Multilevel Monte Carlo Finite Volume Methods for Random Conservation Laws with Discontinuous Flux

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Abstract. We consider a random scalar hyperbolic conservation law in one spatial dimension with bounded random flux functions which are discontinuous in the spatial variable. We show that there exists a unique random entropy solution to the conservation law corresponding to the specific entropy condition used to solve the deterministic case. Assuming the empirical convergence rates of the underlying deterministic problem over a broad range of parameters, we present a convergence analysis of a multilevel Monte Carlo Finite Volume Method (MLMC-FVM). It is based on a pathwise application of the finite volume method for the deterministic conservation laws. We show that the work required to compute the MLMC-FVM solutions is an order lower than the work required to compute the Monte Carlo Finite Volume Method solutions with equal accuracy.

1. Introduction. One dimensional scalar conservation laws with spatially discontinuous flux are often used to model different phenomena such as traffic flow [20], [26] [11], two phase flow in a porous media [9, 27, 10, 13, 12, 14] and sedimentation processes [5, 7, 4]. However, often the data needed describing the equation is not known deterministically, and instead is only available via certain statistical quantities of interest like the mean, the variance and the higher moments. This uncertainty in Cauchy data is carried over to the uncertainty in the solution of the conservation laws. Uncertainty in the Cauchy data and the corresponding solution is frequently modeled in a probability manner. A common point of view is that the Cauchy data is a random variable described by a probability distribution. Development of efficient algorithms to quantify the uncertainty in the solutions of random conservation law is an active field of research. The number of random sources driving the uncertainty may be very large, and possibly countably infinite. The numerical method should be able to deal with the corresponding possibly infinite dimensional spaces efficiently.

There are different methods to quantify the uncertainty in solutions of conservation laws, namely stochastic Galerkin method [1, 6, 21, 25, 30] based on generalized polynomial chaos, stochastic collocation [22, 31] and statistical sampling methods, especially Monte Carlo (MC) methods [23]. As was shown in [24], the MC methods converge to the mean at rate 1/2 as the number of samples $M$ increases. This rate is due to the central limit theorem and hence, optimal for these class of methods. This makes the MC methods computationally expensive. In [8], Giles proposed showed that a multilevel Monte Carlo method can be used to reduce the computational complexity of estimating the expected value of stochastic differential equations. Since, then multiple authors have applied the method to different problems .

For conservation laws, [24] proposed a multilevel Monte Carlo (MLMC) method for a

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random initial condition and a smooth flux. Later, the method was extended to include random but smooth flux in [23]. In the same paper, the authors described a method to determine the optimized combination of sample sizes at each level of spatial and temporal discretization. The optimal number of samples at each level depends on the error estimates of the numerical method. We are interested in extending the method to conservation laws with random initial condition and discontinuous flux in the special case where the discontinuous flux is multiplicative. In this case, the conservation law can be written as

\begin{equation}
\frac{\partial u(\omega;x,t)}{\partial t} + \frac{\partial (k(\omega;x)f(u))}{\partial x} = 0, \quad (\omega,x,t) \in \Omega \times \mathbb{R} \times [0,\infty)
\end{equation}

where \( u \) and \( k \) are random variables satisfying the following conditions: there exists \( a,b \), \( u^* \in [a,b], M \in \mathbb{N}, M < \infty, L > 0, \) and \( \alpha > 0 \), such that for almost every \( \omega \in \Omega \), we have

\begin{equation}
f(a) = f(b) = 0 \quad f \in C^2[a,b]
\end{equation}

\begin{equation}
f'(u) > 0 \text{ for all } a < u < u^* \quad f'(u) < 0 \text{ for all } u^* < u < b
\end{equation}

\begin{equation}
k(\omega;x) \in BV(\mathbb{R}) \quad k'(\omega;x) \in L_{loc}^1(\mathbb{R})
\end{equation}

\begin{equation}
k(\omega;x) \text{ has discontinuities at } D = \{\xi_1,\xi_2,\ldots,\xi_M\} \text{ such that for all } \xi_i = N_iL \text{ for some } N_i \in \mathbb{N}
\end{equation}

\begin{equation}
k' \text{ is bounded, whenever defined, and has one sided limits at points of discontinuity}
\end{equation}

\begin{equation}
k(\omega;x) > \alpha \text{ for all } x \in \mathbb{R}
\end{equation}

\begin{equation}
u_0(\omega;x) \in L^1(\mathbb{R}) \cap L^\infty(\mathbb{R})
\end{equation}

The deterministic case of the equation (1.1) has been studied extensively by [3, 28, 16] and different admissibility conditions have been developed to select a unique solution. However, the different conditions, though yielding uniqueness, give different unique solutions. In this paper, we use a modified Kruzkov entropy condition to select the unique solution. Finite volume methods for the deterministic case have been developed in [28, 16]. The stability of solutions with respect to the Cauchy data was examined and shown in [17].

We define a pathwise entropy condition for the random conservation law based on the modified Kruzkov entropy condition of the deterministic case. Using the results from deterministic case, we then prove the uniqueness and stability of the solution to the random conservation law. In accordance with [23], the next step would be to use the error estimates for the finite volume method from the deterministic case in order to derive the optimal sample
numbers for the MLMC method. However, such error estimates do not yet exist. Moreover, [2] have presented an example where the total variation of the solution is unbounded near the discontinuous interface. This indicates that the determination of the convergence rates which are uniformly valid can be a difficult task. A general practice then has been to estimate such rates only empirically.

In this paper, we use the empirically estimated convergence rates to compute the optimized combination of sample sizes. We use the method of Lagrange multipliers to optimize the values. We then show that the sample sizes thus computed indeed provide a reduction in computational complexity as compared with the Monte Carlo Method. Finally, we present some numerical experiments to verify the theoretical computations.

The rest of the paper is organized as follows: We start by covering some preliminary background in Section 2. In Section 3, we prove that a unique solution exists to (1.1) and in Section 4, we analyze the Monte Carlo and the Multilevel Monte Carlo Methods. Finally, we test the method developed in this section on some numerical examples in Section 5 and describe the conclusions of our analysis in Section 6.

2. Preliminaries.

2.1. Preliminaries from Probability. We first introduce some preliminary concepts which are needed in the exposition. A large part of the exposition has been adapted from [19, 29]. Let \((\Omega, \mathcal{F}, P)\) be a probability space and let \((\mathbb{S}, \mathcal{B}(\mathbb{S}))\) be a Banach space where \(\mathcal{B}(\mathbb{S})\) is the Borel \(\sigma\)-algebra over \(\mathbb{S}\). A map \(G: \Omega \to \mathbb{S}\) is called a \(P\)-simple function if it is of the form

\[
G(\omega) = \sum_{j=1}^{J} g_j 1_{A_j}(\omega), \quad \text{where} \quad 1_A(\omega) := \begin{cases} 1 & \text{if } \omega \in A, \\ 0 & \text{otherwise}. \end{cases}
\]  

(2.1)

\(g_j \in \mathbb{S}\) and \(A_j \in \mathcal{F}\) for \(j = 1, 2, \ldots, J\). A map \(G: \Omega \to \mathbb{S}\) is strongly \(P\)-measurable if there exists a sequence of simple functions \(G_n\) converging to \(G\) in the \(\mathbb{S}\)-norm \(P\)-almost everywhere on \(\Omega\). A strongly \(P\)-measurable map \(G: \Omega \to \mathbb{S}\) is called an \(\mathbb{S}\)-valued random variable. We call two strongly \(P\)-measurable functions, \(G_a, G_b: \Omega \to \mathbb{S}\), \(P\)-versions of each other if they agree \(P\)-almost everywhere on \(\Omega\).

Lemma 2.1. Let \((\Omega, \mathcal{F}, P)\) be a probability space and \(\mathbb{S}_1\) and \(\mathbb{S}_2\) be two Banach spaces. Let \(f: \Omega \to \mathbb{S}_1\) be a strongly measurable function and \(g: \mathbb{S}_1 \to \mathbb{S}_2\) be a continuous function. Then the function \(g \circ f: \Omega \to \mathbb{S}_2\) is a strongly measurable function.

Definition 2.2 (Integration on Banach Spaces). The integral of a simple function \(G: \Omega \to \mathbb{S}\) is defined as

\[
\int_{\Omega} G \, dP := \sum_{j=1}^{N} g_j P(A_j).
\]

(2.2)

A strongly measurable map \(G: \Omega \to \mathbb{S}\) is said to be Bochner integrable if there exists a sequence of simple functions \((G_n)_{n \geq 0}\), converging to \(G\), \(P\)-almost everywhere such that

\[
\lim_{n \to \infty} \int_{\Omega} \| G - G_n \|_{\mathbb{S}} \, dP = 0.
\]

(2.3)
The Bochner integral of a strongly measurable map \( G \) is then defined by

\[
\int_{\Omega} G \, dP := \lim_{n \to \infty} \int_{\Omega} G_n \, dP.
\]

**Theorem 2.3.** A strongly measurable map \( G: \Omega \to S \) is Bochner integrable if and only if

\[
\int_{\Omega} \| G \|_S \, dP < \infty,
\]

in which case, we have

\[
\left\| \int_{\Omega} G \, dP \right\|_S \leq \int_{\Omega} \| G \|_S \, dP.
\]

**Definition 2.4 (\( L^p \) Spaces on Banach Spaces).** For each \( 1 \leq p < \infty \), we define the space \( L^p(\Omega, S) \) to consist of all strongly measurable functions \( G \) for which \( \int_{\Omega} \| G \|_E^p \, dP < \infty \). These spaces are Banach spaces under the norm

\[
\| G \|_{L^p(\Omega, S)} := \int_{\Omega} \| G \|_E^p \, dP.
\]

For \( p = \infty \), we define the space \( L^\infty(\Omega, S) \) as the space of all strongly measurable functions \( G: \Omega \to S \) for which there exists a \( r \geq 0 \) such that \( P(\| f \|_S > r) = 0 \). This space is a Banach space under the norm

\[
\| G \|_{L^\infty(\Omega, S)} := \inf \{ r \geq 0 \mid P(\| G \|_S > r) = 0 \}.
\]

**Definition 2.5 (Banach Space of Type \( p \)).** Let \( Z_i, i \in \mathbb{N} \) be a sequence of independent Rademacher random variables. A Banach space \( S \) is said to have the type \( 1 \leq p \leq 2 \) if there is a constant \( \kappa > 0 \) (known as the type constant) such that for all finite sequences \( (x_i)_{i=1}^M \in S \)

\[
\left\| \sum_{i=1}^M Z_i x_i \right\|_S \leq \kappa \left( \sum_{i=1}^M \| x_i \|_S^p \right)^{\frac{1}{p}}.
\]

**Theorem 2.6 ([19, page 246]).** Let \( 1 \leq q < \infty \) and let \( (\Omega, \mathcal{F}, P) \) be a measure space and let \( S \) be a Banach space having the type \( p \), then the space \( L^q(\Omega, S) \) has the type \( \min(q, p) \). In particular, the Banach space \( L^q(\mathbb{R}^n) \) has the type \( \min(q, 2) \).

**Theorem 2.7 ([19, Proposition 9.11]).** Let \( S \) be a Banach space having the type \( p \) with the type constant \( \kappa \). Then, for every finite sequence \( (X_i)_{i=1}^M \) of zero mean independent random variables in \( L^p(\Omega, S) \), we have

\[
\mathbb{E} \left[ \left\| \sum_{i=1}^M X_i \right\|_S^p \right] \leq (2\kappa)^p \sum_{i=1}^M \mathbb{E} \left[ \| X_i \|_S^p \right].
\]
Given a probability space \((\Omega, \mathcal{F}, \mathbb{P})\) and a Banach space \(\mathbb{S}\), let \(X: (\Omega, \mathcal{F}, \mathbb{P}) \to \mathbb{S}\) be a random variable. Given \(M\) independent, identically distributed samples \((\tilde{X}_i)_{i=1}^M\) of \(X\), the Monte Carlo estimator \(E_M[X]\) of \(\mathbb{E}[X]\) is defined as the sample average

\[
(2.10) \quad E_M[X] := \frac{1}{M} \sum_{i=1}^M \tilde{X}_i.
\]

Theorem 2.8 ([18, Corollary 2.5]). Let the Banach space \(\mathbb{S}\) have the type \(p\) with the type constant \(\kappa\). Let \(X \in L^p(\Omega; \mathbb{S})\) be a zero mean random variable. Then for every finite sequence \((\tilde{X}_i)_{i=1}^M\) of independent, identically distributed samples of \(\hat{X}\),

\[
(2.11) \quad \mathbb{E} \left[ \| E_M[X] \|_\mathbb{S}^p \right] \leq (2\kappa)^p M^{1-p} \mathbb{E} \left[ \| X \|_{L^p(\Omega, \mathbb{S})}^p \right].
\]

Theorem 2.9 ([18, Theorem 4.1]). Let \(X \in L^p(\Omega; L^q(\mathbb{R}))\), then the Monte Carlo estimate \(E_M(X)\) converges in \(L^p(\Omega; L^q(\mathbb{R}))\) for \(p := \min\{2, q\}\) and we have the bound

\[
(2.12) \quad \| \mathbb{E}[X] - E_M[X] \|_{L^p(\Omega; L^q(\mathbb{R}))} \leq 2\kappa M^{\frac{1-p}{p}} \| X \|_{L^p(\Omega; L^q(\mathbb{R}))}.
\]

2.2. Conservation Law with Discontinuous Flux. We next present a series of results for conservation laws with spatially discontinuous flux that we will need later in the paper. In (1.1), for a fixed \(\omega\), the problem reduces to the deterministic conservation law

\[
(2.13a) \quad \frac{\partial u(x, t)}{\partial t} + \frac{\partial (k(x)f(u))}{\partial x} = 0, \quad (x, t) \in \mathbb{R} \times [0, \infty)
\]

\[
(2.13b) \quad u(x, 0) = u_0(x).
\]

Definition 2.10 (Weak Solution). A weak solution to (2.13a) is a bounded measurable function \(u: \mathbb{R} \times \mathbb{R}_+ \to \mathbb{R}\), \(u \in L^\infty(\mathbb{R})\), satisfying, for all \(\varphi \in C_0^\infty(\mathbb{R} \times \mathbb{R}_+)\),

\[
(2.14) \quad \int_{\mathbb{R} \times \mathbb{R}_+} \left[ u(x, t)\varphi_t(x, t) + k(x)f(u)\varphi_x(x, t) \right] \, dx \, dt + \int_{\mathbb{R}} u_0(x)\varphi(x, 0) \, dx = 0.
\]

Theorem 2.11 (Existence of Weak Solution [15]). If the conditions (1.2a), (1.2b), and (1.2g) are satisfied, then there exists a weak solution \(u(x, t)\) to (2.13a), and we have the weak solution \(u \in L^1(\mathbb{R}) \cap L^\infty(\mathbb{R})\) and hence by interpolation for all \(1 \leq q \leq \infty\), \(u \in L^q(\mathbb{R})\) and \(\| u \|_{L^\infty(\mathbb{R})} \leq c = \max(|a|, |b|)\).

Definition 2.12 (Modified Kruzkov Entropy Condition [28]). Let \((V, F)\) be a convex entropy/entropy flux pair for (2.13a), and assume that \(V = C^2[0, 1]\). A weak solution \(u\) for (2.13a) is said to be an entropy solution if for every smooth test function \(\phi \geq 0\) with compact support in \(t > 0, x \in \mathbb{R} \setminus \mathcal{D}\), where \(\mathcal{D}\) is defined in (1.2d) and every \(c \in \mathbb{R}\), \(u\) satisfies the inequality

\[
(2.15) \quad \int_{\mathbb{R} \times \mathbb{R}_+} V(u)\phi_t + kF(u)\phi_x \, dx \, dt - \int_{\mathbb{R} \times \mathbb{R}_+} k'(x)(V'(u)f(u) - F(u))\phi \, dx \, dt \geq 0.
\]
Theorem 2.13 (Uniqueness of Entropy Solution [15]). If in addition to conditions required in Theorem 2.11, conditions in (1.2d) is also satisfied, then there exists a unique weak entropy solution to (2.13a) satisfying the inequality

\[(2.16) \quad \| u \|_{L^1(\mathbb{R})} \leq e^{C_a(k)t} \| u_0 \|_{L^1(\mathbb{R})}\]

where

\[(2.17) \quad C_a(f, k) = \| k' \|_{L^\infty(\mathbb{R} \setminus D)} \| f \|_{L^\infty}\]

Theorem 2.14 (L^1 Stability Result [17]). If in addition to conditions required in Theorem 2.13, conditions in (1.2e) and (1.2f) are also satisfied, then we have

\[(2.18) \quad \| u(\cdot, t) - v(\cdot, t) \|_{L^1(\mathbb{R})} \leq \| u_0 - v_0 \|_{L^1(\mathbb{R})} + t \left( \| f \|_{L^\infty(\mathbb{R})} TV(k - l) + C_s(f, k, u_0) \| k - l \|_{L^\infty(\mathbb{R})} \right)\]

where

\[(2.19a) \quad C_s(f, k, u_0) := \min\left( C_a(f, k, u_0), C_a(f, t, v_0) \right)\]

\[(2.19b) \quad C_a(f, k, u_0) := \frac{5 \max(\| k \|_{L^\infty}, 1) \| f \|_{L^\infty}}{\min(\alpha, \alpha^2)} \left( TV(\Psi(u_0, k)) + TV(k) \right)\]

\[(2.19c) \quad \Psi(u, k)(x) := k(x) \operatorname{sgn}(u - u^*) \frac{f(u^*) - f(u)}{f(u^*))}\]

3. Random Conservation Law with Discontinuous Flux. For a conservation law with a random flux and a random initial condition, we consider the Cauchy problem given in (1.1). In this section, we show that the solutions to (1.1) existence and are pathwise unique under an entropy condition. For the purpose, we first define the allowed space of Cauchy data

Definition 3.1 (Random Data). Define a norm

\[(3.1) \quad \| (u_0, k) \|_\mathcal{D} := \| u_0 \|_{L^1(\mathbb{R})} + \| u_0 \|_{L^\infty(\mathbb{R})} + \| k \|_{L^\infty(\mathbb{R})} + \| k \|_{BV}\]

where \( \| k \|_{BV} = \| k \|_{L^1} + \| k \|_{TV} \). Let \( L > 0 \) be a fixed constant, then we assume that \( \mathcal{D} \) is the the space of functions \((u_0(x), k(x))\) which satisfy the conditions in (1.2) almost everywhere. We note that \( \mathcal{D} \) is a Banach space under the given norm. Let \( \mathcal{B}(\mathcal{D}) \) be the Borel \( \sigma \)-algebra on \( \mathcal{D} \) and let \( M < \infty \) be some fixed constant. Then, we assume that the random data is a strongly measurable map \((u_0, k) : (\Omega, \mathcal{F}) \to (\mathcal{D}, \mathcal{B}(\mathcal{D}))\) such that

\[(3.2) \quad \| (u_0, k) \|_{L^\infty(\Omega; \mathcal{D})} < M\]

From the results for the deterministic conservation law, we would expect the random solution to be a random variable taking values in \( C(\mathbb{R}, L^\infty(\mathbb{R}) \cap L^q(\mathbb{R})) \) for \( 1 \leq q < \infty \). Denote the space of solutions as \( \mathcal{S} \) and write the solution in terms of a mapping \( \mathcal{S} : \mathcal{D} \to \mathcal{S} \), whence we have,

\[(3.3) \quad \mathcal{S} = C\left(\mathbb{R}, L^1(\mathbb{R})\right) \cap L^\infty\left(\mathbb{R}, L^\infty(\mathbb{R})\right) \quad u(\cdot, t) = \mathcal{S}(u_0, k)(t)\]
Definition 3.2 (Random Entropy Solution). Given a probability space \((\Omega, \mathcal{F}, \mathbb{P}) \ni \omega, a\) random variable \(u: (\Omega, \mathcal{F}, \mathbb{P}) \to \mathbb{S}\) is said to be a random entropy solution for (1.1) if the following conditions are satisfied:

1. Weak Solution For \(\mathbb{P}\)-a.e. \(\omega \in \Omega\), \(u(\omega; \cdot, \cdot)\) satisfies

\[
\int_{I \times \mathbb{R}^+} \left[u(\omega; x, t) \phi_t(x, t) + k(\omega; x) f(u(x)) \phi_x(x, t)\right] \, dx \, dt + \int_I u(\omega; x) \phi(x, 0) \, dx = 0.
\]

for all \(\phi \in C^\infty_0(I \times \mathbb{R}^+)\).

2. Entropy Condition For \(\mathbb{P}\)-a.e. \(\omega \in \Omega\), \(u(\omega; \cdot, \cdot)\) satisfies the entropy condition as in Definition Definition 2.12.

\[
\int_{\mathbb{R} \times \mathbb{R}^+} V(u(\omega)) \phi_t + k(\omega) F(u(\omega)) \phi_x \, dx \, dt - \int_{\mathbb{R} \times \mathbb{R}^+} k'(\omega; x) \left(V'(u(\omega)) f(u(\omega)) - F(u(\omega))\right) \phi \, dx \, dt \geq 0
\]

Theorem 3.3 (Existence and \(\omega\)-wise Uniqueness of a Random Entropy Solution). For each \(f\) satisfying (1.2), and \((u_0, k)\) the random data as defined in Definition Definition 3.1, then there exists a unique random entropy solution \(u: \Omega \to \mathbb{S}\) to the random conservation law (1.1).

Proof. By (3.2) for almost all \(\omega \in \Omega\), the random data \((u_0, k)\) is such that there exists a corresponding unique entropy solution \(u(\omega; \cdot, \cdot) \in \mathbb{S}\). By the assumptions of the theorem, the map \((u_0, k): \Omega \to \mathbb{D}\) is a strongly measurable map. Further, by (2.18), the map \(u(x, t): \mathbb{D} \to \mathbb{S}\) is continuous. Then Lemma Lemma 2.1 shows that the map \(u(\omega; \cdot, \cdot): \Omega \to \mathbb{S}\) is strongly measurable. And hence, there exists a random entropy solution to (1.1).

Next, let the random variables \((u_0, k) \in \mathbb{D}\) and \((\tilde{u}_0, \tilde{k}) \in \mathbb{D}\) be \(\mathbb{P}\)-versions of each other. For all times \(t\), let \(u(\cdot, t)\) be the random entropy solution corresponding to \((u_0, k)\) at time \(t\) and \(\tilde{u}(\cdot, t)\) be the random entropy solution corresponding to \((\tilde{u}_0, \tilde{k})\) at time \(t\). Then by (2.18) and (3.1), for \(C_s = \max(C_a(\omega), C_a(\omega))\) and \(\omega \mathbb{P}\)-almost everywhere we have

\[
\|u(\omega; \cdot, t) - \tilde{u}(\omega; \cdot, t)\|_{L^1(\mathbb{R})} \\
\leq \|u_0 - \tilde{u}_0\|_{L^1(\mathbb{R})} + t \left(\|f\|_{L^\infty(\mathbb{R})} \text{TV}(\tilde{k} - \tilde{k}) + C_s \|	ilde{k} - \tilde{k}\|_{L^\infty(\mathbb{R})}\right)
\]

This implies that for \(\omega \mathbb{P}\)-almost everywhere we have \(u(\omega; x, t) = \tilde{u}(\omega; x, t)\) almost everywhere in \(\mathbb{R}\). And hence, for all \(1 \leq q < \infty\), the random entropy solution \(u\) is unique in \(L^\infty(\Omega; L^\infty(\mathbb{R}) \cap L^q(\mathbb{R}); d\mathbb{P})\) and therefore in \(\mathbb{S}\).

Theorem 3.4. Let \(u(\cdot, \cdot, \cdot)\) be a random entropy solution to (1.1) as per Definition Definition 3.2. For any \(1 \leq k < \infty\) and \(1 \leq q < \infty\), we have \(u(\cdot, \cdot, \cdot) \in L^k(\Omega; C([0, T], L^q(\mathbb{R})))\) and

\[
\|u(\cdot, \cdot, \cdot)\|_{L^k(\Omega; C([0, T], L^q(\mathbb{R})))} \leq e^{CT} \|u_0\|_{L^k(\Omega; L^q(\mathbb{R}))}
\]
where $C = \max_{\omega \in \Omega} C_d(f, k(\omega))$ is dependent linearly on $M$, $C = C_0 M$ where $C_0$ is a constant. Given a bounded interval $D$, we also have the estimate

$$\| u(\cdot, \cdot) \|_{L^k(\Omega, C([0,T], L^q(D)))} \leq c |D|^{1/q}$$

where $c$ is as defined in Theorem Theorem 2.11.

**Proof.** By Theorem Theorem 2.11, for any $1 \leq k < \infty$, we have for $\mathbb{P}$-almost everywhere $\omega \in \Omega$,

$$\| u(\cdot, \cdot) \|_{L^k(\Omega, C([0,T], L^q(\mathbb{R})))} \leq \left[ \int_{\Omega} \sup_{t \in [0,T]} \| u(\omega; \cdot, t) \|_{L^q(\mathbb{R})}^k \, d\mathbb{P} \right]^{1/k}$$

$$\leq \left[ \int_{\Omega} e^{C_d(f, k(\omega)T)} \| u(\omega; \cdot, 0) \|_{L^q(\mathbb{R})}^k \, d\mathbb{P} \right]^{1/k}$$

$$\leq e^{CT} \left[ \int_{\Omega} \| u(\omega; \cdot, 0) \|_{L^q(\mathbb{R})}^k \, d\mathbb{P} \right]^{1/k}$$

$$\leq e^{CT} \| u_0 \|_{L^k(\Omega, L^q(\mathbb{R}))}$$

And hence, we have, for all $1 \leq k < \infty$, $u \in L^k(\Omega; C([0,T], L^q(\mathbb{R})))$. Also, by the fact that $\| u \|_{L^\infty(\mathbb{R})} \leq c$, we have

$$\| u(\cdot, \cdot) \|_{L^k(\Omega, C([0,T], L^q(D)))} \leq \left[ \int_{\Omega} \sup_{t \in [0,T]} \| u(\omega; \cdot, t) \|_{L^q(D)}^k \, d\mathbb{P} \right]^{1/k}$$

$$\leq c |D|^{1/q}$$

4. **Multilevel Monte Carlo Finite Volume Method.** Monte Carlo methods are a class of methods where repeated random sampling is used to obtain the mean value and the subsequent moments of the random variable. In our case, the samples are the entropy solution to the deterministic Cauchy problem for the corresponding samples of Cauchy data. The exact solutions to those deterministic problems are however unavailable and instead, we must use a numerical approximation. Here, we use a finite volume method to compute the numerical approximation to the deterministic problem.

The error introduced by the Monte Carlo methods depends on the number of samples used, while the error introduced by the finite volume methods depends on the resolution of the grid. Different combinations of grids can be used to compute the finite volume approximations for different samples. In this section, we will describe and analyze two such combinations, denoted by the Monte Carlo Finite Volume Method (MC-FVM) and the Multilevel Monte Carlo Finite Volume Method (MLMC-FVM). We solve our random conservation law on a compact interval $D = [x_L, x_R]$ and in the time interval $[0, T]$. 
Definition 4.1 (Cauchy Problem Sample, Solution Sample and FVM Solution Sample). In the context of Monte Carlo methods, given a sample \((u_0, k)(\omega_0)\) of the random variable \((u_0, k)\), the corresponding deterministic Cauchy problem will be referred to as the Cauchy problem sample for \(\omega_0\). Similarly, the unique entropy solution and the finite volume solution for the Cauchy problem sample will be referred to as the solution sample \(u(\omega_0; \cdot, \cdot)\) for \(\omega_0\) and the finite volume solution sample \(U(\omega; \cdot, \cdot)\) for \(\omega_0\) respectively.

Definition 4.2 (N-discretization). Let the domain \(D = [x_L, x_R]\). Divide the domain \(D\) into \(N\) uniform cells \(D_j\) of size \(\Delta x = \frac{|D|}{N}\) and \(x_j\) the cell center and the cell length \(h\) are given as

\[
x_j = \frac{x_{j+\frac{1}{2}} + x_{j-\frac{1}{2}}}{2},
\]

\[
\Delta x = \frac{|D|}{N}
\]

4.1. Finite Volume Method For Conservation Law with Discontinuous Flux. Given a Cauchy problem sample and a \(N\)-discretization \(K\) of \(D\) containing \(N\) cells, we now describe a method to compute the FVM solution \(U(x, t)\) to the solution of the given Cauchy problem. The initial conditions of the Cauchy problem dictate that

\[
U^0_j = \frac{1}{h} \int_{D_j} u_0(x) dx
\]

We denote the cell averages of the solution \(U(x, t)\) for the \(j\)-th cell at \(n\)-th time step as \(U_{n,j}\),

\[
U^n_j = \frac{1}{|D_j|} \int_{D_j} U(x, t_n) dx
\]

The function \(k(x)\) is computed at the cell interfaces by considering the cell averages on the staggered grid as shown below

\[
k_{j+\frac{1}{2}} = \frac{1}{\Delta x} \int_{x_j}^{x_{j+1}} k(x) dx
\]

The finite volume scheme is then defined as

\[
U^{n+1}_j = U^n_j - \frac{\Delta t n}{\Delta x} \left[ H_{j+\frac{1}{2}} - H_{j-\frac{1}{2}} \right]
\]

where \(H\) is given by

\[
H_{j+\frac{1}{2}} = k_{j+\frac{1}{2}} F \left( U_{n+1}^{j+1}, U^n_j \right)
\]

where \(F\) is an monotone numerical flux. There are a few different numerical fluxes that are appropriate in this problem. We use the following numerical fluxes motivated by [28].
1. Godunov Flux

\[
F(U_l, U_r) = \begin{cases} 
  f(u^*) & \text{if } U_l \leq u^* \leq U_r \\
  \min_{U_l \leq \theta \leq U_r} f(u) & \text{if } U_l \leq U_r \leq u^* \text{ or } u^* \leq U_l \leq U_r \\
  \min_{U_r \leq \theta \leq U_l} f(u) & \text{if } U_r \leq U_l \leq u^* \text{ or } u^* \leq U_r \leq U_l 
\end{cases}
\]

(4.6)

2. Engquist-Osher Flux

\[
F(U_l, U_r) = f(U_l) + f(U_r) - \frac{1}{2} \int_{U_l}^{U_r} |f'(\theta)| \, d\theta
\]

(4.7)

**Theorem 4.3** ([28, Theorem 3.2]). Let \( u_0, k, f \) satisfy the conditions in (1.2). Additionally, assume

\[
f''(u) > 0 \quad \text{for all } u \in [a, b]
\]

Then, the finite volume scheme (4.5) converges to the entropy solution of the Cauchy problem (2.13a) on \( D \) provided that the time step \( \Delta t \) follows the CFL condition

\[
\Delta t \leq \frac{\Delta x}{k \|f''\|_{\infty}}
\]

(4.9)

**Remark 4.4.** The convergence rates for the numerical methods are yet unknown. However, we do need the convergence rates to determine the optimal sample numbers for the analysis of MLMC method. Hence, we assume that the convergence rate for the \( L^q \)-error between the numerical solution and the exact solution is \( s_q \)

\[
\| U(x, t) - u(x, t) \|_{L^q} < C_b(u_0, q, t) \Delta x^{s_q}
\]

(4.10)

**4.2. Monte Carlo Finite Volume Methods.** We now describe and analyze the MC-FVM to compute the numerical approximation to the random entropy solution \( u \) for conservation law (1.1). The underlying idea of MC-FVM is to use identical uniform discretization to solve each of the Cauchy problem sample.

**Definition 4.5 (MC-FVM Approximation).** Generate \( M \) independent, identically distributed samples \( (\hat{u}_{0,i}, \hat{k}_i) \)\( i=1 \) of each \( \hat{U}_i \). Let \( K \) be a \( N \)-discretization of the spatial domain \( D \). Let \( \hat{U}_i \) denote the FVM solution sample corresponding to \( (\hat{u}_{0,i}, \hat{k}_i) \) at time \( T \). Then, the \( M \)-sample MC-FVM \( E_{MC}(u) \) to \( E[u] \) is defined as

\[
E_{MC}(u) := E_M[U] := \frac{1}{M} \sum_{i=1}^{M} \hat{U}_i
\]

(4.11)

The variance is defined as

\[
\text{Var}_{MC}(u) := E_M[U^2] - E_M[U]^2
\]

(4.12)
Then by Hölder inequality for probability spaces we have
\[
\mathcal{E}_{MC}(u) := \| \mathbb{E}[u] - E_{MC}(u) \|_{L^p(\Omega; L^q(D))} \leq |D|^{\frac{1}{p} + \frac{1}{q} - \frac{3}{2}} 2\kappa M^{\frac{1}{2}} + C_\delta(q) \Delta x^s
\]
where \( s_q \) is the rate of convergence determined empirically from the numerical experiments.

**Proof.** For the first inequality, using the triangle inequality, we can write
\[
\mathbb{E}[u] - E_{MC}(u) = \mathbb{E}[u] - E_{MC}(u) + E_{MC}(u) - E_{MC}(u)
\]
Using the fact that \( p \leq 2 \) and applying Hölder inequality, Theorem 2.9 and (3.6) to the first term, we have
\[
\| \mathbb{E}[u] - E_{MC}(u) \|_{L^p(\Omega; L^q(D))} = \left[ \int \| \mathbb{E}[u] - E_{MC}(\omega, u) \|_{L^q(D)}^p \right]^\frac{1}{p}
\]
\[
= \left[ \int 1 \cdot \| \mathbb{E}[u] - E_{MC}(\omega, u) \|_{L^q(D)}^p \right]^\frac{1}{p}
\]
Let \( r, s > 0 \) be such that
\[
\frac{1}{r} + \frac{1}{s} \leq 1
\]
Then by Hölder inequality for probability spaces we have
\[
\| \mathbb{E}[u] - E_{MC}(u) \|_{L^p(\Omega; L^q(D))} \leq \left[ \int 1^r \mathrm{d}\omega \right]^\frac{1}{r} \cdot \left[ \int \| \mathbb{E}[u] - E_{MC}(\omega, u) \|_{L^q(D)}^p \mathrm{d}\omega \right]^\frac{1}{p}
\]
Since \( p \leq 2 \), we can put \( s = \frac{2}{p} \) and \( r = 1 - \frac{2}{p} \) and obtain
\[
\| \mathbb{E}[u] - E_{MC}(u) \|_{L^p(\Omega; L^q(D))} \leq \left[ \int 1^{\frac{2}{p}} \cdot \left[ \int \| \mathbb{E}[u] - E_{MC}(\omega, u) \|_{L^q(D)}^{\frac{2}{p}} \mathrm{d}\omega \right]^\frac{1}{p} \right]^\frac{1}{r}
\]
\[
\leq |D|^{\frac{1}{p} - \frac{2}{r}} \cdot \left[ \int \| \mathbb{E}[u] - E_{MC}(\omega, u) \|_{L^q(D)} \right]^\frac{1}{2} \mathrm{d}\omega
\]
\[
\leq |D|^{\frac{1}{p} - \frac{2}{r}} \| \mathbb{E}[u] - E_{MC}(u) \|_{L^2(\Omega; L^q(D))}
\]
\[
\leq |D|^{\frac{1}{p} - \frac{2}{r}} 2\kappa M^{\frac{1}{2}} \| u \|_{L^2(\Omega; L^q(D))}
\]
\[
\leq |D|^{\frac{1}{p} - \frac{2}{r} + \frac{1}{q}} 2\kappa M^{\frac{1}{2}}
\] for \( q > 2 \)
For the second term, by (4.10), we have
\[
\| E_M[u] - E_{MC}(u) \|_{L^p(\Omega;L^q(D))} \leq \sup_i \| (\hat{u}_i - \hat{U}_i) \|_{L^q(D)} \\
\leq C_b(u_0, q, T) \Delta x^s
\]

Remark 4.7. We would like to point out that in the proof above, the error bounds are derived by assuming that \( q \geq 2 \). A similar procedure will be carried out for the MLMC-FVM. Furthermore, we use the same error bounds for calculation of optimal sample numbers. Whence, we require that the error bounds and the rate of error used for the optimal sample numbers should be for \( q \geq 2 \).

4.3. Multilevel Monte Carlo Finite Volume Methods. The underlying idea of the MLMC-FVM is to use a hierarchy of nested set of discretization and solve several Cauchy problem samples on each of them.

Definition 4.8 (MLMC-FVM Approximation). Let \((K_l)_{l=0}^L\) be a sequence of nested \( 2^l N \) discretization of the spatial domain \( D \). For each level \( l \), define by \( U_l \) the random Finite Volume approximation on \( K_l \) with \( U_{-1} = 0 \). Then, given \((M_l)_{l=0}^L \in \mathbb{N} \), the MLMC-FVM approximation \( E_{\text{MLMC}}(u) \) to \( E[u] \) is then defined as
\[
(4.15a) \quad E_{\text{MLMC}}(u) = \sum_{l=0}^L E_{M_l}(U_l - U_{l-1})
\]
\[
(4.15b) \quad \text{Var}_{\text{MLMC}}(u) = \sum_{l=0}^L \Delta V_l
\]
\[
(4.15c) \quad \Delta V_l = \text{Var}_{\text{MC}}(U_l - U_{l-1})
\]
\[
(4.15d) \quad = E_{M_l} \left[ (u_l - u_{l-1} - E_{M_l}[u_l - u_{l-1}])^2 \right]
\]

It must be emphasized here that for every discretization \( K_l \) apart from \( K_L \) and, the approximate solution is compute twice, once for the level \( l \) and another time for level \( l+1 \) in an independent manner. This is important to ensure that \( U_l - U_{l-1} \) is independent from \( U_{l-1} - U_{l-2} \).

Theorem 4.9 (MLMC-FVM Error Bound). Assume that \( f \in F_n \) and \((u_0, k)\) is the random data as defined in Definition Definition 3.1, then for the random conservation law (1.1), for \( p = \min\{2, q\} \), the MLMC-FVM approximation converges to \( E[u] \) as \( M_l \to \infty \) for \( l = 0, 1, \ldots, L \) and \( \Delta x \to 0 \). Further, we have the bound
\[
(4.16) \quad \mathcal{E}_{\text{MLMC}}(u) := \| E[u] - E_{\text{MLMC}}(u) \|_{L^p(\Omega;L^q(D))} \leq C_b(u_0, T, q) (\Delta x)^s \left( 2^{-L s q} + C_m(p, q) \sum_{l=0}^L M_l^{-\frac{1}{2}} 2^{-l s q} \right)
\]

where \( C_m(p, q) = |D|^\frac{p}{q} - \frac{1}{2} 2^{p(1 + 2 s q)} \).

Proof. We first derive the error for \( E \). Using the triangle inequality, we can write
\[
\| E[u] - E_{\text{MLMC}}(u) \|_{L^p(\Omega;L^q(D))} \leq \| E[u] - E[U_L] \|_{L^p(\Omega;L^q(D))} + \| E[U_L] - E_{\text{MLMC}}(u) \|_{L^p(\Omega;L^q(D))}
\]

12
For the first term, since $|\Omega| = 1$, we have

$$\| \mathbb{E}[u] - \mathbb{E}[U_L] \|_{L^p(\Omega,L^q(D))} = \mathbb{E}[u - U_L]$$

$$\leq \| u - U_L \|_{L^1(\Omega,L^q(D))}$$

$$\leq \| u - U_L \|_{L^\infty(\Omega,L^q(D))} \quad \text{(Applying Hölder inequality)}$$

$$\leq C_b(u, T, q) 2^{-L_{s_q}(\Delta x)^s_q}$$

For the second term, using the fact that $p \leq 2$, and by Hölder inequality, Theorem 2.9 and Theorem 4.3

$$\| \mathbb{E}[U_L] - E_{\text{MLMC}}(u) \|_{L^p(\Omega,L^q(D))} = \left\| \sum_{l=0}^{L} \mathbb{E}[U_l - U_{l-1}] - \sum_{l=0}^{L} E_M(U_l - U_{l-1}) \right\|_{L^p(\Omega,L^q(D))}$$

$$\leq \sum_{l=0}^{L} \| \mathbb{E}[U_l - U_{l-1}] - E_M(U_l - U_{l-1}) \|_{L^p(\Omega,L^q(D))}$$

Now, following a procedure similar to the one followed in (4.14),

$$\| \mathbb{E}[U_L] - E_{\text{MLMC}}(u) \|_{L^p(\Omega,L^q(D))} \leq \sum_{l=0}^{L} |D|^{\frac{1}{p} - \frac{1}{2}} \| \mathbb{E}[U_l - U_{l-1}] - E_M(U_l - U_{l-1}) \|_{L^2(\Omega,L^q(D))}$$

$$\leq \sum_{l=0}^{L} |D|^{\frac{1}{p} - \frac{1}{2}} 2\kappa M_l^{-\frac{1}{2}} \| U_l - U_{l-1} \|_{L^q(D)}$$

$$\leq \sum_{l=0}^{L} |D|^{\frac{1}{p} - \frac{1}{2}} 2\kappa M_l^{-\frac{1}{2}} \left( \| U_l - u \|_{L^q(D)} + \| U_{l-1} - u \|_{L^q(D)} \right)$$

$$\leq \sum_{l=0}^{L} |D|^{\frac{1}{p} - \frac{1}{2}} 2\kappa C_b(q) (2^{-l} \Delta x)^{s_q} + C_b(q) (2^{-l+1} \Delta x)^{s_q})$$

$$\leq |D|^{\frac{1}{p} - \frac{1}{2}} 2\kappa C_b(q) (\Delta x)^{s_q} (1 + 2^{s_q}) \sum_{l=0}^{L} M_l^{-\frac{1}{2}} 2^{-l s_q}$$

$$\leq C_b(q) C_m(p,q) (\Delta x)^{s_q} \sum_{l=0}^{L} M_l^{-\frac{1}{2}} 2^{-l s_q}$$

4.4. Work Estimates and Sample Number Optimization. The work required to compute a MCFVM or a MLMC-FVM approximation and the corresponding error depends on multiple factors, namely the grid resolution $\Delta x$, number of levels $L$ and the sample numbers at each level $M_l$, $l = 0, 1, \ldots, L$. To ease the process of finding solution of the optimization problem, we fix the number of levels before computing the sample numbers. In order to get optimal error rates, we need to select these parameters to either minimize the work required to be done for a specified error or to minimize the error given the work needed.

13
In this section, we calculate the work required for MC and MLMC methods as a function of sample numbers and then, we use those functions along with the error expressions previously derived to select the optimal parameters. We assume that the time required to compute the finite volume method solution in a single cell for a single time step is a constant, and we denote it as a unit work. For the purpose of optimization, we will assume that all parameters except for the sample numbers are fixed. In particular, we mandate that the number of levels is not a parameter for optimization, and instead, is fixed.

4.4.1. Optimal Sample Numbers for MC-FVM. The error of an MC-FVM approximation for a grid resolution of $\Delta x$ and $M$ samples is given by (4.13). We use the fact that for a fixed domain $N = |D|/\Delta x$ and incorporate terms independent of $M$ and $N$ into constants $A$ and $B$, when we rewrite the error term as below.

$$\epsilon \leq AM^{-\frac{1}{2}} + BN^{-s_q}$$

$A = |D|^\frac{1}{2} + \frac{1}{2} - \frac{1}{2} \cdot 2^{\kappa b}$, $B = |D|^{s_q} C_b(q)$

The work required to compute the solution is given by

$$W = MN^2$$

Assume that we have the fixed the error $\epsilon = \epsilon_0$. Then, using (4.17), we can write

$$N = \left( \frac{\epsilon_0 - AM^{-\frac{1}{2}}}{B} \right)^{-\frac{1}{s_q}}$$

The work as a function of sample numbers can then be written as

$$W = M \left( \frac{\epsilon_0 - AM^{-\frac{1}{2}}}{B} \right)^{-\frac{2}{s_q}}$$

Quick analysis shows that for $s_q \leq 1$ and $M \geq 1$, the attains a minimum at a single point at which the derivative w.r.t $M$ is 0. Performing the analysis gives us

$$M = \left( \frac{A}{B s_q} \right)^2 N^{2s_q}$$

4.4.2. Optimal Sample Numbers for MLMC-FVM. Consider a $L$-level MLMC-FVM with $N$-cells at level 0. By (4.16), the error for the method can be written in terms of the number of samples $M_0, M_1, \ldots, M_L$ as

$$\epsilon = A \left( 1 + B \sum_{l=0}^{L} 2^{-s_q} M_l^{-\frac{1}{2}} \right)$$

$A = C_b(q) N^{-s_q} |D|^{s_q} 2^{-Ls_q}$, $B = C_m(p, q)2^{Ls_q}$

The work done to calculate the MLMC-FVM approximation can be written as

$$W = \sum_{l=0}^{L} M_l N^2 2^{2l}$$
We use the method of Lagrange multipliers in order to optimize the quantities of interest over multiple variables. We will need the following expressions during optimization,

\[(4.24a) \quad \frac{\partial W}{\partial M_l} = N^2 2^l \]
\[(4.24b) \quad \frac{\partial \epsilon}{\partial M_l} = -\frac{1}{2} AB 2^{-\frac{1}{2}} M_l^{-\frac{3}{2}} \]

We fixed the error at \(\epsilon_0\). The Lagrangian \(\mathcal{L}\) is then given by

\[(4.25) \quad \mathcal{L} = W + \lambda (\epsilon - \epsilon_0) \]

\(W\) will be minimum when \(M_l, l = 0, 1, \ldots, L\) are such that the following condition is satisfied

\[(4.26) \quad \frac{\partial \mathcal{L}}{\partial M_l} = 0 \quad l = 0, 1, \ldots, L \]

which gives us

\[(4.27) \quad M_l = \left( \frac{AB}{2} \right)^{\frac{3}{4}} \lambda^\frac{3}{2} N^{-\frac{3}{4}} 2^{-\frac{4}{3}} 2^{-\frac{1}{2} s q} \]

Putting the value in the value for error, we can get the value of \(\lambda\) as

\[(4.28) \quad \lambda^\frac{3}{2} = \left( \frac{1}{B} \right)^{-2} \left( \frac{\epsilon_0}{A} - 1 \right)^{-2} \left( \frac{AB}{2} \right)^{-\frac{2}{3}} N^4 C^2 \]

and the expression for \(M_l\) independent of \(\lambda\) is given by

\[(4.29) \quad M_l = 2^{-\frac{4}{3}} 2^{-\frac{1}{2} s q} B^2 \left( \frac{\epsilon_0}{A} - 1 \right)^{-2} C^2 \]

5. Numerical Experiments. We now present some numerical experiments which validate the method developed over the previous sections\(^1\). The numerical examples are motivated by the traffic flow problems. In particular, we consider the inhomogeneous Lighthill-Whitham-Richards model which can be written as show below, where the multiplying factor of \(k\) can represent space-dependent factors in the equation like the speed limit on a road.

\[(5.1) \quad \frac{\partial u}{\partial t} + \frac{\partial k(x) f(u)}{\partial x} = 0 \quad f(u) = 4u(1-u) \]

The purpose of the numerical experiments is to check whether the multilevel Monte Carlo methods are computationally more efficient than simple Monte Carlo method. To that end, we have designed our setup in such a way, that the errors produced by both the methods, the Monte Carlo and the Multi-Level Monte Carlo methods are almost equal for a given grid. We then measure the computational effort required to compute the two solution and we compare

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\(^1\)The code can be found at [https://gitlab2.informatik.uni-wuerzburg.de/klingons/mlmc-sconlaw-1d](https://gitlab2.informatik.uni-wuerzburg.de/klingons/mlmc-sconlaw-1d)
them. The computational effort is measured by calculating the CPU time required to run the two different programs.

As noted in Remark 4.4, the convergence rates for the deterministic case are not theoretically known, and instead, we have to use an empirical convergence rate for determination of optimal sample numbers. Experience tells us that we should expect a convergence rate of at least 1/2. We verify that for the above problem, that the convergence rates are at least 1/2.

We now describe the relation between the grid used for the multilevel Monte Carlo method and the grid used for the Monte Carlo method. The base grid is with $N$ cells, and then, for multilevel Monte Carlo method, we use a total for 4 levels, resulting in $2^4N$ cells at the finest grid. For comparison with monte carlo method, we have observed that the grid containing $2N$ cells produces an error that is of the same order as the one produced using MLMC method of 4 levels. Hence, we can then compare the two methods purely on the basis of computational work taken to calculate the two solutions.

Next, we consider the Monte Carlo and the multilevel Monte Carlo methods, wherein, we now calculate the sample numbers as described before using the experimental convergence rates of 0.5 and calculate the optimal sample numbers. We then verify that the deterministic convergence rates of the problem are above 1/2 as required in our analysis and the results are shown in Table 5.1. We use a MC-FVM solution calculated on 16384 cells as a reference solution to calculate the convergence rates. Next, we compute the MC-FVM and the MLMC-FVM solutions. We make sure that the errors from both the computations are of the same order and then compare the work done for the both the cases.

Let $U_e$ be the reference solution as mentioned above and let $U_l$ be the computed MC or MLMC solution for a grid with $2^l$ points, then the error is calculated as

$$
err_l = \left( \frac{\sum_{i=0}^{2^l-1} |U_l(i) - U_e(i)|^2}{\left( \sum_{i=0}^{2^l-1} |U_e(i)|^2 \right)^{1/2}} \right)^{1/2}
$$

where $U_e(i)$ is calculated using linear interpolation. The convergence rates are computed as

$$
\eta_l = \frac{\log(err_{l-1}/err_l)}{\log(2)}
$$

5.1. Traffic Flow Problem with Pulse Coefficient. For the first case, we consider the traffic flow problem, where there are two discontinuities in the function $k$. The discontinuities form a constant width pulse whose position is uncertain. One could think of a road passing through a city with speed limits as a motivation for the case where, the pulse indicates a region of high speed limit as compared to the other roads with lower speed limits. We use
Table 5.1
Pulse Coefficient: Convergence Rates for Deterministic Case

<table>
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<tr>
<th>Cells</th>
<th>32</th>
<th>64</th>
<th>128</th>
<th>256</th>
<th>512</th>
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<tbody>
<tr>
<td>Error</td>
<td>1.1603e-01</td>
<td>8.0871e-02</td>
<td>5.6750e-02</td>
<td>3.9971e-02</td>
<td>2.8207e-02</td>
</tr>
<tr>
<td>Rate</td>
<td>-</td>
<td>0.5209</td>
<td>0.5110</td>
<td>0.5057</td>
<td>0.5029</td>
</tr>
</tbody>
</table>

Figure 5.1. Traffic Flow Problem with Pulse Function Coefficient

periodic boundary conditions for the problem.

\[
\begin{align*}
\frac{\partial u}{\partial t} + \frac{\partial k(\omega;x)f(u)}{\partial x} &= 0 \quad (x, t) \in [-2, 2] \times \left[0, \frac{1}{10}\right] \\
u(x, 0) &= \frac{1}{4} \sin\left(\frac{\pi x}{2}\right) + \frac{1}{2} \quad f(u) = 4u(1-u) \\
\end{align*}
\]

where

\[
k(\omega,x) = \begin{cases} 
1 & \text{if } x < -0.5 + \omega \\
2 & \text{if } -0.5 + \omega \leq x < 0.5 + \omega \\
1 & \text{if } 0.5 + \omega \leq x \\
\end{cases} \quad \omega \in \mathcal{U}(-1, 1)
\]

5.2. Traffic Flow Problem with a Brownian Bridge with Jumps Coefficient. For the second example, we consider the case where the coefficient \( k \) is given by a Brownian Bridge with Jumps. The motivation of this test case can be thought of as traffic on a road with potholes or an off-road route. We construct such a bridge from a Brownian bridge pinned at
<table>
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<tr>
<td>MC</td>
<td>6.2149e-2</td>
<td>3.60286e-1</td>
<td>2.4019e-1</td>
<td>1.7014e-1</td>
<td>1.2009e-1</td>
</tr>
<tr>
<td>Rate</td>
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<td>0.784</td>
<td>0.584</td>
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<td>0.502</td>
</tr>
<tr>
<td>MLMC</td>
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<td>3.7205e-1</td>
<td>2.4133e-1</td>
<td>1.5083e-1</td>
<td>1.106e-1</td>
</tr>
<tr>
<td>Rate</td>
<td>-</td>
<td>0.940</td>
<td>0.624</td>
<td>0.678</td>
<td>0.44</td>
</tr>
</tbody>
</table>

Table 5.2
Pulse Coefficient : MC and MLMC Errors

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<th>512</th>
<th>1024</th>
</tr>
</thead>
<tbody>
<tr>
<td>MC</td>
<td>4</td>
<td>18.52</td>
<td>135</td>
<td>1092</td>
<td>8490</td>
</tr>
<tr>
<td>Rate</td>
<td>-</td>
<td>2.211</td>
<td>2.865</td>
<td>3.015</td>
<td>2.958</td>
</tr>
<tr>
<td>MLMC</td>
<td>5.5</td>
<td>15.02</td>
<td>40</td>
<td>132</td>
<td>489</td>
</tr>
<tr>
<td>Rate</td>
<td>-</td>
<td>1.449</td>
<td>1.413</td>
<td>1.722</td>
<td>1.889</td>
</tr>
</tbody>
</table>

Table 5.3
Pulse Coefficient : MC and MLMC Work (in compute seconds)

both ends by adding discontinuities at random points in the interval. Let $b(x)$ be a Brownian bridge pinned at 2 at $x = -2, 2$. Next, we start introducing jumps of random magnitude $h_j$ in the Brownian bridge $b(x)$ at random points $x_j, j = 1, 2, \ldots, n$. We ensure that the number of jumps are finite and that $b(x) > 1$ to fulfill the condition $k(x) > 1$. The resultant function $B(x)$ can be written as

$$B(x) = b(x) + \sum_{k=0}^{j} h_k$$

for $x_j < x < x_{j+1}, x_0 = -2, x_{n+1} = 2$

$$\frac{\partial u}{\partial t} + \frac{\partial k(\omega; x)f(u)}{\partial x} = 0 \quad (x, t) \in [-2, 2] \times \left[0, \frac{1}{10}\right]$$

$$u(x, 0) = \frac{1}{4} \sin\left(\frac{\pi x}{2}\right) + \frac{1}{2} \quad f(u) = 4u(1 - u)$$

6. Conclusion. In this paper, we have considered a scalar conservation law with discontinuous flux in space in one dimension. We have defined a random entropy solution for the conservation law and have proved its existence and uniqueness. Further, we have adapted the Multilevel Monte Carlo Finite Volume Method for the problem and have compared its performance with the Monte Carlo Finite Volume Method, wherein, we have shown that the Multilevel Monte Carlo Method behaves as expected in the theoretical analysis. In particular, we show that the Multilevel Monte Carlo method is a more efficient alternative to Monte Carlo methods.

7. Acknowledgements. The work of Jayesh Badwaik was supported by German Priority Programme 1648 (SPPEXA) and the ModCompShock EU Project. The work of Nils Henrik
Figure 5.2. One Instance of Brownian Bridge with Jumps

Figure 5.3. Traffic Flow Problem with Brownian Bridge with Jumps
<table>
<thead>
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<th>Cells</th>
<th>64</th>
<th>128</th>
<th>256</th>
<th>512</th>
<th>1024</th>
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</thead>
<tbody>
<tr>
<td>Error</td>
<td>5.3921e-02</td>
<td>3.7057e-02</td>
<td>2.6009e-02</td>
<td>1.6771e-02</td>
<td>1.6382e-02</td>
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<tr>
<td>Rate</td>
<td>-</td>
<td>0.5411</td>
<td>0.5107</td>
<td>0.6331</td>
<td>0.0338</td>
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Table 5.4
Brownian Bridge with Jumps: Convergence Rates for Deterministic Case

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<tbody>
<tr>
<td>MC-FVM Rate</td>
<td>2.132e-1</td>
<td>1.3872e-1</td>
<td>1.003e-1</td>
<td>7.6139e-2</td>
<td>5.7780e-2</td>
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<tr>
<td>MLMC-FVM Rate</td>
<td>2.3452e-1</td>
<td>1.3925e-1</td>
<td>9.8519e-2</td>
<td>6.6764e-2</td>
<td>5.299e-1</td>
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Table 5.5
Brownian Bridge with Jumps: MC and MLMC Errors

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</thead>
<tbody>
<tr>
<td>MC-FVM Rate</td>
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<tr>
<td>MLMC-FVM Rate</td>
<td>10.82</td>
<td>30.85</td>
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<td>252</td>
<td>922</td>
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</tbody>
</table>

Table 5.6
Brownian Bridge with Jumps: MC and MLMC Work (in compute second)

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REFERENCES


