Report

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MULTILEVEL MONTE CARLO FOR RANDOM DEGENERATE SCALAR
CONVECTION DIFFUSION EQUATION

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Abstract. We consider the numerical solution of scalar, nonlinear degenerate convection-
diffusion problems with random diffusion coefficients and with random flux functions. Building
on recent results on the existence, uniqueness and continuous dependence of weak solutions on
data in the deterministic case, we develop a definition of random entropy solution. We establish
existence, uniqueness, measurability and integrability results for these random entropy solu-
tions, generalizing [28, 29] to possibly degenerate hyperbolic-parabolic problems with random
data. We next address the numerical approximation of random entropy solutions, specifically
the approximation of the deterministic first and second order statistics. To this end, we consider
explicit and implicit time discretization and Finite Difference methods in space, and single as
well as Multi-Level Monte-Carlo methods to sample the statistics. We establish convergence rate
estimates with respect to the discretization parameters, as well as with respect to the overall
work, indicating substantial gains in efficiency are afforded under realistic regularity assump-
tions by the use of the Multi-Level Monte-Carlo method. Numerical experiments are presented
which confirm the theoretical convergence estimates.

1. Introduction

Many problems in physics and engineering are modeled by nonlinear, possibly strongly degen-
erate, convection-diffusion equation. The Cauchy problem for such equations takes the form

\begin{equation}
\begin{cases}
  u_t + \text{div} f(u) = \Delta A(u), & (x, t) \in \Pi_T, \\
  u(0, x) = u_0(x), & x \in \mathbb{R}^d,
\end{cases}
\end{equation}

where \( \Pi_T = \mathbb{R}^d \times (0, T) \) with \( T > 0 \) fixed, \( u : \Pi_T \rightarrow \mathbb{R} \) is the unknown function, \( f = (f_1, \ldots, f_d) \) the flux function, and \( A \) the nonlinear diffusion. Regarding this, the basic assumption is that
\( a(u) := A'(u) \geq 0 \) for all \( u \). When (1.1) is nondegenerate, i.e., \( a(u) > 0 \), it is well known that (1.1)
admits a unique classical solution [34]. This contrasts with the degenerate case where \( a(u) \) may
vanish for some values of \( u \). A simple example of a degenerate equation is the porous medium
equation

\[ u_t = \Delta (u^m), \quad m > 1, \]

which degenerates at \( u = 0 \). This equation has served as a simple model to describe processes
involving fluid flow, heat transfer or diffusion. Examples of applications are in the description of
the flow of an isentropic gas through a porous medium, modelled by Leibenzon [27] and Muskat
in plasmas, Zel’dovich and collaborators around 1950, [38]. In general, a manifestation of the
degeneracy in (1.1) is the finite speed of propagation of disturbances. If \( a(0) = 0 \), and if at some
fixed time the solution \( u \) has compact support, then it will continue to have compact support for
all later times.

By the term “strongly degenerate” we mean that there is an open interval such that \( a(u) = 0 \)
if \( u \) is in this interval. Hence, the class of equations under consideration is very large and contains
the heat equation, the porous medium equation and scalar conservation laws. Independently of
the smoothness of the initial data, due to the degeneracy of the diffusion, singularities may form
in the solution \( u \). Therefore we consider weak solutions which are defined as follows.

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Definition 1.1. Set $\Pi_T = \mathbb{R}^d \times (0, T)$. A function
$$u(t, x) \in C \left( \left[ 0, T \right]; L^1(\mathbb{R}^d) \right) \cap L^\infty(\Pi_T)$$
is a weak solution of the initial value problem (1.1) if it satisfies:

D.1 grad $A(u) \in L^\infty(\Pi_T)$.

D.2 For all test functions $\varphi \in \mathcal{D}(\mathbb{R}^d \times [0, T])$

$$\iint_{\Pi_T} (u \varphi_t + f(u) \cdot \text{grad} \varphi + A(u) \Delta \varphi) \, dx \, dt + \int_{\mathbb{R}^d} u_0(x) \varphi(x, 0) \, dx = 0.$$ (1.2)

In view of the existence theory, the condition D.1 is natural, and thanks to this we can replace (1.2) by

$$\iint_{\Pi_T} u \varphi_t + (f(u) - \text{grad} A(u)) \cdot \text{grad} \varphi \, dx \, dt + \int_{\mathbb{R}^d} u_0(x) \varphi(x, 0) \, dx = 0.$$ (1.2')

If $A$ is constant on a whole interval, then weak solutions are not uniquely determined by their initial data, and one must impose an additional entropy condition to single out the physically relevant solution. A weak solution satisfies the entropy condition if

$$q(u)_t + \text{div} q(u) - \Delta r(u) \leq 0 \text{ in } \mathcal{D}'(\Pi_T),$$ (1.3)

for all convex, twice differentiable functions $q : \mathbb{R} \to \mathbb{R}$, where $q$ and $r$ are defined by

$$q(u) = q(u)'(u), \quad \text{and} \quad r(u) = r(u)A'(u).$$

Via a standard limiting argument this implies that (1.3) holds for the Kružkov entropies $q(u) = |u - c|$ for all constants $c$. We call a weak solution satisfying the entropy condition an entropy solution.

For scalar conservation laws, the entropy framework (usually called entropy conditions) was introduced by Kružkov [25] and Vol’pert [36], while for degenerate parabolic equations entropy solution were first considered by Vol’pert and Hudajev [37]. Uniqueness of entropy solutions to (1.1) was first proved by Carrillo [4].

Over the years, there has been a growing interest in numerical approximation of entropy solutions to degenerate parabolic equations. Finite difference and finite volume schemes for degenerate equations were analysed by Evje and Karlsen [12, 11, 10, 13] (using upwind difference schemes), Holden et al. [19, 20] (using operator splitting methods), Kurganov and Tadmor [26] (central difference schemes), Bouchut et al. [2] (kinetic BGK schemes), Afif and Amaziane [1] and Ohlberger, Gallouët et al. [33, 15, 16] (finite volume methods), Cockburn and Shu [7] (discontinuous Galerkin methods) and Karlsen and Risebro [24, 23] (monotone difference schemes). Many of the above papers show that the approximate solutions converge to the unique entropy solution as the discretization parameter vanishes. Rigorous estimates of the convergence rate of finite volume schemes for degenerate parabolic equations were proved in [21] (1-d) and [22] (multi-d).

This classical paradigm for designing efficient numerical schemes assumes that data for (1.1), i.e., initial data $u_0$, convective flux and diffusive flux are known exactly.

In many situations of practical interest, however, these data are not known exactly due to inherent uncertainty in modelling and measurements of physical parameters such as, for example, the specific heats in the equation of state for compressible gases, or the relative permeabilities in models of multi-phase flow in porous media. Often, the initial data are known only up to certain statistical quantities of interest like the mean, variance, higher moments, and in some cases, the law of the stochastic initial data. In such cases, a mathematical formulation of (1.1) is required which allows for random data. The problem of random initial data was considered in [29], and the existence and uniqueness of a random entropy solution was shown, and a convergence analysis for MLMC FV discretizations was given. The MLMC discretization of balance laws with random source terms was investigated in [31].

In [29] a mathematical framework was developed for scalar conservation laws with random initial data. This framework was extended to include random flux functions in [28].

The aim of this paper is to extend this mathematical framework to include degenerate convection diffusion equations with random convective and diffusive flux functions with possibly correlated...
We set, for simple random variables, i.e., if it has the explicit form (with the norm $\|\cdot\|_E$ denoting the set of all elementary events, and $\mathcal{F}$ a $\sigma$-algebra of all possible events in our probability model. If $(E, \mathcal{G})$ denotes a second measurable space, then an $E$-valued random variable (or random variable taking values in $E$) is any mapping $X: \Omega \rightarrow E$ such that the set $\{\omega \in \Omega : X(\omega) \in A\} = \{X \in A\} \in \mathcal{F}$ for any $A \in \mathcal{G}$, i.e., such that $X$ is a $\mathcal{G}$-measurable mapping from $\Omega$ into $E$.

Assume now that $E$ is a metric space; with the Borel $\sigma$-field $\mathcal{B}(E)$, $(E, \mathcal{B}(E))$ is a measurable space and we shall always assume that $E$-valued random variables $X: \Omega \rightarrow E$ will be $(\mathcal{F}, \mathcal{B}(E))$ measurable. If $E$ is a separable Banach space with norm $\|\cdot\|_E$ and (topological) dual $E^*$, then $\mathcal{B}(E)$ is the smallest $\sigma$-field of subsets of $E$ containing all sets
\[ \{x \in E : \varphi(x) \leq \alpha\}, \varphi \in E^*, \alpha \in \mathbb{R}. \]

Hence if $E$ is a separable Banach space, $X: \Omega \rightarrow E$ is an $E$-valued random variable iff for every $\varphi \in E^*$, $\omega \mapsto \varphi(X(\omega)) \in \mathbb{R}$ is an $\mathbb{R}$-valued random variable. Moreover, by [8, Lemma 1.5, p.19] the norm $\Omega \ni \omega \mapsto \|X(\omega)\|_E \in \mathbb{R}$ is a measurable mapping.

The random variable $X: \Omega \rightarrow E$ is called Bochner integrable if, for any probability measure $\mathbb{P}$ on the measurable space $(\Omega, \mathcal{F})$,
\[ \int_{\Omega} \|X(\omega)\|_E \mathbb{P}(d\omega) < \infty. \]

A probability measure $\mathbb{P}$ on $(\Omega, \mathcal{F})$ is any $\sigma$-additive set function from $\Omega$ into $[0,1]$ such that $\mathbb{P}(\Omega) = 1$, and the measure space $(\Omega, \mathcal{F}, \mathbb{P})$ is called probability space. We shall assume that $(\Omega, \mathcal{F}, \mathbb{P})$ is complete.

If $X: (\Omega, \mathcal{F}) \rightarrow (E, \mathcal{E})$ is a random variable, $\mathcal{L}(X)$ denotes the law of $X$ under $\mathbb{P}$, i.e.,
\[ \mathcal{L}(X)(A) = \mathbb{P}\{\omega \in \Omega : X(\omega) \in A\} \quad \forall A \in \mathcal{E}. \]

The image measure $\mu_X = \mathcal{L}(X)$ on $(E, \mathcal{E})$ is called law or distribution of $X$.

A random variable taking values in $E$ is called simple if it can take only finitely many values, i.e., if it has the explicit form (with $\chi_A$ the indicator function of $A \in \mathcal{F}$)
\[ X = \sum_{i=1}^{N} x_i \chi_{A_i}, \quad A_i \in \mathcal{F}, \ x_i \in E, \ N < \infty. \]

We set, for simple random variables $X$ taking values in $E$ and for any $B \in \mathcal{F}$,
\[ \int_B X(\omega) \mathbb{P}(d\omega) = \int_B X d\mathbb{P} := \sum_{i=1}^{N} x_i \mathbb{P}(A_i \cap B). \]
By density, for such \( X(\cdot) \), and all \( B \in \mathcal{F} \),
\[
\left\| \int_B X(\omega) \mathbb{P}(d\omega) \right\|_E \leq \int_B \|X(\omega)\|_E \mathbb{P}(d\omega).
\]
For any random variable \( X : \Omega \to E \) which is Bochner integrable, there exists a sequence \( \{X_m\}_{m \in \mathbb{N}} \) of simple random variables such that, for all \( \omega \in \Omega \), \( \|X(\omega) - X_m(\omega)\|_E \to 0 \) as \( m \to \infty \). Therefore, (2.1) and (2.1) extend in the usual fashion by continuity to any \( E \)-valued random variable. We denote the integral
\[
\int_\Omega X(\omega) \mathbb{P}(d\omega) = \lim_{m \to \infty} \int_\Omega X_m(\omega) \mathbb{P}(d\omega) \in E
\]
by \( \mathbb{E}[X] \) (“expectation” of \( X \)). We shall require for \( 1 \leq p \leq \infty \) Bochner spaces of \( p \)-summable random variables \( X \) taking values in the Banach space \( E \). By \( L^1(\Omega, \mathcal{F}, \mathbb{P}; E) \) we denote the set of all (equivalence classes of) integrable, \( E \)-valued random variables \( X \), equipped with the norm
\[
\|X\|_{L^1(\Omega, E)} = \int_\Omega \|X(\omega)\|_E \mathbb{P}(d\omega) = \mathbb{E}(\|X\|_E).
\]
More generally, for \( 1 \leq p < \infty \), we define \( L^p(\Omega, \mathcal{F}, \mathbb{P}; E) \) as the set of \( p \)-summable random variables taking values in \( E \) and equip it with norm
\[
\|X\|_{L^p(\Omega, E)} := (\mathbb{E}(\|X\|_E^p))^\frac{1}{p}, \ 1 \leq p < \infty.
\]
For \( p = \infty \), we denote by \( L^\infty(\Omega, \mathcal{F}, \mathbb{P}; E) \) the set of all \( E \)-valued random variables which are essentially bounded. This set is a Banach space equipped with the norm
\[
\|X\|_{L^\infty(\Omega, E)} := \text{ess sup}_{\omega \in \Omega} \|X(\omega)\|_E.
\]
If \( T < \infty \) and \( \Omega = [0, T], \mathcal{F} = \mathcal{B}([0, T]) \), we write \( L^p(0, T; E) \). Note that for any separable Banach space \( E \), and for any \( r \geq p \geq 1 \),
\[
L^r(0, T; E), \ C^0(0, T; E) \in \mathcal{B}(L^p(0, T; E)).
\]
In the following, we will be interested in random variables \( X : \Omega \to E_j, j = 1, 2 \), mapping from some probability space \( (\Omega, \mathcal{F}, \mathbb{P}) \) into subsets of the Banach spaces \( E_j, j = 1, 2 \), equipped with the Borel \( \sigma \)-algebra \( \mathcal{B}(E_j) \), where \( E_1 = L^1(\mathbb{R}) \times C^1(I) \times C^1(I) \), for a closed and bounded interval \( I = [M_-, M_+] \subset (-\infty, \infty), -\infty < M_- < M_+ < \infty \), and \( E_2 = C([0, T]; L^1(\mathbb{R})), T > 0 \). On \( C^1(I) \), we choose the norm
\[
\|f\|_{C^1(I)} = \sup_{x \in I} |f(x)| + \sup_{x \in I} |f'(x)|, \quad f \in C^1(I),
\]
on \( E_1 \), we will use
\[
\|g\|_{E_1} = \|g_1\|_{L^1(\mathbb{R})} + \|g_2\|_{C^1(I)} + \|g_3\|_{C^1(I)}, \quad g = (g_1, g_2, g_3) \in E_1,
\]
and on \( E_2 \),
\[
\|h\|_{E_2} = \sup_{0 \leq t \leq T} \int_{\mathbb{R}} |h(t, x)| dx, \quad h \in E_2.
\]
Furthermore, we will need the following special case of the fact that a continuous mapping is measurable:

**Lemma 2.1.** Let \( (\Omega, \mathcal{F}) \) be a measurable space, \( B_1, B_2 \) be Banach spaces equipped with the Borel \( \sigma \)-algebras \( \mathcal{B}(B_j) \), and let \( j = 1, 2 \), \( X : \Omega \to B_1 \) be a random variable and \( \Psi : B_1 \to B_2 \) a continuous mapping, that is for \( x_1, x_2 \in B_1 \),
\[
\|\Psi(x_1) - \Psi(x_2)\|_{B_2} \leq \lambda(\|x_1 - x_2\|_{B_1}),
\]
where \( \lambda : \mathbb{R}_{\geq 0} \to \mathbb{R}_{\geq 0} \) is a continuous function which satisfies \( \lambda(0) = 0 \) and which increases monotonically in \( \mathbb{R}_{\geq 0} \).

Then the mapping \( \Omega \ni \omega \mapsto \Psi(X(\omega)) \in B_2 \) is \( (B_2, \mathcal{B}(B_2)) \)-measurable, i.e., it is a \( B_2 \)-valued random variable.
Proof. We have to show that for any \( A_2 \in \mathcal{B}(B_2), \ F = (\Psi \circ X)^{-1}(A_2) \in \mathcal{F}. \) Since \((\Psi \circ X)^{-1}(A_2) = X^{-1}(\Psi^{-1}(A_2))\) and by the assumption that \( X \) is a random variable \( X^{-1}(A_1) \in \mathcal{F} \) for every \( A_1 \in \mathcal{B}(B_1), \) this amounts to showing that \( \Psi^{-1}(A_2) \in \mathcal{B}(B_1) \) for any \( A_2 \in \mathcal{B}(B_2). \) Since the Borel \( \sigma \)-algebra is generated by the open sets and the inverse image of a mapping \( f : \Omega_1 \to \Omega_2 \) has the two fundamental properties
\[
\bigcup_{i \in \mathcal{I}} f^{-1}(C_i) = f^{-1}\left(\bigcup_{i \in \mathcal{I}} C_i\right), \quad \bigcap_{i \in \mathcal{I}} f^{-1}(C_i) = f^{-1}\left(\bigcap_{i \in \mathcal{I}} C_i\right),
\]
for a countable index set \( \mathcal{I} \) and any countable collection \( \{C_i\}_{i \in \mathcal{I}} \) of sets \( C_i \subset \Omega_2, \) it is enough to verify this for an arbitrary open, nonempty set \( A_2 \in \mathcal{B}(B_2). \) That \( \Psi^{-1}(A_2) \) is an open set if \( A_2 \) is open, then follows by the continuity of \( \Psi. \)

\[
\square
\]

3. Degenerate Convection Diffusion Equation with Random Diffusive Flux

We develop a theory of random entropy solutions for degenerate convection diffusion equation with a class of random flux functions, proving in particular the existence and uniqueness of a random entropy solution. To this end, we first review classical results on degenerate convection diffusion equation with deterministic data.

3.1. Deterministic Scalar Degenerate Convection Diffusion Equation. We consider the Cauchy problem for degenerate convection diffusion equation of the form
\[
\begin{cases}
    u_t + \text{div} \ f(u) = \text{div} \ (a(u) \ \text{grad} \ u), & (x, t) \in \Omega_T, \\
    u(0, x) = u_0(x), & x \in \mathbb{R}^d,
\end{cases}
\]
(3.1)

3.2. Entropy Solutions. It is well-known that if \( f \) is Lipschitz continuous and \( a(u) \geq 0, \) then the deterministic Cauchy problem (3.1) admits, for each \( u_0 \in L^1(\mathbb{R}^d) \cap L^\infty(\mathbb{R}^d), \) a unique entropy solution (see, e.g., [17, 35, 9]). Moreover, for every \( t > 0, \) \( u(\cdot, t) \in L^1(\mathbb{R}^d) \cap L^\infty(\mathbb{R}^d) \) and several properties of the (nonlinear) data-to-solution operator
\[
S : (u_0, f, A) \mapsto u(\cdot, t) = S(t)(u_0, f, A), \quad t > 0,
\]
will be crucial for our subsequent development. To state these properties of \( \{S(t)\}_{t \geq 0}, \) following [12] we introduce the set of admissible initial data
\[
\mathcal{A}(f, A) := \{z \in L^1(\mathbb{R}^d) \cap BV(\mathbb{R}^d) \mid |f(z) - \text{grad} \ A(z)|_{BV} < \infty\}.
\]
(3.2)

We collect next fundamental results regarding the entropy solution \( u \) of (3.1) in the following theorem, for a proof see [37, 5].

**Theorem 3.1.** Let \( f \) and \( A \) be locally Lipschitz continuous functions. Then

1. For every \( u_0 \in \mathcal{A}(f, A), \) the initial value problem (3.1) admits a unique BV entropy weak solution \( u \in C ([0, T]; L^1_{\text{loc}}(\mathbb{R}^d))).
2. For every \( t > 0, \) the (nonlinear) data-to-solution map \( S(t) \) given by
\[
u(\cdot, t) = S(t)(u_0, f, A)
\]
satisfies
i) For fixed \( f, A \in \text{Lip}(\mathbb{R}), \) \( S(t)(\cdot, f, A) : L^1_{\text{loc}}(\mathbb{R}^d) \to L^1(\mathbb{R}^d) \) is a (contractive) Lipschitz map, i.e.,
\[
\|S(t)(u_0, f, A) - S(t)(v_0, f, A)\|_{L^1(\mathbb{R}^d)} \leq \|u_0 - v_0\|_{L^1(\mathbb{R}^d)}.
\]
(3.3)

ii) For every \( u_0 \in \mathcal{A}(f, A), \) \( f, A \in \text{Lip}_{\text{loc}}(\mathbb{R})\)
\[
\|S(t)(u_0, f, A)\|_{L^\infty(\mathbb{R}^d)} \leq \|u_0\|_{L^\infty(\mathbb{R}^d)},
\]
(3.4)
\[
\|S(t)(u_0, f, A)\|_{L^1(\mathbb{R}^d)} \leq \|u_0\|_{L^1(\mathbb{R}^d)},
\]
(3.5)
\[
\|S(t)(u_0, f, A)\|_{BV(\mathbb{R}^d)} \leq \|u_0\|_{BV(\mathbb{R}^d)},
\]
(3.6)
\[
|f(u(\cdot, t)) - \text{grad} \ A(u(\cdot, t))|_{BV(\mathbb{R}^d)} \leq |f(u_0) - \text{grad} \ A(u_0)|_{BV(\mathbb{R}^d)}.
\]
(3.7)
iii) Lipschitz continuity in time: For any \( t_1, t_2 > 0 \), \( u_0 \in A(f, A) \),

\[
\| S(t_1)u_0, f, A) - S(t_2)u_0, f, A) \|_{L^1(\mathbb{R}^d)} \leq \| f(u_0) - \text{grad} A(u_0) \|_{BV(\mathbb{R}^d)} |t_1 - t_2|.
\]

Point 1) of Theorem 3.1 is proved in [37] or [5, Thm 1.1], (3.3), (3.5) also follow from [5, Thm 1.1], (3.4) was proved in [5, Thm 1.2], and (3.6), (3.7), (3.8) were proved in [37]. In our convergence analysis of MC-FD discretizations of degenerate convection diffusion equation with random fluxes, we will need the following result regarding continuous dependence of \( S \) with respect to \( f \) and \( A \) (6, Thm. 3)

**Theorem 3.2.** Assume \( u_0, v_0 \in BV(\mathbb{R}^d) \cap L^1(\mathbb{R}^d) \cap L^\infty(\mathbb{R}^d) \), and \( f(\cdot), g(\cdot), A(\cdot), B(\cdot) \in \text{Lip}_{\text{loc}}(\mathbb{R}) \) with \( A', B' \geq 0 \).

Then the unique entropy solutions \( u(t, \cdot) = S(t)(u_0, f, A) \) and \( v(t, \cdot) = S(t)(v_0, g, B) \) of (3.1) with initial data \( u_0, v_0 \), convective flux functions \( f \) and \( g \) and with diffusive flux functions \( A \) and \( B \) satisfy the Kružkov entropy conditions, and the a priori continuity estimate

\[
\| u(\cdot, t) - v(\cdot, t) \|_{L^1(\mathbb{R}^d)} \leq \| u_0 - v_0 \|_{L^1(\mathbb{R}^d)} + C \left( t \| f' - g' \|_{L^\infty(M_-, M_+)} + 4\sqrt{t} \left| \sqrt{A} - \sqrt{B} \right|_{L^\infty(M_-, M_+)} \right),
\]

where \( M_- \leq u_0 \leq M_+ \) and \( C = \| u_0 \|_{BV(\mathbb{R}^d)} < \infty \). The above estimate holds for every \( 0 \leq t \leq T \).

**Remark 3.3.** Using that for nonnegative numbers \( a, b \geq 0, a \neq 0 \),

\[
\sqrt{a} - \sqrt{b} = \sqrt{a - b} \frac{\sqrt{a} - \sqrt{b}}{\sqrt{a} + \sqrt{b}} \leq \sqrt{|a - b|},
\]

it follows from (3.9) that under the assumptions of Theorem 3.2,

\[
\| u(\cdot, t) - v(\cdot, t) \|_{L^1(\mathbb{R}^d)} \leq \| u_0 - v_0 \|_{L^1(\mathbb{R}^d)} + C \left( t \| f' - g' \|_{L^\infty(M_-, M_+)} + 4\sqrt{t} \left| \sqrt{A} - \sqrt{B} \right|_{L^\infty(M_-, M_+)} \right),
\]

hence the mapping \( S(t) : L^1(\mathbb{R}^d) \times W^{1, \infty}([M_-, M_+]) \times W^{1, \infty}([M_-, M_+]) \to L^1(\mathbb{R}^d) \), \( (u_0, f, A) \mapsto u(t, \cdot) \) is continuous as a mapping between Banach spaces if restricted to initial data \( u_0 \in U_1 := \{ u_0 \in L^1(\mathbb{R}^d) : M_- \leq u_0(x) \leq M_+, \text{ a.e. } x \in \mathbb{R} \} \subset L^1(\mathbb{R}^d) \) and \( A \) satisfying \( A' \geq 0 \). Moreover, since for \( f, g, A, B \in C^1([M_-, M_+]) \) with the above properties and bounded derivatives it holds

\[
\| u(\cdot, t) - v(\cdot, t) \|_{L^1(\mathbb{R}^d)} \leq \| u_0 - v_0 \|_{L^1(\mathbb{R}^d)} + C \left( t \sup_{z \in [M_-, M_+]} |f'(z) - g'(z)| + 4\sqrt{t} \sup_{z \in [M_-, M_+]} |A'(z) - B'(z)| \right),
\]

it follows that \( S(t)(\cdot, \cdot, \cdot) \) is a continuous mapping between the separable Banach spaces \( E_1 := L^1(\mathbb{R}^d) \times C^1([M_-, M_+]) \times C^1([M_-, M_+]) \) if restricted to initial data in the set \( U_1 \).

3.3. Random Entropy Solutions. We are interested in the case where the initial data \( u_0 \), the convective flux function \( f \) and the diffusive flux function \( A \) in (1.1) are uncertain. Existence and uniqueness for random initial data \( u_0 \) and random flux \( f \) for \( A \equiv 0 \) was proved in [29, 28]. Based on Theorem 3.1, we will now formulate (1.1) for random initial data \( u_0(\omega; \cdot) \), random convective flux \( f(\omega; \cdot) \) and random diffusive flux \( A(\omega; \cdot) \). To this end, we denote \( (\Omega, \mathcal{F}, \mathbb{P}) \) a probability space and consider random variables

\[
\begin{align*}
X := (u_0, f, A) : (\Omega, \mathcal{F}) &\longmapsto (E_1, B(E_1)), \\
\omega &\longmapsto X(\omega) := (u_0(\omega; \cdot), f(\omega; \cdot), A(\omega; \cdot)),
\end{align*}
\]

where \( E_1 := L^1(\mathbb{R}) \times C^1(I) \times C^1(I) \) and \( I := [M_-, M_+] \subset \mathbb{R}, -\infty < M_- < M_+ < \infty \). In order to establish the appropriate framework for the random degenerate convection diffusion equation
(3.19), we will restrict ourselves to random data \( X = (u_0, f, A) \in E_1 \) which satisfy \( \mathbb{P}\text{-a.s.} \) the following assumptions:

\[
\begin{align*}
(3.12) \quad & -\infty < M_- \leq u_0(\omega; x) \leq M_+ < \infty, \text{ a.e. } x \in \mathbb{R}^d, \\
(3.13) \quad & |u_0(\omega; \cdot)|_{BV(\mathbb{R}^d)} \leq C_{TV} < \infty, \\
(3.14) \quad & \|f'(\omega; \cdot)\|_{C^0([M_-; M_+])} \leq C_f < \infty, \\
(3.15) \quad & A'(\omega; \cdot) \geq 0, \\
(3.16) \quad & \|A'(\omega; \cdot)\|_{C^0([M_-; M_+])} \leq C_A < \infty, \\
(3.17) \quad & |f(\omega; u_0(\omega; \cdot)) - \text{grad } A(\omega; u_0(\omega; \cdot))|_{BV(\mathbb{R}^d)} \leq C_{A,f} < \infty.
\end{align*}
\]

Since \( L^1(\mathbb{R}^d) \) and \( C^1(I) \) are separable, (3.11) is well defined. Moreover, by Lemma [8, Lemma 1.5, p.19] each of the expressions on the left hand sides of (3.12) - (3.17) is a random variable and we may impose for \( k \in \mathbb{N} \) the \( k\)-th moment condition:

\[
(3.18) \quad \|u_0\|_{L^k(\Omega; L^1(\mathbb{R}^d))} < \infty,
\]
where the Bochner spaces with respect to the probability measure are defined in Section 2. Then we are interested in random solutions of the random degenerate convection diffusion equation

\[
(3.19) \quad \begin{cases}
  u_t(\omega; x, t) + \text{div}(f(\omega; u(\omega; x, t))) = \Delta A(\omega; u(\omega; x, t)), \ t > 0, \ x \in \mathbb{R}^d, \\
  u(\omega; x, 0) = u_0(\omega; x), \ x \in \mathbb{R}^d.
\end{cases}
\]

**Definition 3.4.** A random field \( u : \Omega \ni \omega \to u(\omega; x, t) \), i.e., a measurable mapping from \( (\Omega, \mathcal{F}) \) to \( C([0, T]; L^1(\mathbb{R}^d)) \), is called a random entropy solution of (3.1) with random initial data \( u_0 \), flux function \( f \) and diffusive flux \( A \) satisfying (3.11) and (3.12) - (3.18) for some \( k \geq 2 \), if it satisfies:

(i.) Weak solution: for \( \mathbb{P}\text{-a.e. } \omega \in \Omega \), \( u(\omega; \cdot, \cdot) \) satisfies

\[
\int_0^\infty \int_{\mathbb{R}^d} \left( u(\omega; x, t) \varphi_t + (f(\omega; u(\omega; x, t))) \cdot \text{grad } \varphi \right) dx \, dt + \int_{\mathbb{R}^d} u_0(x, \omega) \varphi(x, 0) \, dx = 0,
\]

for all test functions \( \varphi \in C^1_0(\mathbb{R}^d \times [0, \infty)) \).

(ii.) Entropy condition: For any pair consisting of a (deterministic) entropy \( \eta \) and (stochastic) entropy flux \( q(\omega; \cdot) \) and \( r(\omega; \cdot) \) i.e., \( \eta, q \) and \( r \) are functions such that \( \eta \) is convex and such that \( \eta'(\omega; \cdot) = \eta f'(\omega; \cdot), \ r'(\omega; \cdot) = \eta A'(\omega; \cdot) \) and for \( \mathbb{P}\text{-a.s. } \omega \in \Omega \), \( u \) satisfies the following integral identity:

\[
\int_0^\infty \int_{\mathbb{R}^d} \left( \eta(u(\omega; x, t)) \varphi_t + \text{grad } q(\omega; u(\omega; x, t)) \cdot \text{grad } \varphi + r(\omega; u(\omega; x, t)) \Delta \varphi \right) dx \, dt + \int_{\mathbb{R}^d} \eta(u_0(\omega; x)) \varphi(x, 0) \, dx \geq 0,
\]

for all test functions \( 0 \leq \varphi \in C^1_0(\mathbb{R}^d \times [0, \infty)) \).

We state the following theorem regarding the random entropy solution of (3.19):

**Theorem 3.5.** Consider the degenerate convection diffusion equation (3.1) with random initial data \( u_0 \), flux function \( f \) and random diffusion operator \( A \), as in (3.11), and satisfying (3.12) - (3.17) and the \( k\)-th moment condition (3.18) for some integer \( k \geq 2 \). Then there exists a unique random entropy solution \( u : \Omega \ni \omega \to C([0, T]; L^1(\mathbb{R}^d)) \) which is “pathwise”, i.e., for \( \mathbb{P}\text{-a.s. } \omega \in \Omega \), described in terms of a nonlinear mapping \( S(t) \), depending only on the random flux and diffusion,

\[
u(\omega; t) = S(t)(u_0(\omega; \cdot), f(\omega; \cdot), A(\omega; \cdot)), \quad t > 0, \ \mathbb{P}\text{-a.e. } \omega \in \Omega
\]
such that for every \( k \geq m \geq 1 \) and for every \( 0 \leq t \leq T < \infty \)
\begin{align}
\|u\|_{L^1(\Omega;C([0,T];L^1(\mathbb{R}^d)))} \leq \|u_0\|_{L^k(\Omega;L^1(\mathbb{R}^d))}, \\
\|S(t)(u_0, f, A)(\omega)\|_{L^1(\mathbb{R}^d)} \leq \|u_0(\omega;\cdot)\|_{L^1(\mathbb{R}^d)}
\end{align}
and such that we have \( \mathbb{P}\text{-a.s.} \)
\begin{align}
|S(t)(u_0, f, A)(\omega)|_{BV(\mathbb{R}^d)} \leq |u_0(\omega;\cdot)|_{BV(\mathbb{R}^d)},
\end{align}
\begin{align}
|f(\omega; u(\omega;\cdot, t)) - \text{grad } A(\omega; u(\omega;\cdot, t))|_{BV(\mathbb{R}^d)} \leq |f(\omega; u_0(\omega;\cdot)) - \text{grad } A(\omega; u_0(\omega;\cdot))|_{BV(\mathbb{R}^d)},
\end{align}
\begin{align}
\|u(\omega;\cdot, t_1) - u(\omega;\cdot, t_2)\|_{L^1(\mathbb{R}^d)} \leq |f(\omega; u_0(\omega;\cdot)) - \text{grad } A(\omega; u_0(\omega;\cdot))|_{BV(\mathbb{R}^d)} |t_1 - t_2|.
\end{align}
and, with \( \overline{M} := \max\{M_-, M_+\} \) for \( M_-, M_+ \) as in (3.12),
\begin{align}
\sup_{0 \leq t \leq T} \|u(\omega;\cdot, t)\|_{L^\infty(\mathbb{R}^d)} \leq \overline{M} \quad \mathbb{P}\text{-a.s.} \quad \omega \in \Omega.
\end{align}

Proof. For \( \omega \in \Omega \), we define, motivated by Theorem 3.1, for \( \mathbb{P}\text{-a.e. } \omega \in \Omega \) a random function \( u(\omega; t, x) \) by
\begin{align}
u(\omega; \cdot) = S(t)(u_0, f, A)(\omega).
\end{align}
By the properties of the solution mapping \( (S(t))_{t \geq 0} \), see Theorem 3.1, the random field defined in (3.26) is well defined; for \( \mathbb{P}\text{-a.e. } \omega \in \Omega \), \( u(\omega; \cdot) \) is a weak entropy solution of the degenerate diffusion equation (3.1). Moreover, we obtain from Theorem 3.1 that \( \mathbb{P}\text{-a.s.} \) all bounds (3.21)–(3.24) hold, with assumption (3.12) also (3.25). The measurability of the mapping \( \Omega \ni \omega \mapsto u(\omega;\cdot, t) \in L^1(\mathbb{R}) \), \( 0 \leq t \leq T \) follows from Lemma 2.1, (3.10) and the assumption that the mapping \( \Omega \ni \omega \mapsto (u_0, f, A)(\omega) \in E_1 \) is a random variable. Finally, (3.20) follows from (3.18) together with (3.5) in Theorem 3.1. \( \square \)

Theorem 3.5 generalizes the existence of random entropy solutions for random initial data from [29] and random convective flux function [28]. It ensures the existence of a unique random entropy solution \( u(\omega; x, t) \) with finite \( k \)-th moments provided that \( u_0 \in L^k(\Omega, F, \mathbb{P}; L^1(\mathbb{R}^d)) \) for some \( k \geq 2 \).

Remark 3.6. All existence and continuous dependence results stated so far are formulated for the deterministic Cauchy problem (3.1). By the ‘usual arguments’, verbatim the same results will also hold for solutions defined in a bounded, aziparallel domain \( D \subset \mathbb{R}^d \), provided that periodic boundary conditions in each coordinate are enforced on the weak solutions. Weak solutions for these periodic problems cannot coincide with weak solutions of the Cauchy problem (3.1) since the \( D\)-periodic extension of these solutions belongs to \( L^1_{\text{loc}}(\mathbb{R}^d) \), but does not belong to \( L^1(\mathbb{R}^d) \).

4. Numerical approximation of random degenerate convection diffusion equation

We wish to compute various quantities of interest, such as the expectation and higher order moments, of the solution \( u \) to the random degenerate diffusion equation (3.19). We choose to split the approximation into two steps: On one hand, we need to approximate in the stochastic domain \( \omega \in \Omega \) and on the other hand, since in general exact solutions to (1.1) are not available, we need an approximation in the physical domain \( (x, t) \in \mathbb{H}_T \). In this paper, we will consider a Multilevel Monte Carlo Finite Difference Method (MLMC-FDM), that is, a combination of the multilevel Monte Carlo method with a deterministic finite difference discretization. We will briefly review the two methods and mention some relevant results in the following sections.

4.1. Monte Carlo method. We view the Monte Carlo method as a “discretization” of the random degenerate diffusion equation data \( u_0(\omega;\cdot), f(\omega;\cdot), A(\omega;\cdot) \) with respect to \( \omega \in \Omega \). We assume that \( (u_0(\omega;\cdot), f(\omega;\cdot), A(\omega;\cdot)) \in E_1 \) satisfying in addition (3.12)–(3.17). We also assume (3.18), i.e., the existence of \( k \)-th moments of \( u_0 \) for some \( k \in \mathbb{N} \), to be specified later. We shall be interested in the statistical estimation of the first and higher moments of \( u \), i.e., \( \mathcal{M}^k(u) \in (L^1(\mathbb{R}^d))^k \). For \( k = 1 \), \( \mathcal{M}^1(u) = \mathbb{E}[u] \). The Monte Carlo (MC) approximation of \( \mathbb{E}[u] \) is defined
as follows: Given $M$ independent, identically distributed samples $(\tilde{\omega}_i^0, \tilde{f}_i, \tilde{A}^i)$, $i = 1, \ldots, M$, of initial data, flux function and diffusion, the MC estimate of $\mathbb{E}[u(\cdot, t; \omega)]$ at time $t$ is given by

$$E_M[u(\cdot, t)] := \frac{1}{M} \sum_{i=1}^{M} \tilde{u}^i(\cdot, t)$$

where $\tilde{u}^i(\cdot, t)$ denote the $M$ unique entropy solutions of the $M$ Cauchy problems (1.1) with initial data $\tilde{\omega}_i^0$, flux function $\tilde{f}_i$ and diffusion operator $\tilde{A}^i$. Since $\tilde{u}^i(\cdot, t) = S(t)(\tilde{\omega}_i^0, \tilde{f}_i, \tilde{A}^i)$, we have for every $M$ and for every $0 < t < \infty$, by (3.5),

$$\|E_M[u(\cdot, t; \omega)]\|_{L^1(\mathbb{R}^d)} = \left\| \frac{1}{M} \sum_{i=1}^{M} S(t)(\tilde{\omega}_i^0, \tilde{f}_i, \tilde{A}^i)(\omega) \right\|_{L^1(\mathbb{R}^d)}$$

$$\leq \frac{1}{M} \sum_{i=1}^{M} \left\| S(t)(\tilde{\omega}_i^0, \tilde{f}_i, \tilde{A}^i)(\omega) \right\|_{L^1(\mathbb{R}^d)}$$

$$\leq \frac{1}{M} \sum_{i=1}^{M} \|\tilde{\omega}_i^0(\cdot; \omega)\|_{L^1(\mathbb{R}^d)}.$$ 

Using the i.i.d. property of the samples $\{(\tilde{\omega}_i^0, \tilde{f}_i, \tilde{A}^i)\}_{i=1}^{M}$ and therefore of $\{\tilde{\omega}_i^0\}_{i=1}^{M}$, and the linearity of the expectation $\mathbb{E}[-]$, we obtain the bound

$$\mathbb{E}[\|E_M[u(\cdot, t)]\|_{L^1(\mathbb{R}^d)}] \leq \mathbb{E}\left[\|u_0\|_{L^1(\mathbb{R}^d)}\right] = \|u_0\|_{L^1(\Omega; L^1(\mathbb{R}^d))} < \infty.$$ 

As the sample size $M \to \infty$, the sample averages (4.1) converge and the convergence result from [29, 28] holds as well:

**Theorem 4.1.** Assume that in (3.19) the random variable $(u_0, f, A)(\omega)$ as in (3.11) satisfies (3.12) and $A'(\omega; \cdot) \geq 0$, a.s. $\omega \in \Omega$ and $u_0 \in L^2(\Omega; L^1(\mathbb{R}^d))$.

Then the MC estimates $E_M[u(\cdot, t)]$ in (4.1) converge as $M \to \infty$, to $M^1(u(\cdot, t)) = \mathbb{E}[u(\cdot, t)]$ and, for any $M \in \mathbb{N}$, $0 < t < \infty$, and we have the bound

$$\|E[u(\cdot, t)] - E_M[u(\cdot, t)]\|_{L^2(\Omega; L^1(\mathbb{R}^d))} \leq 2M^{-\frac{1}{2}} \|u_0\|_{L^2(\Omega; L^1(\mathbb{R}^d))}.$$ 

The proof of this result proceeds completely analogous to the proof of [29, Thm. 4.1], using the measurability and square integrability (3.20) (with $k = 2$) of Theorem 3.5.

So far, we addressed the MC estimation of the mean field or first moment. A similar result holds for the MC sample averages of the $k$-th moment $M^k u := E[(u)^{(k)}] \in (L^1(\mathbb{R}^d))^{(k)}$.

**Theorem 4.2.** Consider the random degenerate advection diffusion equation (3.19) with random data $(u_0, f, A) : \Omega \to E_1$ as in (3.11) and satisfying (3.12) and $A'(\omega; \cdot) \geq 0$, a.s. Assume furthermore that for some $k \in \mathbb{N}$ holds $u_0 \in L^{2k}(\Omega; L^1(\mathbb{R}^d))$. Then, as $M \to \infty$, the MC sample averages

$$E_M[u(\cdot, t)]^{(k)} := \frac{1}{M} \sum_{i=1}^{M} (\tilde{u}_i^i(\cdot, t))^{(k)}$$

with the $M$ i.i.d. samples $\tilde{u}_i^i(\cdot, t)$, $i = 1, 2, \ldots$, converge to the $k$-th moment (or spatial $k$-point correlation function) $(M^k u)(t)$. Moreover, we have the error bound

$$\left\| (M^k u)(t) - E_M[(u(\cdot, t; \omega))^{(k)}] \right\|_{L^2(\Omega; L^1(\mathbb{R}^d))} \leq 2M^{-1/2} \|u_0\|_{L^{2k}(\Omega; L^1(\mathbb{R}^d))}^{(k)}.$$ 

The proof of this theorem is omitted since it is identical to the proof of Theorem 4.2. in [29].
4.2. Finite Difference Methods for degenerate convection diffusion equations. So far, we considered the MCM under the assumption that the entropy solutions \( \tilde{w}(x, t; \omega) = S(t)(\tilde{u}_0, \tilde{f}, \tilde{A})(\omega) \) for the Cauchy problem (1.1) with the data samples \((\tilde{u}_0, \tilde{f}, \tilde{A})\) are available exactly. In practice, however, we must use numerical approximations of \( S(t)(\tilde{u}_0, \tilde{f}, \tilde{A}) \).

The presentation will, from now on, be restricted to the one-dimensional case, i.e., we consider
\[
\begin{aligned}
&\begin{cases}
  u_t + f(u)_x = A(u)_{xx}, & t > 0, \ x \in \mathbb{R}, \\
  u(x, 0) = u_0(x).
\end{cases}
\end{aligned}
\]

We shall examine the class of fully discrete monotone difference schemes for which Karlsen, Risebro and Storrøsten obtained a convergence in \( L^1 \) rate of \( \Delta x^{1/3} \), where \( \Delta x \) is the discretization parameter, in [21]. These schemes are easily generalized to several space dimensions, but rigorous results regarding convergence rates are much worse. To date, the best convergence rate in \( L^1(\mathbb{R}^d) \) for a fully discrete, implicit in time scheme is \( \Delta x^{1/(1+d)} \), see [22].

For \( \Delta x, \Delta t > 0 \), we discretize the physical domain \( \Pi_T \) by a grid with grid cells
\[
I_n^j = [x_{j-1/2}, x_{j+1/2}] \times (t_{n-1}, t_n], \quad n \geq 0, \ j \in \mathbb{Z},
\]
where \( x_{j\pm1/2} = (j \pm 1/2)\Delta x, \ j \in \mathbb{Z} \), and \( t_n = n\Delta t, \ n \in \mathbb{N} \). We define cell averages of the initial data via
\[
u^n_j = \frac{1}{\Delta x} \int_{I_n^j} u_0(x) \, dx, \quad j \in \mathbb{Z}.
\]

Then we consider the following implicit scheme
\[
D^- u^n_j + D_- F(u^n_j, u^n_{j+1}) = D_- D_+ A(u^n_j), \quad n \geq 1, \ j \in \mathbb{Z},
\]
and the explicit scheme,
\[
D^+ u^n_j + D_+ F(u^n_j, u^n_{j+1}) = D_- D_+ A(u^n_j), \quad n \geq 0, \ j \in \mathbb{Z},
\]
where we have denoted for a quantity \( \{\sigma^n_j\}_{j \in \mathbb{Z}, n \in \mathbb{N}}, \)
\[
D^+ \sigma^n_j = \pm \frac{1}{\Delta t}(\sigma^n_{j+1} - \sigma^n_j), \quad D^- \sigma^n_j = \pm \frac{1}{\Delta x}(\sigma^n_{j+1} - \sigma^n_j).
\]

We then define the piecewise constant approximation to (4.3) by
\[
u_\Delta(x, t) = u^n_j, \quad (x, t) \in I_n^j,
\]
where \( u^n_j \) is defined by either (4.5) or (4.6). The numerical flux \( F \in C^1(\mathbb{R}^2) \) is chosen such that it is consistent with \( f \), that is, \( F(u, u) = f(u) \) for all \( u \in \mathbb{R} \), and monotone, i.e.
\[
\frac{\partial}{\partial u} F(u, v) \geq 0 \quad \text{and} \quad \frac{\partial}{\partial v} F(u, v) \leq 0.
\]

In order to obtain convergence rates, it is furthermore necessary to choose \( F \) Lipschitz continuous and such that it can be written
\[
F(u, v) = F_1(u) + F_2(v), \quad F'_1(u) + F'_2(u) = f'(u),
\]
see [21]. Examples of monotone numerical fluxes satisfying (4.8) are the Engquist-Osher flux as well as the Lax-Friedrichs and the upwind flux. In order to show convergence of the explicit scheme, the following CFL-condition is needed,
\[
\Delta t \leq C \Delta x^{2},
\]
[12] and in order to show a convergence rate, one even needs
\[
\Delta t \leq C \Delta x^{8/3},
\]
see [21]. Whether this restrictive CFL-condition is sharp in order to prove a convergence rate is not known. Naturally, no CFL-condition is needed to ensure stability of the implicit scheme, [14].
In order to obtain à priori estimates for the explicit scheme, the numerical flux function $F$ and the diffusion operator $A$ have to satisfy the following condition

\begin{equation}
\frac{\Delta t}{\Delta x} (F'(z) - F'(w)) + 2 \frac{\Delta t}{\Delta x^2} A'(w) \leq 1, \quad \text{for all } z \text{ and } w,
\end{equation}

see [12]. Then we have the following stability and convergence results for the schemes (4.5) and (4.6), [12, 10, 21]

**Theorem 4.3.** Let $u_0 \in BV(\mathbb{R}) \cap L^1(\mathbb{R})$, $f$, $A$ locally $C^1$, $A' \geq 0$ and $u_0 \in \mathcal{B}(f,A)$, where $\mathcal{B}(f,A)$ is defined in (3.2). Let $F$ be a monotone numerical flux function consistent with $f$, satisfying (4.8). Denote by $u_\Delta(x,t)$ the piecewise constant function defined in (4.7), where $u_j^n$ are computed by either the explicit scheme (4.6) or the implicit scheme (4.5). Assume for the explicit scheme in addition that $\Delta t$ satisfies (4.9) and that (4.11) holds. Then we have

i) The approximations $u_\Delta$ converge, as the discretization parameters $(\Delta x, \Delta t) \to 0$ to the unique entropy solution of (4.3). Moreover they satisfy

\begin{align*}
\|u_\Delta(\cdot,t)\|_{L^1(\mathbb{R})} & \leq \|u_0\|_{L^1(\mathbb{R})}, \\
\|u_\Delta(\cdot,t)\|_{L^\infty(\mathbb{R})} & \leq \|u_0\|_{L^\infty(\mathbb{R})}, \\
\|u_\Delta(\cdot,t)\|_{BV(\mathbb{R})} & \leq \|u_0\|_{BV(\mathbb{R})}, \\
\sup_j |F(u_j^n, u_{j+1}^n) - D_+ A(u_j^n)| & \leq \sup_j |F(u_j^0, u_{j+1}^0) - D_+ A(u_j^0)|, \\
\sum_j |D_- F(u_j^n, u_{j+1}^n) - D_- D_+ A(u_j^n)| & \leq \sum_j |D_- F(u_j^0, u_{j+1}^0) - D_- D_+ A(u_j^0)|.
\end{align*}

Furthermore, $u_\Delta$ is $L^1(\mathbb{R})$-Lipschitz continuous in time, viz., for any $t_n, t_m > 0$,

$$\|u_\Delta(\cdot,t_n) - u_\Delta(\cdot,t_m)\|_{L^1(\mathbb{R})} \leq |f(u_0) - A(u_0)|_{BV(\mathbb{R})} |t_n - t_m|.$$ 

ii) If for the explicit scheme in addition (4.10) holds, the approximations $u_\Delta$ converge at the rate $1/3$ to the entropy solution $u$ of (4.3):

$$\|u_\Delta(\cdot,t_n) - u(\cdot,t_n)\|_{L^1(\mathbb{R})} \leq \|u_\Delta(\cdot,0) - u_0\|_{L^1(\mathbb{R})} + C_T \Delta x^{1/3},$$

where the constant $C_T$ takes the form

$$C(1 + T) \left( 1 + \|f\|_{Lip} \right) |u_0|_{BV(\mathbb{R})} + \|A(u_0)x\|_{L^1(\mathbb{R})} + |f(u_0) - A(u_0)x|_{BV(\mathbb{R})},$$

with $C$ independent of $u_0$, $f$ and $A$.

Point i) was proved in [12, Thm. 3.9, Cor. 3.10] for the explicit scheme and [10, Thm. 3.9, Lem. 3.3, 3.4, 3.5] for the implicit scheme , ii) in [21].

For the purpose of analyzing the efficiency of the MC- and MLMC-method, it is important to have an estimate on the computational work used to compute one approximation of the solution by the deterministic FD-schemes and how it increases with respect to mesh refinement. By (computational) work or cost of an algorithm, we mean the number of floating point operations performed during the execution of the algorithm. We assume that this is proportional to the run time of the algorithm. In the actual computations we deal with bounded domains, so that the number of grid cells in one dimension scales as $1/\Delta x$.

**4.2.1. Work estimate explicit scheme (4.6).** In case of the explicit scheme, the number of operations in one time step scales linearly with the number of grid cells which in turn scales as $\Delta x^{-1}$ (we assume the computational domain is bounded). Hence the work can be bounded as $W_{\Delta}^{exp} \leq C \Delta x^{-1} \Delta x^{-1}$. Taking the CFL-condition (4.10) into account, we obtain the (likely pessimistic) work bound

$$W_{\Delta}^{exp} = O(\Delta x^{-1/3}).$$
4.2. Work estimate implicit scheme (4.5). In the implicit scheme we have to solve the nonlinear equation (4.5) for \( u^{n+1} := (\ldots, u_{n-1}^{n+1}, u_n^{n+1}, u_{n+1}^{n+1}, \ldots) \) in each timestep. Since solving this equation exactly is either impossible or computationally very expensive, we prefer to solve it only approximately by an iterative method. We consider here the case that this method is the Newton iteration, which we iterate until the residual is of order \( \Delta x \Delta t \) (this is possible since the mapping \( u^n \rightarrow u^{n+1} := \Psi(u^n) \) defined by (4.5) is a contraction for sufficiently small \( \Delta t \) and CFL constant. In general the Lipschitz constant should scale as \( 1/\Delta x \), so a small value of \( \Delta t \) alone is not sufficient for the contraction property to hold. For details, we refer to [10]. The additional error introduced by finite termination of the iterative nonlinear system solver will not increase the overall error:

\[
\| u_\Delta(\cdot, t_n) - u(\cdot, t_n) \|_{L^1(\mathbb{R})} = \left\| u^{n}(n) - u(\cdot, t_n) \right\|_{L^1(\mathbb{R})}
\]

\[
\leq \sum_{m=0}^{n-1} \left\| u^{n,m+1}(m+1) - u^{n,m}(m) \right\|_{L^1(\mathbb{R})} + \left\| u^{n,0}(0) - u(\cdot, t_n) \right\|_{L^1(\mathbb{R})}
\]

\[
\leq \sum_{m=0}^{n-1} \left\| u^{m+1, m+1} - u^{m+1, m} \right\|_{L^1(\mathbb{R})} + C_T \Delta x^{1/3} + t_n \Delta x + C_T \Delta x^{1/3} \leq \bar{C}_T \Delta x^{1/3},
\]

where we have used the \( L^1 \)-contraction property of the scheme for the third last inequality. If the starting value for the Newton iteration is chosen such that it is in a sufficiently small neighborhood of the fixpoint, the convergence order of the Newton method is locally quadratic. In order to achieve an error of less than \( C \Delta x \Delta t \) in one timestep by solving the nonlinear system only approximately, it suffices to perform \( O(\log(\Delta x^{-1} \Delta t^{-1})) \) many Newton iterations. If we take \( \Delta t = \theta \Delta x \) for some constant \( \theta > 0 \), these are altogether \( O(\log(\Delta x^{-2})) = O(\log(\Delta x^{-1})) \) Newton steps. In each step of the Newton iteration, we invert and multiply a tridiagonal matrix of size \( O(\Delta x^{-2}) \) with a vector of length \( O(\Delta x^{-1}) \) and subtract it from another vector of length \( O(\Delta x^{-1}) \). The tridiagonal matrix can be inverted in \( O(\Delta x^{-1}) \) operations using the Thomas algorithm (in case of periodic boundary conditions we use the Sherman-Morrison formula). Hence the total number of floating point operations which are necessary for one Newton step is \( O(\Delta x^{-1}) \). It follows that the work done in one timestep is of order \( O(\log(\Delta x^{-2}) \Delta x^{-1}) \). As there are altogether \( n = T/\Delta t \) timesteps, and since we can choose the timestep of order \( \Delta t = \theta \Delta x \), we obtain the following bound on the total work for one execution of the implicit scheme,

\[
W_{\Delta t}^{im} = O(\Delta x^{-2} \log(\Delta x^{-1})).
\]

In the Monte Carlo Finite Difference Methods (MC-FDMs), we combine MC sampling of the random initial data with the FDMs (4.5) and (4.6). In the convergence analysis of these schemes, we shall require the application of the FDMs (4.5) and (4.6) to random initial data, flux function and diffusion operator \((u_0, f, A) \in L^p(\Omega; E_1)\) for some \( 1 \leq p \leq \infty \). Given a draw \((u_0(\omega; \cdot), f(\omega; \cdot), A(\omega; \cdot))\) of \((u_0, f, A)\), the FDMs (4.4) with (4.6) or (4.5) define families \( u_\Delta(\omega; x, t) \) of grid functions. We have the following

**Proposition 4.4.** Consider the FDMs (4.4)–(4.6), (4.5) for the approximation of the entropy solution corresponding to the draw \((u_0, f, A)(\omega)\) of the random data.
Then, the random grid functions $\Omega \ni \omega \mapsto u_\Delta(\omega; x, t)$ defined by (4.7) satisfy, for every $0 < T < \infty$, $0 < \Delta x < 1$, and every $k \in \mathbb{N} \cup \{\infty\}$ the stability bounds:
\[
\|u_\Delta(\cdot, \cdot, T)\|_{L^k(\Omega; L^\infty(\mathbb{R}))} \leq \|u_0\|_{L^k(\Omega; L^\infty(\mathbb{R}))},
\]
\[
\|u_\Delta(\cdot, \cdot, T)\|_{L^k(\Omega; L^1(\mathbb{R}))} \leq \|u_0\|_{L^k(\Omega; L^1(\mathbb{R}))}.
\]
We also have the bound
\[
\|u(\cdot, \cdot, T) - u_\Delta(\cdot, \cdot, T)\|_{L^k(\Omega; L^1(\mathbb{R}))} \leq \|u_0 - u(\cdot, \cdot, 0)\|_{L^k(\Omega; L^1(\mathbb{R}))} + C(1 + \bar{T}) \Delta x^{1/3} \left\{ \left\| (1 + \|f(\omega; \cdot, \cdot)\|_{\text{Lip}}) |(u_0)(\omega)|_{BV(\mathbb{R})} \right\|_{L^k(\Omega)} + \left\| (f(u_0) - A(u_0))_x(\omega)|_{BV(\mathbb{R})} \right\|_{L^k(\Omega)} \right\}.
\]

**Remark 4.5.** Under the assumptions (3.12) - (3.17), (4.12) becomes
\[
\|u(\cdot, \cdot, T) - u_\Delta(\cdot, \cdot, T)\|_{L^k(\Omega; L^1(\mathbb{R}))} \leq \|u_0 - u(\cdot, \cdot, 0)\|_{L^k(\Omega; L^1(\mathbb{R}))} + C(1 + \bar{T}) \Delta x^{1/3} \left\{ (1 + C_f + C_A) C_{TV} + C_{A,f} \right\}.
\]

**Remark 4.6.** We see from (4.12) that in order to obtain the convergence rate of $1/3$ in $L^k(\Omega)$ it would suffice to assume (3.18), (3.12), (3.15), $\|f(u_0) - A(u_0)_x\|_{BV(\mathbb{R})} \in L^k(\Omega)$, $A', f' \in L^{pk}(\Omega)$, $|u_0|_{BV(\mathbb{R})} \in L^{pk}(\Omega)$ for some $p, q \geq 1$ satisfying $1/p + 1/q = 1$. However, in order to obtain a uniform CFL-condition for the explicit scheme (which gives us the same asymptotic work estimate for each simulation with the explicit scheme), we need (3.14) and (3.16) to hold as well.

### 4.3. MC-FDM Scheme

We next define and analyze the MC-FDM scheme. It is based on the straightforward idea of generating, possibly in parallel, independent samples of the random initial data and then, for each sample of the random initial data, flux function and diffusion operator, to perform one FD simulation. The error of this procedure is bound by two contributions: a (statistical) sampling error and a (deterministic) discretization error. We express the asymptotic efficiency of this approach (in terms of overall error versus work). It will be seen that the efficiency of this approach (in terms of overall error versus work). It will be seen that the efficiency of the MC-FDM is, in general, inferior to that of the deterministic schemes (4.6) and (4.5).

The present analysis will constitute a key technical tool in our subsequent development and analysis of the multilevel MC-FDM (“MLMC-FDM” for short) which does not suffer from this drawback.

#### 4.3.1. Definition of the MC-FDM Scheme

We consider once more the initial value problem (3.19) with random data $(u_0, f, A)$ satisfying (3.12) – (3.17) and (3.18) for sufficiently large $k \in \mathbb{N}$ (to be specified in the convergence analysis). The MC-FDM scheme for the MC estimation of the mean of the random entropy solutions then consists in the following:

**Definition 4.7. (MC-FDM Scheme)** Given $M \in \mathbb{N}$, generate $M$ i.i.d. samples $\{(\tilde{u}_0, \bar{f}, \bar{A})\}_{i=1}^M$. Let $\{\tilde{u}^i(\cdot, t)\}_{i=1}^M$ denote the unique entropy solutions of the degenerate convection diffusion equations (1.1) for these data samples, i.e.,
\[
\tilde{u}^i(\cdot, t) = S(t) \left( \tilde{u}_0, \bar{f}, \bar{A} \right), \quad i = 1, \ldots, M.
\]
Then the MC-FDM approximations of $M^k(u(\cdot, t))$ are defined as statistical estimates from the ensemble
\[
\{\tilde{u}_\Delta^i(\cdot, t)\}_{i=1}^M
\]
obtained from the FD approximations by (4.6) or (4.5) of (1.1) with data samples $\{(\tilde{u}_0, \bar{f}, \bar{A})\}_{i=1}^M$.

Specifically, the first moment of the random solution $u(\omega; \cdot, t)$ at time $t > 0$, is estimated as
\[
M^1(u(\cdot, t)) \approx E_M[u_\Delta(\cdot, t)] := \frac{1}{M} \sum_{i=1}^M \tilde{u}_\Delta^i(\cdot, t),
\]
and, for \( k \geq 1 \), the \( k \)th moment (or \( k \)-point correlation function) \( M^k(u(\cdot), t) = \mathbb{E}[(u(\cdot), t)]^k \) is estimated by

\[
E_M^{(k)}[u_\Delta(\cdot), t] := \frac{1}{M} \sum_{i=1}^{M} (\overline{u}_\Delta \odot \cdots \odot \overline{u}_\Delta)(\cdot, t).
\]

More generally, for \( k > 1 \), we consider time instances \( t_1, \ldots, t_k \in (0, T) \), \( T < \infty \), and define the statistical FDM estimate of \( M^k(u)(t_1, \ldots, t_k) \) by

\[
E_M^{(k)}(t_1, \ldots, t_k) := \frac{1}{M} \sum_{i=1}^{M} (\overline{u}_\Delta(t_1) \odot \cdots \odot \overline{u}_\Delta(t_k)).
\]

4.3.2. Convergence Analysis of MC-FDM. We next address the convergence of \( E_M[u_\Delta] \) to the mean \( \mathbb{E}(u) \). Arguing as in \([28, 29]\), and using the error bounds in Proposition 4.4, we obtain the following result.

**Theorem 4.8.** Assume that

\[ u_0 \in L^2(\Omega, L^1(\mathbb{R})) \]

and that (3.12) – (3.17) hold. Then the MC estimate \( E_M[u_\Delta(\cdot), t] \) defined in (4.13) as in Definition 4.7 satisfies, for every \( M \), the error bound

\[
\|\mathbb{E}[u(\cdot), t] - E_M[u_\Delta(\cdot), t, \omega]\|_{L^2(\Omega, L^1(\mathbb{R}))} \leq C \left( M^{-1/2} \|u_0\|_{L^2(\Omega, L^1(\mathbb{R}))} + \|u_0 - u_\Delta(\cdot, 0)\|_{L^2(\Omega, L^1(\mathbb{R}))} + \Delta x^{1/3}(1 + 7) \right) \left\{ \|A(u_0)x\|_{L^2(\Omega, L^1(\mathbb{R}))} + \|f(u_0) - A(u_0)x\|_{BV(\Omega, L^2(\mathbb{R}))} \right\}.
\]

where \( C > 0 \) is independent of \( M \) and of \( \Delta x \) as \( M \to \infty \) and as \( \Delta x, \Delta t \downarrow 0 \).

4.3.3. Work estimates. We have seen in Sections 4.2.1 and 4.2.2 that the computational work to obtain \( \{u_\Delta(\cdot, t)\}_{0 \leq t \leq T} \), computed by the explicit or implicit scheme respectively, is asymptotically, as \( \Delta x, \Delta t \to 0 \), of order

\[
W^\text{ex}_\Delta \leq C \Delta x^{-11/3}, \quad W^\text{im}_\Delta \leq C \Delta x^{-2} \log(\Delta x^{-1}),
\]

which implies that the work for the computation of the MC estimate \( E_M[u_\Delta(\cdot, t)] \) is of order

\[
W^\text{ex}_{\Delta, M} \leq C M \Delta x^{-11/3}, \quad W^\text{im}_{\Delta, M} \leq C M \Delta x^{-2} \log(\Delta x^{-1}),
\]

so that we obtain from (4.16) the convergence order in terms of work: To this end we equilibrate in (4.16) the two bounds by choosing \( M^{-1/2} \sim \Delta x^{1/3} \), i.e. \( M = C \Delta x^{-2/3} \). Inserting in (4.17) yields

\[
W^\text{ex}_{\Delta, M} \leq C \Delta x^{-13/3}, \quad W^\text{im}_{\Delta, M} \leq C \Delta x^{-8/3} \log(\Delta x^{-1}),
\]

so that we obtain from (4.16)

\[
\begin{align*}
\|\mathbb{E}[u(\cdot), t] - E_M[u_\Delta(\cdot), t]\|_{L^2(\Omega, L^1(\mathbb{R}))} & \leq C_{u_0, t, A, f} \Delta x^{1/3} \leq C_{u_0, t, A, f} (W^\text{ex}_{\Delta, M})^{-1/13}, \\
\|\mathbb{E}[u(\cdot), t] - E_M[u_\Delta(\cdot), t]\|_{L^2(\Omega, L^1(\mathbb{R}))} & \leq C_{u_0, t, A, f} (W^\text{im}_{\Delta, M})^{-1/8},
\end{align*}
\]

where \( C_{u_0, t, A, f} \) is given by

\[
C_{u_0, t, A, f} = C(1 + t) \left\{ \|1 + \|f(\cdot, \cdot)\|_{L^p}) \|u_0\|_{BV(\Omega, L^2(\mathbb{R}))} \right\} L^2(\Omega) + \|A(u_0)x\|_{L^2(\Omega, L^1(\mathbb{R}))} + \|f(u_0) - A(u_0)x\|_{BV(\Omega, L^2(\mathbb{R}))} \|L^2(\Omega)\right\}.
\]

On the other hand, in the deterministic case we have the convergence rates,

\[
\begin{align*}
\|u(\cdot, t) - u_\Delta(\cdot, t)\|_{L^1(\mathbb{R})} & \leq C_T \Delta x^{1/3} \leq C_T (W^\text{ex}_{\Delta, M})^{-1/11}, \\
\|u(\cdot, t) - u_\Delta(\cdot, t)\|_{L^1(\mathbb{R})} & \leq C_T (W^\text{im}_{\Delta, M})^{-1/6},
\end{align*}
\]

with respect to work.
4.4. Multilevel MC-FDM. We next present and analyze a scheme that allows us to achieve almost the accuracy versus work bound (4.20) of the deterministic FDM also for the stochastic data \((u_0, f, A)\), rather than the single level MC-FDM error bound (4.18). The key ingredient in the Multilevel Monte Carlo Finite Difference (MLMC-FDM) scheme is simultaneous MC sampling on different levels of resolution of the FDM, with level dependent numbers \(M_k\) of MC samples. To define these, we introduce some notation.

4.4.1. Notation. The MLMC-FDM is defined as a multilevel discretization in \(x\) and \(t\) with level dependent numbers \(M_k\) of samples. To this end, we assume we are given a family of nested grids with cell sizes

\[
\Delta x_\ell = 2^{-K\ell} \Delta x_0, \quad \ell \in \mathbb{N}_0,
\]

for some \(\Delta x_0 > 0\), \(K\) such that \(2^K \in \mathbb{N} \setminus \{0, 1\}\). Similarly, we denote,

\[
\Delta t_\ell = C \Delta x_\ell^{8/3},
\]

the size of the time step for the explicit scheme corresponding to grid size \(\Delta x_\ell\) and

\[
\Delta t_\ell = \theta \Delta x_\ell,
\]

the size of the time step for the implicit scheme at level \(\ell\). We denote by \(u_\ell\) the approximation to (4.3) computed by (4.6) or (4.5) on the grid with cell and time step size \(\Delta x_\ell := (\Delta x_\ell, \Delta t_\ell)\).

4.4.2. Derivation of MLMC-FDM. As in plain MC-FDM, our aim is to estimate, for \(0 < t < \infty\), the expectation (or “ensemble average”) \(\mathbb{E}[u(\cdot, t)]\) of the random entropy solution of (3.19) with random data \((u_0, f, A)(\omega)\), \(\omega \in \Omega\), satisfying (3.11) – (3.18) for sufficiently large values of \(k\) (to be specified in the sequel). As in the previous section, \(\mathbb{E}[u(\cdot, t)]\) will be estimated by replacing \(u(\cdot, t)\) by a FDM approximation.

We generate a sequence of approximations, \(\{u_{\ell}(\cdot, t)\}_{\ell=0}^\infty\) on the nested meshes with cell sizes \(\Delta x_{\ell}\), time steps of sizes \(\Delta t_{\ell}\). In the following we set \(u_{-1}(\cdot, t) := 0\). Then, given a target level \(L \in \mathbb{N}\) of spatial resolution, we have

\[
\mathbb{E}[u_L(\cdot, t)] = \mathbb{E}\left[ \sum_{\ell=0}^{L} (u_{\ell}(\cdot, t) - u_{\ell-1}(\cdot, t)) \right].
\]

We next estimate each term in (4.22) statistically by a MCM with a level-dependent number of samples, \(M_L\); this gives the MLMC-FDM estimator

\[
\mathbb{E}^L[u(\cdot, t)] = \sum_{\ell=0}^{L} \mathbb{E}_{M_{\ell}}[u_{\ell}(\cdot, t) - u_{\ell-1}(\cdot, t)]
\]

where \(\mathbb{E}_{M}[u(\cdot, t)]\) is as in (4.13), and where \(u_{\ell}(\cdot, t)\) is computed on the mesh with grid size \(\Delta x_{\ell}\) and time step \(\Delta t_{\ell}\).

Statistical moments \(\mathbb{M}^k(u)(t_1, ..., t_k)\) of order \(k \geq 2\) (resp. the \(k\)-th order space-time correlation functions) of the random entropy solution \(u\) can be estimated in the same way: based on (4.14) in Definition 4.7, the straightforward generalization along the lines of the MLMC estimate (4.23) of the MC estimate (4.15) for \(\mathbb{M}^k(u)(t)\) leads to the definition of the MLMC-FDM estimator

\[
\mathbb{E}^L(k)[u(\cdot, t)] := \sum_{\ell=0}^{L} \mathbb{E}_{M_{\ell}}[(u_{\ell}(\cdot, t))^{(k)} - (u_{\ell-1}(\cdot, t))^{(k)}], \quad 0 < t < \infty.
\]

This generalizes (4.23) to moments \(\mathbb{M}^k(u)(t)\) of order \(k > 1\). \(^1\)

\(^1\) We assume here for notational convenience that \(t_1 = t_2 = \ldots = t_k = t\). This implies that our \(k\)-th moment estimate only requires access to the FDM solutions at time \(t\). The following developments directly generalize to the analysis of \(k\)-point temporal correlation functions of the random entropy solution as well; in this case, however, access to the full history of FDM solutions \(v_\ell(\cdot, t)\) for \(0 \leq t \leq T < \infty\) is required for the MC estimation of these correlations.
4.4.3. **Convergence Analysis.** We first analyze the MLMC-FDM mean field error
\begin{equation}
W_{L,\text{MLMC}}^{m} = \sum_{t=0}^{L} M_t W_{\Delta t}^{m} = O \left( \sum_{t=0}^{L} M_t \Delta x_t^{-11/3} \right),
\end{equation}
\begin{equation}
W_{L,\text{MLMC}}^{M} = \sum_{t=0}^{L} M_t W_{\Delta t}^{M} = O \left( \sum_{t=0}^{L} M_t \Delta x_t^{-2} \log(\Delta x_t^{-1}) \right).
\end{equation}

To estimate (4.25), we write (recall that $u_{-1} := 0$) using the triangle inequality, the linearity of the mathematical expectation $E[\cdot]$ and the definition (4.23) of the MLMC estimator
\begin{align*}
E[u(t)] - E^L[u(t)] 
&= \|E[u(t)] - E[u_L(t)]\|_{L^2(\Omega, L^1(\mathbb{R}))} + \|E[u_L(t)] - E^L[u(t)]\|_{L^2(\Omega, L^1(\mathbb{R}))} \\
&= E \left[ \left| u(t) - u_L(t) \right| + \left| u_L(t) - E^L[u(t)] \right| \right] \\
&= I + II.
\end{align*}

We estimate terms I and II separately. By linearity of the expectation, term I equals
\begin{equation}
I = \|E[u(t)] - u_L(t)\|_{L^1(\mathbb{R})} = \|u(t) - u_L(t)\|_{L^1(\Omega, L^1(\mathbb{R}))},
\end{equation}
which can be bounded by (4.12) with $k = 1$. We hence focus on term II, i.e.,
\begin{align*}
II &\leq \sum_{t=0}^{L} \|E[(u_L - u_{-1})(t)] - E_M[(u_L - u_{-1})(t)]\|_{L^2(\Omega, L^1(\mathbb{R}))} \\
&\leq \sum_{t=0}^{L} M_t^{-\frac{1}{2}} \left( \int_{\Omega} \|u_L(t; \omega) - u_{-1}(t; \omega)\|^2_{L^1(\mathbb{R})} d\mathbb{P}(\omega) \right)^{\frac{1}{2}} \\
&= \sum_{t=0}^{L} M_t^{-\frac{1}{2}} \|u_L(t) - u_{-1}(t)\|_{L^2(\Omega, L^1(\mathbb{R}))}.
\end{align*}

We estimate for every $\ell \geq 0$ the size of the detail $u_{\ell} - u_{\ell-1}$ with the triangle inequality
\begin{align*}
\|u_{\ell}(t) - u_{\ell-1}(t)\|_{L^2(\Omega, L^1(\mathbb{R}))} &\leq \|u(t) - u_{\ell}(t)\|_{L^2(\Omega, L^1(\mathbb{R}))} + \|u(t) - u_{\ell-1}(t)\|_{L^2(\Omega, L^1(\mathbb{R}))}.
\end{align*}

Using here (4.12) with $t = k = 2$, (4.19) and (4.21), we obtain for every $\ell \in \mathbb{N}$ the estimate
\begin{align*}
\|u_{\ell}(t) - u_{\ell-1}(t)\|_{L^2(\Omega, L^1(\mathbb{R}))} &\leq \|u(t) - u_{\ell}(t)\|_{L^2(\Omega, L^1(\mathbb{R}))} + \|u(t) - u_{\ell-1}(t)\|_{L^2(\Omega, L^1(\mathbb{R}))} + C_{u, t, A, f} (1 + 2^{K/3}) \Delta x_t^{1/3}.
\end{align*}

Using that for $0 \leq s \leq 1$, the cell-averages $u_{\ell}(\cdot, 0)$ satisfy, for every $k \in \mathbb{N}$ and for every $1 \leq q \leq \infty$,
\begin{align*}
\|u_0 - u_{\ell}(\cdot, 0)\|_{L^q(\Omega, L^q(\mathbb{R}))} &\leq C_{u_0, t, A, f} (1 + 2^{K/3}) \Delta x_t^{2/3} \|u_0\|_{BV(\mathbb{R})},
\end{align*}
we arrive at the error bound
\begin{align*}
\|u_{\ell}(t) - u_{\ell-1}(t)\|_{L^2(\Omega, L^1(\mathbb{R}))} &\leq \left( C_{u_0, t, A, f} (1 + 2^{K/3}) + C\Delta x_t^{2/3} \right) \|u_0\|_{BV(\mathbb{R})} \Delta x_t^{1/3}.
\end{align*}

Summing this error bound over all discretization levels $\ell = 0, \ldots, L$, we prove the main result of the present paper.
Theorem 4.9. Assume (3.12) – (3.18) for some $k \geq 2$ and (4.21). Then, for any sequence $\{M_\ell\}_\ell \rightarrow \infty$ of sample sizes at mesh level $\ell$, we have for the MLMC-FDM estimate $E^L[u(\cdot,t)]$ in (4.23) the error bound
\[
\left\|E[u(\cdot,t)] - E^L[u(\cdot,t)]\right\|_{L^2(\Omega;L^1(\mathbb{R}))} \leq C \left\{C_{u_0,t,A,f}^1 \Delta x_L^{1/3} + C_{u_0,t,A,f}^2 \Delta x_L^1 + \Delta x_L^3 \left\|u_0\right\|_{BV(\Omega)}\right\}
\]
\[
+ C \left\{\sum_{\ell=0}^{L} M_\ell^{-1/2} \Delta x_L^{1/3} \left(C_{u_0,t,A,f}^2 \Delta x_L^2 + \Delta x_L^3 \left\|u_0\right\|_{BV(\Omega)}\right)\right\}
\]
where we have denoted
\[
C_{u_0,t,A,f}^j = C (1 + t) \left\{(1 + \left\|f(\cdot)\right\|_{L^2(\Omega)} \left\|u_0\right\|_{L^1(\Omega)}\right\} + \left\|A(u_0)x\right\|_{L^1(\Omega)}\right\}
\]
j = 1, 2 and $C > 0$ is a constant that is independent of the parameters $u_0, f, t$ and $A$.

The upper bound obtained in Theorem 4.9 is the basis for an optimization of the numbers $M_\ell$ of MC samples across the mesh levels. Our selection of the level dependent Monte Carlo sample sizes $M_\ell$ will be based on the last term in the error bound (4.27); we select in (4.27) the $M_\ell$ such that as $\Delta \downarrow 0$, all terms equal the error estimate $\Delta x_L^{1/3}$ at the finest level $L$. This motivates choosing $M_\ell$ such that
\[
M_\ell^{-1/2} \Delta x_L^{1/3} = C \Delta x_L^{1/3}, \quad \ell = 0, \ldots, L - 1.
\]
Here, $C$ is some positive integer that is independent of $\ell, L$. Using
\[
\Delta x_L = 2^{-\ell K} \Delta x_0, \quad \ell = 0, 1, 2, \ldots,
\]
we find $M_\ell = C \Delta x_L^{2/3} \Delta x_L^{-2/3} = C 2^{K(L-\ell)/3}$. This implies in (4.27) the bound
\[
\left\|E[u(\cdot,t)] - E^L[u(\cdot,t)]\right\|_{L^2(\Omega;L^1(\mathbb{R}))} \leq (L + 1) \left(1 + 2^{K/3}\right)C_{u_0,t,A,f}^1 \Delta x_L^{1/3},
\]
where $C_{u_0,t,A,f}^1 = \max_{j \in \{1,2\}} \left\{C_{u_0,t,A,f}^1 + \left\|u_0\right\|_{BV(\Omega)}\right\}$, while the total cost is, using (4.26), bounded by
\[
W_{\text{ex},\text{LMC}}^\ell \leq C \sum_{\ell=0}^{L} M_\ell \Delta x_0^{11/3} = C \sum_{\ell=0}^{L} 2^{2K\ell/3 + 3\ell K} = C 2^{11K/3} = C \left\{\Delta x_L^{-1/3}\right\}
\]
\[
W_{\text{im},\text{LMC}}^\ell \leq C \sum_{\ell=0}^{L} M_\ell \Delta x_0^{-2} \log(\Delta x_0^{-1}) = CK \log(2) 2^{2K\ell/3} \sum_{\ell=0}^{L} 2^{4K\ell/3}
\]
\[
= C 2^{K\ell} \log(2^{K\ell}) = C \left\{\Delta x_L^{2/3} \log(\Delta x_L^{-1})\right\}.
\]
We observe that this is asymptotically the same work as the one needed for one deterministic approximation of (4.3) using (4.6) or (4.5) with grid size $\Delta x_L$ and corresponding time step $\Delta t_L$.

Inserting (4.29) into the asymptotic error bound (4.28), we obtain the following error estimate in terms of work
\[
\left\|E[u(\cdot,t)] - E^L[u(\cdot,t)]\right\|_{L^2(\Omega;L^1(\mathbb{R}))} \leq (L + 1) \left(1 + 2^{K/3}\right)C_{u_0,t,A,f}^1 \left(W_{\text{ex},\text{LMC}}^\ell\right)^{-1/11},
\]
\[
\left\|E[u(\cdot,t)] - E^L[u(\cdot,t)]\right\|_{L^2(\Omega;L^1(\mathbb{R}))} \leq (L + 1) \left(1 + 2^{K/3}\right)C_{u_0,t,A,f}^1 \left(W_{\text{ex},\text{LMC}}^\ell\right)^{-1/11}.
\]
We observe that the MLMC-FDM (4.29) behaves, in terms of accuracy versus work, as $L \rightarrow \infty$, as the deterministic FDM up to log-terms, where the error vs. work was estimated in (4.20). Now one can balance $L$ and $K$ in order to obtain as small a constant as possible.
5. Numerical Experiments

In this section, we will test the method on some numerical examples from two-phase flow in porous media. In one space dimension, the time evolution of the water saturation \( s := s^w \in [0, 1] \) can be modeled by the conservation law
\[
s_t + f(s)_x = (a(s)s_x)_x, \quad (t, x) \in [0, T] \times D,\]
\[
s(0, x) = s_0(x), \quad x \in D,
\]
where \( D \in \mathbb{R} \) is a bounded interval, \( f \) and \( a \) are of the form
\[
f(s) = q \frac{\lambda^w(s)}{\lambda^w(s) + \lambda^o(s)}, \quad a(s) = \nu K \frac{\lambda^w(s)\lambda^o(s)}{\lambda^w(s) + \lambda^o(s)} p_c(s)
\]
where \( q \) denotes total flow rate, \( K \) the rock permeability (we will set \( K = q = 1 \) for simplicity), \( \nu \) a small number, and \( p_c \) the capillary pressure for which we will use the expression
\[
p_c(s) = \left( s^{-4/3} - 1 \right)^{1/4},
\]
which is taken from [18], and \( \lambda^w, \lambda^o \) are the phase mobilities/relative permeabilities of the water and the oil phase respectively. The relative permeability of the water phase \( \lambda^w \) is a monotone function with \( \lambda^w(0) = 0, \lambda^w(1) = 1 \), and the relative permeability of the oleic phase \( \lambda^o \) is a monotone decreasing function such that \( \lambda^o(0) = 1 \) and \( \lambda^o(1) = 0 \). Often one uses the simple expressions
\[
\lambda^w(s) = s^2, \quad \lambda^o(s) = (1 - s)^2.
\]
Such a form of the relative permeability is of course a simplification, and more accurate models are based on experiments, and these functions therefore have some uncertainty associated with them. Hence it is natural to model the relative permeabilities as random variables. Equations (5.1) have to be augmented with suitable boundary conditions. In the ensuing numerical experiments, we use the domains \( D = (0, 2) \) and \( D = (0, 0.5) \) and periodic boundary conditions, in order to avoid issues related to unbounded domains or to boundary effects.

5.1. Random exponent. For this example we will model the relative permeabilities by
\[
\lambda^w(s) = |s|^p(\omega), \quad \lambda^o(s) = |1 - s|^p(\omega),
\]
where the random exponent \( p \) is uniformly distributed in the interval \([1.5, 2.5]\). As initial data, we use
\[
s_0(x) = \begin{cases} 0.1, & x \in [0, 0.1] \cup [1, 2), \\ 0.8, & x \in [0.1, 1), \end{cases}
\]
and periodically extended outside \([0, 2]\). Figure 1 shows a sample \( s(\omega; t, \cdot) \) of the random entropy solution at time \( T = 0.3 \), and an estimate of the mean \( \mathbb{E}[s(\cdot, 0.3)] \) computed by the explicit multilevel Monte Carlo finite difference method with \( M_0 = 8, L = 8, \Delta x_0 = 2^{-3}, K = 1 \) and CFL-number 0.4. We will use this sample of the MLMC estimator as a reference solution when estimating the approximation errors and computing the convergence rates.

In order to compute an estimate on the error of the approximation of the mean by the MLMC estimator \( \mathbb{E}^L[s(t)] \) in the \( L^2(\Omega, L^1(\mathbb{R})) \)-norm, we use the relative error estimator introduced in [29] based on a Monte Carlo quadrature in the stochastic domain: By \( U_{\text{ref}} \) we denote a reference solution and \( \{U_k\}_{k=1}^{N} \) a sequence of independent approximate solutions \( \mathbb{E}^L[s(t)] \) obtained by running the MLMC-FDM solver \( N \) times, corresponding to \( N \) realizations in the stochastic domain. Then we estimate the relative error by
\[
\mathcal{R}E = \sqrt{\frac{\sum_{k=1}^{N}(\mathcal{R}E_k)^2}{N}},
\]
where
\[
\mathcal{R}E_k = 100 \times \frac{\|U_{\text{ref}} - U_k\|_{\ell^1}}{\|U_{\text{ref}}\|_{\ell^1}}.
\]
given. We observe that they slightly increase, but not as much as the bounds might indicate that we are not in the asymptotic regime yet. In the last two columns of Tables 1. Numerical experiments, we use $N = 5$ which was shown to be sufficient for most problems [29, 30]. In Table 1 the errors (5.5) versus the resolution $\Delta x_L$ at the finest level $L$ of the MLMC estimator and versus the average time (in seconds) needed to compute one sample of the MLMC estimator are shown ($L = 0, \ldots, 5$). We observe that the calculated convergence rates are $\approx 0.66$ (explicit scheme) and $\approx 0.75$ (implicit scheme) with respect to the resolution and $\approx 0.32$ (explicit scheme) and $0.38$ (implicit scheme) with respect to work. This is better than what we would expect from the theory, cf. (4.28) and (4.30a), (4.30b). However, they decrease as we refine the mesh, which might indicate that we are not in the asymptotic regime yet. In the last two columns of Tables 1, the average total variation and $L^{\infty}$-norm of $E^L(s(t))$ at the different refinement levels are given. We observe that they slightly increase, but not as much as the bounds

\[
|E^L(s(t))|_{BV(\mathbb{R})} = \left| \sum_{\ell=0}^{L} \frac{1}{M_{\ell}} \sum_{i=0}^{M_{\ell}} (s^i_{\ell} - s^i_{\ell-1}) \right|_{BV(\mathbb{R})} \leq 2(L + 1) \| s_0 \|_{BV(\mathbb{R})}
\]

\[
\|E^L(s(t))\|_{L^{\infty}(\mathbb{R})} = \left\| \sum_{\ell=0}^{L} \frac{1}{M_{\ell}} \sum_{i=0}^{M_{\ell}} (s^i_{\ell} - s^i_{\ell-1}) \right\|_{L^{\infty}(\mathbb{R})} \leq 2(L + 1) \| s_0 \|_{L^{\infty}(\mathbb{R})}
\]

In [29], the sensitivity of the error with respect to the parameter $N$ is investigated. In the present numerical experiments, we use $N = 5$ which was shown to be sufficient for most problems [29, 30]. In Table 1 the errors (5.5) versus the resolution $\Delta x_L$ at the finest level $L$ of the MLMC estimator and versus the average time (in seconds) needed to compute one sample of the MLMC estimator are shown ($L = 0, \ldots, 5$). We observe that the calculated convergence rates are $\approx 0.66$ (explicit scheme) and $\approx 0.75$ (implicit scheme) with respect to the resolution and $\approx 0.32$ (explicit scheme) and $0.38$ (implicit scheme) with respect to work. This is better than what we would expect from the theory, cf. (4.28) and (4.30a), (4.30b). However, they decrease as we refine the mesh, which might indicate that we are not in the asymptotic regime yet. In the last two columns of Tables

| $L$ | $\mathcal{RE}$ | $\Delta x_L$ | run time | $|E^L(s(t))|_{BV([0,2])}$ | $\|E^L(s(t))\|_{L^{\infty}([0,2])}$ |
|-----|----------------|-------------|----------|--------------------------|--------------------------|
| 0   | 16.54          | $2^{-4}$    | 0.45     | 1.37                     | 0.79                     |
| 1   | 10.25          | $2^{-4}$    | 2.48     | 1.4                      | 0.8                      |
| 2   | 6.13           | $2^{-5}$    | 10.31    | 1.42                     | 0.81                     |
| 3   | 3.53           | $2^{-6}$    | 40.58    | 1.44                     | 0.81                     |
| 4   | 2.06           | $2^{-7}$    | 159.6    | 1.48                     | 0.81                     |
| 5   | 1.68           | $2^{-8}$    | 632.37   | 1.58                     | 0.82                     |

Table 1. Relative mean square errors (as defined in (5.5)) versus grid size at highest level and time (in seconds), for problem (5.1) with (5.4), (5.2) and (5.3), for the MLMC solver with the explicit difference scheme.
the error estimator defined in (5.5) and on the right hand side we have plotted a sample of the MLMC-FDM estimator with periodic boundary conditions.

The resulting \((s_0, f, A)(\omega_1, \omega_2, \cdot)\) again satisfies assumptions (3.11) – (3.17), so that the random entropy solution from Definition 3.4 exists and Theorems 3.5, 4.9 apply. In Figure 2 on the left hand side, we have plotted a sample \(s(\omega; t, \cdot)\) of the random entropy solution at time \(T = 0.3\) and on the right hand side we have plotted a sample of the MLMC-FDM estimator \(E^L(s(t))\) for \(M_0 = 8, \ L = 8, \ \Delta x_0 = 2^{-3}, \ K = 1\) and CFL-number 0.4. We observe that the variance is larger compared to the variance in the previous example. We will use this sample of the MLMC estimator as a reference solution when estimating the approximation errors and computing the convergence rates. Moreover, we will again compute an estimate of the \(L^2(\Omega; L^1(\mathbb{R}))\)-error using the error estimator defined in (5.5) with \(N = 5\).

| \(L\) | \(RE\) | \(\Delta x_L\) | run time | \(|E^L(s(t))|_{BV([0, 2])}\) | \(||E^L(s(t))||_{L^2([0, 2])}\) |
|------|------|----------|----------|-----------------|-----------------|
| 0    | 22.89| 2^{-1}  | 0.65     | 1.3             | 0.76            |
| 1    | 14.69| 2^{-2}  | 3.53     | 1.39            | 0.8             |
| 2    | 9.27 | 2^{-3}  | 13.29    | 1.43            | 0.81            |
| 3    | 5.57 | 2^{-4}  | 47.7     | 1.44            | 0.81            |
| 4    | 3.15 | 2^{-5}  | 174.8    | 1.47            | 0.81            |
| 5    | 1.68 | 2^{-6}  | 659.7    | 1.5             | 0.81            |

Table 2. Relative mean square errors (as defined in (5.5)) versus grid size at highest level and CPU time (in seconds), for problem (5.1) with (5.4), (5.2) and (5.3), for the MLMC solver with time-stepping by the implicit difference scheme.

would imply.

5.2. Random residual saturation. In the following numerical example, we will model the relative permeabilities by the random variables

\[
\lambda^w(s) = 1_{s > s^*_w(\omega_1)}(s) \frac{(s - s^*_w(\omega_1))^2}{(1 - s^*_w(\omega_1))^2}, \quad \lambda^o(s) = 1_{s \leq s^*_w(\omega_2)}(s) \left(1 - \frac{s}{s^*_w(\omega_2)}\right)^2,
\]

with \(s^*_w(\omega_1) \sim \mathcal{U}(0.05, 0.35), \ s^*_w(\omega_2) \sim \mathcal{U}(0.6, 0.95), \ s^*_w(\omega_1) \perp s^*_w(\omega_2),\)

That is we assume that the residual saturations \(s^*_w, \ s^*_o\) are independent, uniformly distributed random variables. As initial data, we use again use (5.4) with periodic boundary conditions.

Figure 2. Left: One sample of the random entropy solution of (5.1) with (5.4), (5.2) and (5.6) at time \(T = 0.3\) computed on a mesh with 4096 points. Right: A sample of the estimator \(E^L(s(\cdot, t))\) for (5.1) with (5.4), (5.2) and (5.6) at time \(T = 0.3\) (solid line), the dashed lines denote \(E^L(s(\cdot, t)) \pm \text{standard deviation}\).
In Tables 3, 4 the errors (5.5) versus the resolution $\Delta x_L$ at the finest level $L$ of the MLMC estimator and versus the average time (in seconds) needed to compute one sample of the MLMC estimator are shown ($L = 0, \ldots, 5$). We observe that the approximate convergence rates are $\approx 0.43$ (explicit scheme) and $\approx 0.57$ (implicit scheme) with respect to the resolution and $\approx 0.21$ (explicit scheme) and $\approx 0.37$ (implicit scheme) with respect to work, which is again better than what we would expect from the theory, cf. (4.28) and (4.30a), (4.30b). However, it decreases as we refine the mesh, which might indicate that we are not in the asymptotic regime yet. We also note that the rates are lower than in the previous example.

### Table 3.

<table>
<thead>
<tr>
<th>$L$</th>
<th>$RE$</th>
<th>$\Delta x_L$</th>
<th>run time</th>
<th>$|E^L(s(t))|_{BV([0,2])}$</th>
<th>$|E^L(s(t))|_{L^\infty([0,2])}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>12.36</td>
<td>$2^{-4}$</td>
<td>0.48</td>
<td>1.31</td>
<td>0.76</td>
</tr>
<tr>
<td>1</td>
<td>8.67</td>
<td>$2^{-4}$</td>
<td>2.69</td>
<td>1.38</td>
<td>0.78</td>
</tr>
<tr>
<td>2</td>
<td>5.44</td>
<td>$2^{-5}$</td>
<td>10.82</td>
<td>1.47</td>
<td>0.82</td>
</tr>
<tr>
<td>3</td>
<td>4.33</td>
<td>$2^{-6}$</td>
<td>41.97</td>
<td>1.63</td>
<td>0.83</td>
</tr>
<tr>
<td>4</td>
<td>3.32</td>
<td>$2^{-7}$</td>
<td>164.53</td>
<td>1.73</td>
<td>0.82</td>
</tr>
<tr>
<td>5</td>
<td>2.77</td>
<td>$2^{-8}$</td>
<td>679.27</td>
<td>2.04</td>
<td>0.82</td>
</tr>
<tr>
<td>average rate</td>
<td>0.43</td>
<td>-0.21</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 4.

<table>
<thead>
<tr>
<th>$L$</th>
<th>$RE$</th>
<th>$\Delta x_L$</th>
<th>run time</th>
<th>$|E^L(s(t))|_{BV([0,2])}$</th>
<th>$|E^L(s(t))|_{L^\infty([0,2])}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>16.0</td>
<td>$2^{-4}$</td>
<td>1.16</td>
<td>1.23</td>
<td>0.72</td>
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<tr>
<td>1</td>
<td>9.34</td>
<td>$2^{-4}$</td>
<td>3.9</td>
<td>1.37</td>
<td>0.78</td>
</tr>
<tr>
<td>2</td>
<td>5.54</td>
<td>$2^{-5}$</td>
<td>11.52</td>
<td>1.44</td>
<td>0.8</td>
</tr>
<tr>
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<td>4.54</td>
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<td>31.29</td>
<td>1.61</td>
<td>0.82</td>
</tr>
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<td>0.81</td>
</tr>
<tr>
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<td>2.05</td>
<td>0.81</td>
</tr>
<tr>
<td>average rate</td>
<td>0.57</td>
<td>-0.37</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 5.3. Sine wave initial data.

As a third example, we have tested the convergence rates on Problem (5.1), (5.2), (5.3) with sine wave initial data,

(5.7) \[ s_0(x) = \sin(4\pi x), \quad x \in [0, 0.5], \]

In Figure 3, on the left hand side, we have plotted a sample of the solution computed on a mesh with 2048 points at time $T = 0.5$ and on the right hand side a sample of the MLMC estimator for $L = 7$, $\Delta x_0 = 1/16$, $M_0 = 8$ and CFL-number 0.4, also at time $T = 0.5$. We observe that the approximation looks quite smooth and that the variance is evenly distributed over the whole spatial domain in contrast to the previous examples. In Tables 5, 6 the estimates (5.5) on the $L^2(\Omega; L^1(\mathbb{R}))$-error for $N = 5$ are displayed and compared to the mesh resolution at the finest level and the run time.

We find a convergence rate of $\approx 0.53$ (explicit scheme) and $\approx 0.39$ (implicit scheme) versus resolution and $\approx 0.25$ (explicit scheme) and $\approx 0.19$ (implicit scheme) versus run time. We also observe that the rates improve when the mesh is refined. Interestingly, for this example the convergence rates for the MLMC solver with the implicit scheme are worse than those for the explicit scheme in contrast to the previous examples. The reason could be the samples of the implicit scheme at level $L = 1$ which are closer to the reference solution than the following ones at higher levels. This decreases the average rate for the implicit scheme.
Figure 3. Left: One sample of the random entropy solution of (5.1) with (5.7), (5.2) and (5.3) at time $T = 0.5$ computed on a mesh with 2048 points. Right: A sample of the estimator $E^L[s(\cdot, t)]$ for (5.1) with (5.7), (5.2) and (5.3) at time $T = 0.5$ (solid line), the dashed lines denote $E^L[s(\cdot, t)] \pm$ standard deviation.

<table>
<thead>
<tr>
<th>$L$</th>
<th>$RE$</th>
<th>$\Delta x_L$</th>
<th>run time</th>
<th>$|E^L(s(t))|_{BV([0,2])}$</th>
<th>$|E^L(s(t))|_{L^\infty([0,2])}$</th>
</tr>
</thead>
<tbody>
<tr>
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<td>8.11</td>
<td>$2^{-4}$</td>
<td>1.68</td>
<td>0.008</td>
<td>0.5</td>
</tr>
<tr>
<td>1</td>
<td>6.71</td>
<td>$2^{-5}$</td>
<td>9.94</td>
<td>0.055</td>
<td>0.51</td>
</tr>
<tr>
<td>2</td>
<td>5.26</td>
<td>$2^{-6}$</td>
<td>43.36</td>
<td>0.131</td>
<td>0.53</td>
</tr>
<tr>
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<td>3.35</td>
<td>$2^{-7}$</td>
<td>179.02</td>
<td>0.18</td>
<td>0.54</td>
</tr>
<tr>
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<td>1.85</td>
<td>$2^{-8}$</td>
<td>721.99</td>
<td>0.253</td>
<td>0.56</td>
</tr>
<tr>
<td>Average Rate</td>
<td>0.53</td>
<td>-0.25</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5. Relative mean square errors (as defined in (5.5)) versus grid size at highest level and time, for problem (5.1) with (5.7), (5.2) and (5.3) (explicit deterministic solver in MLMC method).

<table>
<thead>
<tr>
<th>$L$</th>
<th>$RE$</th>
<th>$\Delta x_L$</th>
<th>run time</th>
<th>$|E^L(s(t))|_{BV([0,2])}$</th>
<th>$|E^L(s(t))|_{L^\infty([0,2])}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>19.23</td>
<td>$2^{-4}$</td>
<td>0.7</td>
<td>0.27</td>
<td>0.58</td>
</tr>
<tr>
<td>1</td>
<td>5.71</td>
<td>$2^{-4}$</td>
<td>3.94</td>
<td>0.13</td>
<td>0.54</td>
</tr>
<tr>
<td>2</td>
<td>9.78</td>
<td>$2^{-5}$</td>
<td>16.33</td>
<td>0.08</td>
<td>0.52</td>
</tr>
<tr>
<td>3</td>
<td>6.6</td>
<td>$2^{-6}$</td>
<td>62.58</td>
<td>0.08</td>
<td>0.52</td>
</tr>
<tr>
<td>4</td>
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<td>$2^{-7}$</td>
<td>235.8</td>
<td>0.14</td>
<td>0.53</td>
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<tr>
<td>5</td>
<td>3.52</td>
<td>$2^{-8}$</td>
<td>808.15</td>
<td>0.22</td>
<td>0.55</td>
</tr>
<tr>
<td>Average Rate</td>
<td>0.39</td>
<td>-0.19</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6. Relative mean square errors (as defined in (5.5)) versus grid size at highest level and time, for problem (5.1) with (5.7), (5.2) and (5.3) (implicit solver in MLMC method).

References


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