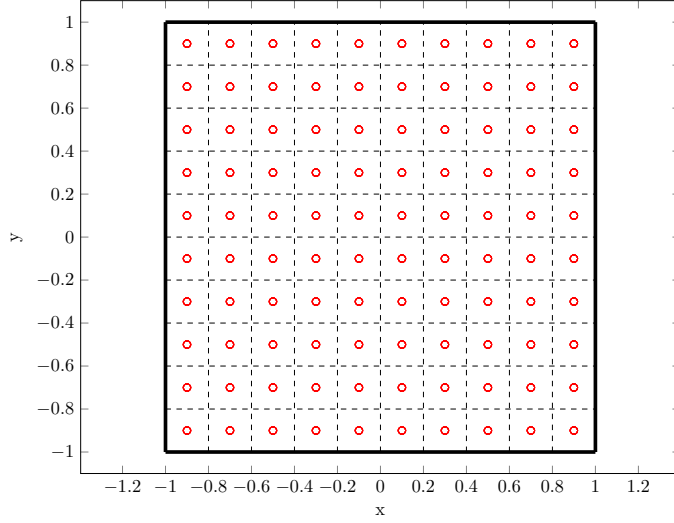


Figure 11: Grid used for interpolation of  $\hat{u}$ . Dots represent the interpolation points.

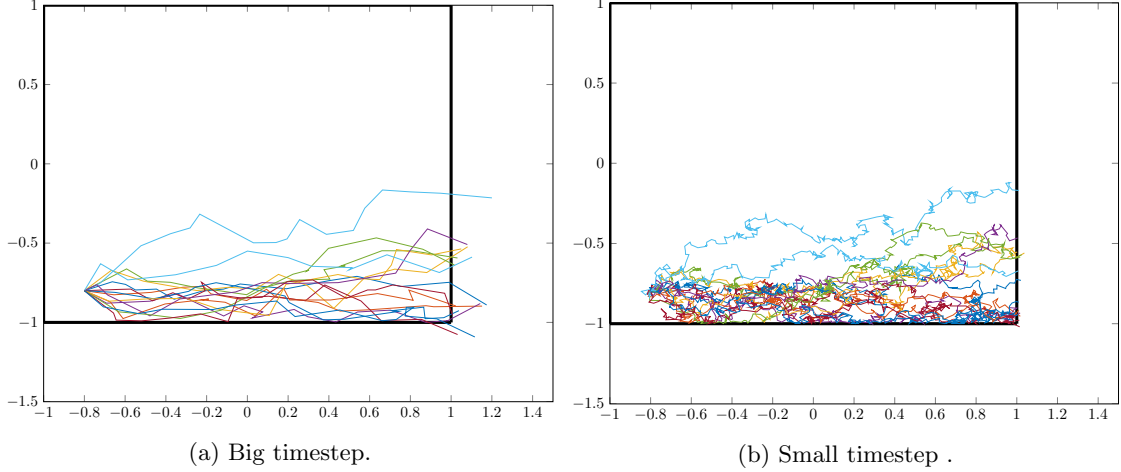


Figure 12: Trajectories of the numerical solution of (42) with DEM.

SDE, at the  $i$ -th step of the integration  $\tilde{u}$  is evaluated as follows

$$\tilde{u}(X_h(t_i)) = \begin{pmatrix} U_x(\lceil (X_{h,1}(t_i) + 1)/\Delta_u \rceil, \lceil (X_{h,2}(t_i) + 1)/\Delta_u \rceil) \\ U_y(\lceil (X_{h,1}(t_i) + 1)/\Delta_u \rceil, \lceil (X_{h,2}(t_i) + 1)/\Delta_u \rceil) \end{pmatrix}, \quad (46)$$

where  $X_{h,1}, X_{h,2}$  denote the first and second components of  $X_h$  and  $U_x(i, j)$  represents the element  $(i, j)$  of the matrix  $U_x$  (respectively  $U_y$ ). Then, given the step size  $h$ , one step of DEM will be defined as

$$X_h(t_{i+1}) = \tilde{u}(X_h(t_i))h + \sigma(W(t_{i+1}) - W(t_i)). \quad (47)$$

Given an input initial value  $X_0$  for (42), we approximate the solution using DEM and CEM using the strategy above. In Figure 12 we display 15 trajectories for  $X_0 = (-0.8, -0.8)^T$  with two different timesteps. The choice of the initial point is made in order to observe reflections on the lower boundary of the domain  $D$  on which we compute the solution, as well as the killing boundary at the right side.

## 2.4 Summary

Let us summarize the procedure we use for approximating the solution of (42).

1. Generate  $A$  on a grid with spacing  $\Delta_A$  with a Fourier transform method.
2. Approximate the solution of (41) with the Finite Element methods on a fine triangulation  $T_p$  with maximum element size  $\Delta_p$ .
3. Compute the velocity field from the FEM solution and interpolate it on a grid with spacing  $\Delta_u$  to obtain a piece-wise constant field  $\tilde{u}$ .
4. Solve (42) with DEM or CEM to evaluate the mean exit time  $\bar{\tau}$  using  $\tilde{u}$  as the transport field.

## 2.5 Theoretical investigation

### 2.5.1 Analysis of analytical convergence

The procedure explained above could give rise to theoretical issues concerning the existence and uniqueness of the solution of (42). In particular, when performing step 3. of the procedure as in the list above, the hypothesis that the transport field of the SDE is Lipschitz continuous is not valid anymore, and therefore we have no guarantee that (42) is well-posed. On the other side, we can hope that if  $\tilde{u}$  tends uniformly to the exact solution  $u$  of (41), provided that the latter is a smooth function, the solution of the SDE that has  $\tilde{u}$  as a transport field tends to the solution given by  $u$ . In the following we present a result that supports our numerical procedure. Let us consider  $\sigma \in \mathbb{R}, f: \mathbb{R}^d \rightarrow \mathbb{R}^d, W_1(t)$  a standard  $d$ -dimensional Wiener process and the following SDE

$$\begin{cases} dX(t) = f(X(t))dt + \sigma IdW_1(t), & 0 < t \leq T, \\ X(0) = X_0, \end{cases} \quad (48)$$

where  $I$  is the identity matrix in  $\mathbb{R}^{d \times d}$ . Moreover, let us consider a perturbation of the transport field  $f^\varepsilon: \mathbb{R}^d \rightarrow \mathbb{R}^d$  and a standard  $d$ -dimensional Wiener process  $W_2(t)$  not necessarily independent of  $W_1(t)$ . Then, we consider the perturbed SDE

$$\begin{cases} dX^\varepsilon(t) = f^\varepsilon(X^\varepsilon(t))dt + \sigma IdW_2(t), & 0 < t \leq T, \\ X^\varepsilon(0) = X_0. \end{cases} \quad (49)$$

We can state the following preliminary result

**Lemma 2.1.** *With the notation above, let us consider  $d = 1, W_1 = W_2 = W$  almost everywhere. Then, given a real constant  $K$  and with the following assumptions*

1.  $|f(x) - f(y)| \leq K|x - y|, \forall x, y \in \mathbb{R}$
2.  $\sup_{x \in \mathbb{R}} |f(x) - f^\varepsilon(x)| \xrightarrow{\varepsilon \rightarrow 0} 0,$

*the solution  $X^\varepsilon(t)$  of (49) converges strongly to the solution  $X(t)$  of (48) in  $L^2(\Omega)$ , i.e.*

$$\mathbb{E} \sup_{0 \leq t \leq T} |X^\varepsilon(t) - X(t)|^2 \xrightarrow{\varepsilon \rightarrow 0} 0.$$

*Proof.* For almost all  $\omega$

$$\begin{aligned} |X^\varepsilon(t) - X(t)|^2 &= \left| \int_0^t (f^\varepsilon(X^\varepsilon(s)) - f(X(s)))ds \right|^2 \\ &\leq T \int_0^t |f^\varepsilon(X^\varepsilon(s)) - f(X(s))|^2 ds \quad \{\text{Cauchy-Schwarz inequality}\} \\ &\leq 2T \int_0^t |f^\varepsilon(X^\varepsilon(s)) - f(X^\varepsilon(s))|^2 ds \\ &\quad + 2T \int_0^t |f(X^\varepsilon(s)) - f(X(s))|^2 ds \quad \{\text{Triangular inequality, Young inequality}\} \\ &\leq 2T^2 \sup_{x \in \mathbb{R}} |f(x) - f^\varepsilon(x)|^2 \\ &\quad + 2T^2 K^2 \int_0^t |X^\varepsilon(s) - X(s)|^2 ds. \quad \{\text{Assumption 2. and 1.}\} \end{aligned}$$



We then apply Gronwall's inequality, which gives

$$|X^\varepsilon(t) - X(t)|^2 \leq 2T^2 \sup_{x \in \mathbb{R}} |f(x) - f^\varepsilon(x)|^2 e^{2K^2 T^2}, \quad a.e. \quad (50)$$

Since the right hand side of the inequality is constant, we can then take the supremum over time and the expectation at both sides, *i.e.*,

$$\mathbb{E} \sup_{0 \leq t \leq T} |X^\varepsilon(t) - X(t)|^2 \leq 2T^2 \sup_{x \in \mathbb{R}} |f(x) - f^\varepsilon(x)|^2 e^{2K^2 T^2}.$$

Then, assumption 2. gives the result.  $\square$

We now consider the case of two independent Wiener processes.

**Lemma 2.2.** *With the notation above and the assumptions 1. and 2. of Lemma 2.1, let us consider  $W_1$  independent of  $W_2$  and  $d = 1$ . Then*

$$\mathbb{E} \sup_{0 \leq t \leq T} |X^\varepsilon(t) - X(t)|^2 \leq 4T(T \sup_{x \in \mathbb{R}} |f(x) - f^\varepsilon(x)|^2 + 4\sigma^2) e^{2K^2 T^2}.$$

*Proof.* Let us compute the difference between  $X^\varepsilon(t)$  and  $X(t)$ . Applying Young's inequality, we get

$$\begin{aligned} \mathbb{E} \sup_{0 \leq t \leq T} |X^\varepsilon(t) - X(t)|^2 &\leq 2\mathbb{E} \sup_{0 \leq t \leq T} \left| \int_0^t (f^\varepsilon(X^\varepsilon(s)) - f(X(s))) ds \right|^2 \\ &\quad + 2\sigma^2 \mathbb{E} \sup_{0 \leq t \leq T} \left| \int_0^t dW_1(s) - \int_0^t dW_2(s) \right|^2. \end{aligned}$$

For the first term, we can apply Lemma 2.1. Let us define  $Z(t) := W_1(t) - W_2(t)$ .  $Z(t)$  is a standard Wiener process with variance  $2t$ , thus it is a martingale. Hence, we can apply Doob's martingale inequality (*e.g.*, [11]) to the second term, obtaining

$$\mathbb{E} \sup_{0 \leq t \leq T} \left| \int_0^t dW_1(s) - \int_0^t dW_2(s) \right|^2 = \mathbb{E} \sup_{0 \leq t \leq T} |Z(t)|^2 \leq 4\mathbb{E}|Z(T)|^2 = 8T.$$

Therefore, we get the result

$$\mathbb{E} \sup_{0 \leq t \leq T} |X^\varepsilon(t) - X(t)|^2 \leq (4T^2 \sup_{x \in \mathbb{R}} |f(x) - f^\varepsilon(x)|^2 + 16T\sigma^2) e^{2K^2 T^2}.$$

$\square$

With those preliminary results, we can now consider the general case of a  $d$ -dimensional SDE.

**Proposition 2.1.** *With the notation above and if  $f: \mathbb{R}^d \rightarrow \mathbb{R}^d$ ,  $f^\varepsilon: \mathbb{R}^d \rightarrow \mathbb{R}^d$ , satisfy*

$$1. \|f(x) - f(y)\| \leq K\|x - y\|_2, \quad \forall x, y \in \mathbb{R}^d,$$

$$2. \sup_{x \in \mathbb{R}} |f_i(x) - f_i^\varepsilon(x)| \xrightarrow{\varepsilon \rightarrow 0} 0, \quad i = 1, \dots, d,$$

*then it is true for  $X(t)$ ,  $X^\varepsilon(t)$  the solutions of (48) and (49) that*

$$\mathbb{E} \|X^\varepsilon(t) - X(t)\|_2^2 \leq \left( 4T^2 \sum_{i=1}^d \sup_{x \in \mathbb{R}} |f_i(x) - f_i^\varepsilon(x)|^2 + 16Td\sigma^2 \right) e^{2dK^2 T^2}. \quad (51)$$

*Proof.* The proof follows from Lemma 2.2. Let us denote by  $X_i(t)$ ,  $X_i^\varepsilon(t)$  the  $i$ -th component of the solution,  $i = 1, \dots, d$ . Then

$$\begin{aligned} \mathbb{E} \|X^\varepsilon(t) - X(t)\|_2^2 &= \mathbb{E} \sum_{i=1}^d |X_i^\varepsilon(t) - X_i(t)|^2 \\ &= \sum_{i=1}^d \mathbb{E} |X_i^\varepsilon(t) - X_i(t)|^2 \end{aligned}$$

Then, applying Lemma 2.2 to each component of the solution, one obtains (51).  $\square$

**Remark 2.1. (Convergence considerations.)** The result of Proposition 2.1 shows that in case one uses two different Wiener processes  $W_1, W_2$  for the standard and the perturbed SDEs, the strong convergence is not granted. In fact, while the first term in estimation (51) disappears due to the uniform convergence of the perturbed transport field towards the non-perturbed one, the error due to the different Wiener processes is not disappearing with respect to  $\varepsilon$ . However, in underground flow models the variance  $\sigma$  of the Brownian diffusion is often small with respect to the transport field. Therefore, one could consider the solution  $X^\varepsilon(t)$  of (49) to be practically converging to the solution  $X(t)$  of (48).

**Remark 2.2. (Interpolation results.)** Let us consider a domain  $D \in \mathbb{R}^d$  where  $f$  and  $f^\varepsilon$  are defined and  $f^\varepsilon$  to be a polynomial interpolation of  $f$  on  $D$ . Then, the interpolation error of can be estimated if  $f$  is regular enough. In particular, the following results are valid [9, Chapter 8] for a grid of size  $\varepsilon$

1.  $f$  Lipschitz continuous of constant  $K$ ,  $f^\varepsilon$  piecewise constant interpolation,  $C_0$  a real constant

$$\sup_{x \in D} \|f(x) - f^\varepsilon(x)\| \leq C_0 K \varepsilon.$$

2.  $f$  of class  $\mathcal{C}^1$ ,  $f^\varepsilon$  piecewise constant interpolation,  $C_1$  a real constant

$$\sup_{x \in D} \|f(x) - f^\varepsilon(x)\| \leq C_1 \varepsilon \sup_{x \in D} \|f'(x)\|.$$

3.  $f$  of class  $\mathcal{C}^2$ ,  $f^\varepsilon$  piecewise linear interpolation,  $C_2$  a real constant

$$\sup_{x \in D} \|f(x) - f^\varepsilon(x)\| \leq C_2 \varepsilon^2 \sup_{x \in D} \|f''(x)\|.$$

In all these cases, it is true that  $f^\varepsilon$  converges uniformly to  $f$  with respect to  $\varepsilon$ , therefore  $f^\varepsilon$  satisfies the assumptions of Proposition 2.1.

### 2.5.2 Analysis of numerical convergence

We now consider the Euler-Maruyama method applied to the perturbed equation (49). We would like to find a balance between the error due to the numerical integration of the SDE with step size  $h$  and the approximation of the transport field  $f$  with  $f^\varepsilon$ . In this way, one can choose wisely the two parameters  $\varepsilon, h$  in order to avoid extra computational time.

Let us consider  $X(t), X^\varepsilon(t)$  the solution of (48) and (49) respectively, and let us denote with  $X_n, X_n^\varepsilon$  the numerical solution obtained with Euler-Maruyama method applied to the two equations at time  $t_n = hn, t_N = T$ . It is known that if  $f$  is Lipschitz continuous with constant  $K$ , and if  $\sigma$  is a constant, then the strong error for  $X_n$  approximating  $X(t)$  is given by

$$\sup_{n=1, \dots, N} \mathbb{E}|X(nh) - X_n| \leq Ch, \quad (52)$$

for a constant  $C$  independent of  $h$ . It is possible to obtain a similar estimate for  $X_n^\varepsilon$  estimating  $X(t)$ .

**Proposition 2.2.** *Let us consider (48), (49) with  $d = 1$  and  $W_1 = W_2 = W$  almost everywhere. Given  $h > 0$  such that  $hN = T$  for  $N \in \mathbb{N}^*$ , let us consider  $X_n^\varepsilon$  the numerical solution given by the Euler-Maruyama method applied to (49), i.e.,*

$$\begin{cases} X_{n+1}^\varepsilon = X_n^\varepsilon + f^\varepsilon(X_n^\varepsilon)h + \sigma(W(t_{n+1}) - W(t_n)), & n = 0, \dots, N-1, \\ X_0^\varepsilon = X_0. \end{cases}$$

*Then, if  $f, f^\varepsilon$  satisfy the assumptions 1. and 2. of Lemma 2.1*

$$\sup_{n=1, \dots, N} \mathbb{E}|X(nh) - X_n^\varepsilon| \leq Ch + \sup_{x \in \mathbb{R}} |f^\varepsilon(x) - f(x)| \frac{e^{KT} - 1}{K}, \quad (53)$$

*with  $C$  a real constant independent of  $h$  and depending only on the final time  $T$  and the Lipschitz constant  $K$  of  $f$ .*

*Proof.* We consider  $X_n$  the numerical approximation of  $X(t)$  obtained using Euler-Maruyama with the same initial condition  $X_0$ . If we add and subtract  $X_n$  and apply the triangular inequality we obtain

$$\mathbb{E}|X_n^\varepsilon - X(nh)| \leq \mathbb{E}|X_n^\varepsilon - X_n| + \mathbb{E}|X_n - X(nh)|.$$

Since  $f$  is regular enough and  $\sigma$  is a constant, for the second term it is known that

$$\sup_{n=1,\dots,N} \mathbb{E}|X_n - X(nh)| \leq Ch. \quad (54)$$

We can then make a recursive analysis of the first term. For almost all  $\omega$

$$\begin{aligned} |X_n^\varepsilon - X_n| &\leq |X_{n-1}^\varepsilon - X_{n-1}| + h|f^\varepsilon(X_{n-1}^\varepsilon) - f(X_{n-1})| \\ &\leq |X_{n-1}^\varepsilon - X_{n-1}| + h|f^\varepsilon(X_{n-1}^\varepsilon) - f(X_{n-1}^\varepsilon)| + h|f(X_{n-1}^\varepsilon) - f(X_{n-1})| \\ &\leq h \sup_{x \in \mathbb{R}} |f^\varepsilon(x) - f(x)| + (1+hK)|X_{n-1}^\varepsilon - X_{n-1}| \\ &\leq h \sup_{x \in \mathbb{R}} |f^\varepsilon(x) - f(x)| \\ &\quad + (1+hK)(h \sup_{x \in \mathbb{R}} |f^\varepsilon(x) - f(x)| + (1+hK)|X_{n-2}^\varepsilon - X_{n-2}|) \\ &\leq (\dots) h \sup_{x \in \mathbb{R}} |f^\varepsilon(x) - f(x)| \sum_{i=0}^{n-1} (1+hK)^i + (1+hK)^n |X_0^\varepsilon - X_0| \end{aligned}$$

Since  $X_0^\varepsilon = X_0$  and using the geometric sum

$$\begin{aligned} |X_n^\varepsilon - X_n| &\leq h \sup_{x \in \mathbb{R}} |f^\varepsilon(x) - f(x)| \frac{(1+hK)^n - 1}{hK} \\ &\leq \sup_{x \in \mathbb{R}} |f^\varepsilon(x) - f(x)| \frac{(1+hK)^N - 1}{K} \\ &\leq \sup_{x \in \mathbb{R}} |f^\varepsilon(x) - f(x)| \frac{e^{KT} - 1}{K}, \end{aligned}$$

where the last inequality is valid since  $N = T/h$  and  $K, T, h$  are all positive real numbers. Since the bound we found is independent of  $\omega$  and  $n$ , we can take the expectation and the supremum, obtaining

$$\sup_{n=0,\dots,N} \mathbb{E}|X_n^\varepsilon - X_n| \leq \sup_{x \in \mathbb{R}} |f^\varepsilon(x) - f(x)| \frac{e^{KT} - 1}{K}. \quad (55)$$

This result combined with (54) concludes the proof.  $\square$

**Remark 2.3.** If  $f^\varepsilon$  is the interpolation of  $f$  on a regular grid of size  $\varepsilon$ , the result of Proposition 2.2 allows to balance the interpolation error and the error due to numerical integration. In fact, we reported above some results on interpolation of  $f$  with piecewise polynomials  $f^\varepsilon$ , which we can plug in (53) as follows

1. if  $f$  is Lipschitz continuous of constant  $K$  or of class  $\mathcal{C}^1$  and  $f^\varepsilon$  is piecewise constant, then

$$\sup_{n=0,\dots,N} \mathbb{E}|X_n^\varepsilon - X_n| = O(h) + O(\varepsilon).$$

2. if  $f$  is of class  $\mathcal{C}^2$ , and  $f^\varepsilon$  is piecewise linear, then

$$\sup_{n=0,\dots,N} \mathbb{E}|X_n^\varepsilon - X_n| = O(h) + O(\varepsilon^2).$$

Therefore, in the first case the step size  $h$  should be of the same order of magnitude as  $\varepsilon$ , while in the second case it should scale as  $\varepsilon^2$ .

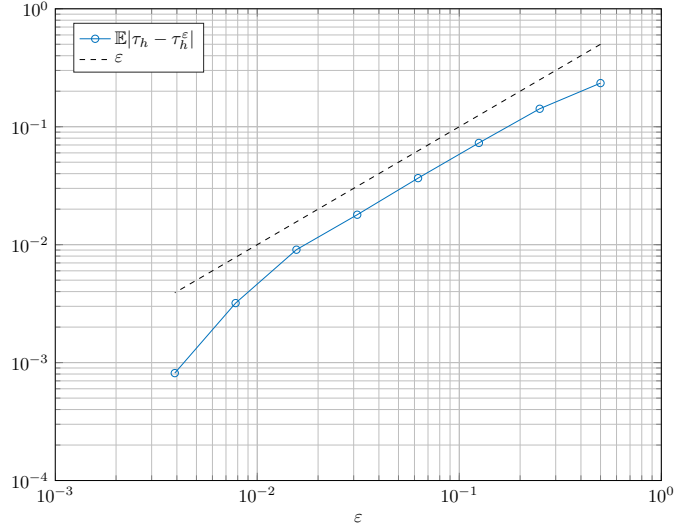


Figure 13: Convergence with respect to the interpolation characteristic size  $\varepsilon$  for a test case.

### 2.5.3 Numerical confirmation of the theory

Let us consider a numerical experiment on a test case in order to clarify the theory presented above. Let us consider the domain  $D = [-1, 1]^2$  endowed with mixed reflecting and killing boundary conditions and the deterministic transport field given by

$$f(x, y) = (|x|, y)^T.$$

In the domain, the transport field is Lipschitz continuous with constant  $K = 1$ . Furthermore, let us consider  $\sigma = 1$  and the time final time to be  $T = 10$ . The perturbed transport field  $f^\varepsilon$  is given by a piecewise constant interpolation of  $f$  on a structured grid of equal spacing  $\varepsilon$  in the two directions. We estimate the mean exit time  $\bar{\tau}$  from the domain by means of a Montecarlo simulation exploiting CEM performed both on the perturbed and the non-perturbed equations. We fix  $h = T/2^{10}$  and we consider  $M = 10000$  realizations of the numerical solution in order to make both the statistical error and the error relative to the numerical integration negligible. We perform the simulation for eight different values  $\varepsilon_i$  given by  $\varepsilon_i = 2^{-i}, i = 1, \dots, 8$ . Numerical results (Figure 13) show a convergence of first order, thus confirming the theoretical bound given by (55). Let us remark that the order of convergence with respect to  $\varepsilon$  is preserved even though the theoretical results we presented concern the value of the solution while in this numerical experiment we consider the mean exit time.

## 2.6 Numerical Experiment - Grid refinements

We aim to verify numerically the convergence of the solution as explained in the previous section. Hence, we consider four values for  $\Delta_u$ , which range between a coarse and a fine grid of the domain  $D$ , and we compute the mean exit time using CEM. We consider the parameter values  $\nu = 0.5, L_C = 0.05, \sigma_A = 1, \Delta_A = 0.0039$  for the generation of the random field  $A$ , the final time  $T = 10$ , the constant  $\sigma = 0.3$ , the step size to vary in the range  $h_i = 10/N_i, N_i = 2^i, i = 0, 1, \dots, 8$ . The values we choose for  $\Delta_u$  are 1, 0.25, 0.0625, 0.0039. We perform a Montecarlo simulation over  $M = 50000$  trajectories in order to kill the statistical error. Results (Figure 14) show that for the two smallest values of  $\Delta_u$ , the solution is very similar for  $h$  sufficiently small. On the other hand, if  $\Delta_u$  is chosen to be too large, the mean exit time  $\bar{\tau}$  is badly estimated.

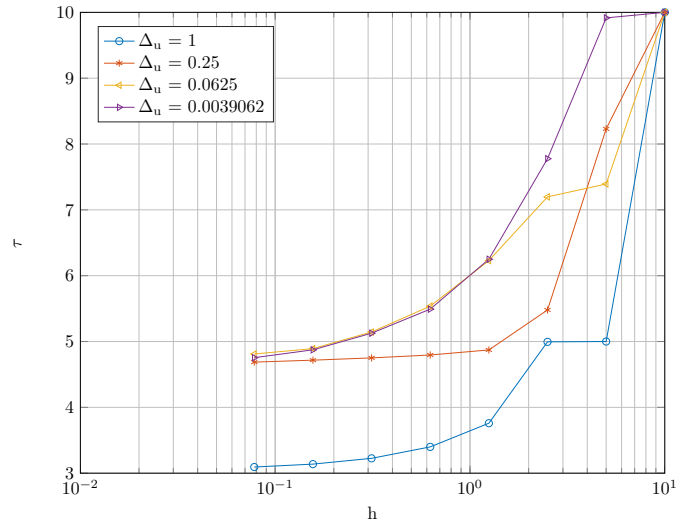


Figure 14: Results for four different values of  $\Delta_u$  and convergence with respect to  $h$  of the mean exit time.

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