

STABILITY ANALYSIS FOR STOCHASTIC MCKEAN–VLASOV EQUATION

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Abstract

The p th ($p \geq 1$) moment exponential stability, almost surely exponential stability and stability in distribution for stochastic McKean–Vlasov equation are derived based on some distribution-dependent Lyapunov function techniques.

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1. Introduction

McKean–Vlasov stochastic differential equations (SDEs), originating from the seminal works [15, 18], are also known as mean-field SDEs or distribution-dependent SDEs which are used to study the interacting particle system and mean-field games. There are numerous works on the well-posedness, ergodicity and large deviations [10, 13, 17, 19]. Moreover, there are also several works on the stability of the McKean–Vlasov SDEs. Recently, Ding and Qiao [5] considered the stability for the McKean–Vlasov SDEs with non-Lipschitz coefficients

$$\begin{aligned}dX(t) &= b(X(t), \mathcal{L}(X(t))) dt + \sigma(X(t), \mathcal{L}(X(t))) dW(t), \\X(0) &= x_0,\end{aligned}\tag{1.1}$$

where $\mathcal{L}(X(t))$ is the distribution of $X(t)$, $W = (W^1, W^2, \dots, W^l)$ is a \mathcal{F}_t -adapted standard Brownian motion and the coefficients $b : \mathbb{R}^d \times \mathcal{M}_{\lambda^2}(\mathbb{R}^d) \rightarrow \mathbb{R}^d$ and $\sigma : \mathbb{R}^d \times \mathcal{M}_{\lambda^2}(\mathbb{R}^d) \rightarrow \mathbb{R}^d \times \mathbb{R}^l$ are Borel measurable functions. The definition of $\mathcal{M}_{\lambda^2}(\mathbb{R}^d)$ is defined in the next section. Sufficient conditions are given for the exponential stability of the second moments for their solutions in terms of a Lyapunov

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function [12]. Furthermore, the almost surely (a.s.) asymptotic stability of their solutions is also discussed. Lv and Shan [14] considered the long time behaviour of stochastic McKean–Vlasov equations, and the exponential and logarithmic decay are discussed. Bahlali et al. [1] discussed the existence and uniqueness of solutions under a non-Lipschitz condition and derived various stability properties with respect to initial data, coefficients and driving processes. Wu et al. [20] studied the stability of solutions of McKean–Vlasov SDEs via feedback control based on discrete-time state observation and derived the H_∞ stability, asymptotic stability and exponential stability in mean square for the controlled systems.

In this paper, we first provide a sufficient condition for the p th moment exponential stability and a.s. exponential stability for (1.1) (Theorem 3.2) by using the classical Lyapunov function method. Furthermore, asymptotic stability in distribution is derived by introducing a distribution-dependent operator, together with a similar discussion as that for SDE with Markovian switching [21].

There are many recent works on the stability in distribution for stochastic differential equations with distribution-independent coefficients. Yuan et al. [22] discussed the stochastic differential equations with Markovian switching and investigated the stability in distribution of the equations. Further, Du et al. [6] improved the result of Yuan et al. [22] by giving a new sufficient condition for stability in distribution. Bao et al. [2] considered a neutral stochastic differential delay equation with Markovian switching and obtained sufficient conditions for stability in distribution. Fei et al. [8] considered the stability in distribution for a highly nonlinear stochastic differential equation driven by G -Brownian motion [16].

The rest of the paper is organized as follows. In Section 2, we recall some preliminary knowledge. The p th moment exponential stability and a.s. exponential stability is presented in Section 3.1. The stability in distribution is established in Section 3.2.

2. Preliminary and main result

Let $C(\mathbb{R}^d)$ be the collection of continuous functions on \mathbb{R}^d . For convenience, we denote the norm of vectors and matrices by $|\cdot|$ and $\|\cdot\|$, respectively. Furthermore, let $\langle \cdot, \cdot \rangle$ denote the scalar product in \mathbb{R}^d . Let $\mathcal{B}(\mathbb{R}^d)$ be the Borel σ -algebra on \mathbb{R}^d and $\mathcal{P}(\mathbb{R}^d)$ denote the space of all probability measures defined on $\mathcal{B}(\mathbb{R}^d)$ with the topology of weak convergence.

For $\lambda(x) = 1 + |x|$, $x \in \mathbb{R}^d$, define the Banach space

$$C_\lambda(\mathbb{R}^d) = \left\{ \phi \in C(\mathbb{R}^d) \mid \|\phi\|_{C_\lambda(\mathbb{R}^d)} = \sup_{x \in \mathbb{R}^d} \frac{|\phi(x)|}{\lambda^2(x)} + \sup_{x \neq y} \frac{|\phi(x) - \phi(y)|}{|x - y|} < \infty \right\}.$$

Let $\mathcal{M}_{\lambda^p}^s(\mathbb{R}^d)$ be the space of signed measures m on $\mathcal{B}(\mathbb{R}^d)$ satisfying

$$\|m\|_{\lambda^p}^p = \int_{\mathbb{R}^d} \lambda^p(x) |m|(dx) < \infty, \quad p \geq 2,$$

where $|m| = m^+ + m^-$, and $m = m^+ - m^-$ is the Jordan decomposition of m . Let $\mathcal{M}_{\lambda^p}(\mathbb{R}^d) = \mathcal{M}_{\lambda^p}^s(\mathbb{R}^d) \cap \mathcal{P}(\mathbb{R}^d)$ be the set of probability measures on $\mathcal{B}(\mathbb{R}^d)$ with finite p th moments equipped with the metric,

$$\rho(\mu, \nu) \triangleq \sup_{\|\phi\|_{C^1(\mathbb{R}^d)} \leq 1} \left| \int_{\mathbb{R}^d} \phi(x) \mu(dx) - \int_{\mathbb{R}^d} \phi(x) \nu(dx) \right|.$$

Then, $(\mathcal{M}_{\lambda^p}(\mathbb{R}^d), \rho)$ is a complete metric space.

Given a complete filtered probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \in [0, \infty)}, \mathbb{P})$, we recall the definition of the derivative for a function with respect to a probability measure [4]. A function $f : \mathcal{M}_{\lambda^p}^s(\mathbb{R}^d) \rightarrow \mathbb{R}$ is differential at $\mu \in \mathcal{M}_{\lambda^p}^s(\mathbb{R}^d)$ if for $\tilde{f}(\xi) \triangleq f(\mathbb{P}_\xi)$, $\xi \in L^p(\Omega; \mathbb{R}^d)$, there exists some $\zeta \in L^p(\Omega; \mathbb{R}^d)$ with $\mathbb{P}_\zeta = \mu$ such that \tilde{f} is the Fréchet differential at ζ , that is, there exists a linear continuous mapping $D\tilde{f}(\zeta) : L^p(\Omega; \mathbb{R}^d) \rightarrow \mathbb{R}$ such that for all $\eta \in L^p(\Omega; \mathbb{R}^d)$,

$$\tilde{f}(\zeta + \eta) - \tilde{f}(\zeta) = D\tilde{f}(\zeta)(\eta) + o(|\eta|_{L^p}), \quad |\eta|_{L^p} \rightarrow 0.$$

Since $D\tilde{f}(\zeta) \in L(L^p(\Omega; \mathbb{R}^d), \mathbb{R})$, by the Riesz representation theorem [3], there exists a \mathbb{P} -a.s. unique random variable $\theta \in L^p(\Omega; \mathbb{R}^d)$ such that for $\eta \in L^p(\Omega; \mathbb{R}^d)$,

$$D\tilde{f}(\zeta)(\eta) = (\theta, \eta)_{L^p} = \mathbb{E}[\theta \cdot \eta].$$

Thus, there exists a Borel measurable function $h : \mathbb{R}^d \rightarrow \mathbb{R}^d$ which depends on the distribution \mathbb{P}_ζ rather than ζ itself such that $\theta = h(\zeta)$, and for $\xi \in L^2(\Omega; \mathbb{R}^d)$,

$$f(\mathbb{P}_\xi) - f(\mathbb{P}_\zeta) = \mathbb{E}[h(\zeta)(\xi - \zeta)] + o(|\xi - \zeta|_{L^2}).$$

We call $\partial_\mu f(\mathbb{P}_\zeta)(y) \triangleq h(y)$, $y \in \mathbb{R}^d$ as the derivative of $f : \mathcal{M}_{\lambda^p}(\mathbb{R}^d) \rightarrow \mathbb{R}$ at \mathbb{P}_ζ , $\zeta \in L^p(\Omega; \mathbb{R}^d)$.

DEFINITION 2.1. Function f is said to be in $C^1(\mathcal{M}_{\lambda^p}(\mathbb{R}^d))$ if for each $\xi \in L^2(\Omega; \mathbb{R}^d)$, there exists a \mathbb{P}_ξ -modification of $\partial_\mu f(\mathbb{P}_\zeta)(\cdot)$ which is denoted by $\partial_\mu f(\mathbb{P}_\xi)(\cdot)$ again, such that $\partial_\mu f : \mathcal{M}_{\lambda^p}(\mathbb{R}^d) \times \mathbb{R}^d \rightarrow \mathbb{R}^d$ is continuous and we identify the function $\partial_\mu f$ with the derivative of f .

DEFINITION 2.2. A function f belongs to $C_b^{1,1}(\mathcal{M}_{\lambda^p}(\mathbb{R}^d))$ if $f \in C^1(\mathcal{M}_{\lambda^p}(\mathbb{R}^d))$, and $\partial_\mu f$ is bounded and Lipschitz continuous, that is there exists a real number $C > 0$ such that:

- (i) $|\partial_\mu f(\mu)(x)| \leq C$, $\mu \in \mathcal{M}_{\lambda^p}(\mathbb{R}^d)$;
- (ii) $|\partial_\mu f(\mu)(x) - \partial_\mu f(\nu)(y)| \leq C(\rho(\mu, \nu) + |x - y|)$, $\mu, \nu \in \mathcal{M}_{\lambda^p}(\mathbb{R}^d)$

for $x, y \in \mathbb{R}^d$.

DEFINITION 2.3. The function f is said to be in $C^2(\mathcal{M}_{\lambda^p}(\mathbb{R}^d))$ if for every $\mu \in \mathcal{M}_{\lambda^p}(\mathbb{R}^d)$, $f \in C^1(\mathcal{M}_{\lambda^p}(\mathbb{R}^d))$ and $\partial_\mu f(\mathbb{P}_\xi)(\cdot)$ is differentiable and its derivative $\partial_y \partial_\mu f : \mathcal{M}_{\lambda^p}(\mathbb{R}^d) \times \mathbb{R}^d \rightarrow \mathbb{R}^d \times \mathbb{R}^d$ is continuous.

DEFINITION 2.4. The function f is said to be in $C_b^{2,1}(\mathcal{M}_{\lambda^p}(\mathbb{R}^d))$ if $f \in C^2(\mathcal{M}_{\lambda^p}(\mathbb{R}^d)) \cap C_b^{1,1}(\mathcal{M}_{\lambda^p}(\mathbb{R}^d))$ and its derivative $\partial_y \partial_\mu f$ is bounded and continuous.

DEFINITION 2.5. The function $\Phi \in C_b^{2,2,1}(\mathcal{M}_{\lambda^p}(\mathbb{R}^d) \times \mathbb{R}^d)$ if:

- (i) Φ is bi-continuous with respect to (x, μ) ;
- (ii) for any $x, \Phi(x, \cdot) \in C_b^{2,1}(\mathcal{M}_{\lambda^p}(\mathbb{R}^d))$ and for any $\mu \in \mathcal{M}_{\lambda^p}(\mathbb{R}^d), \Phi(\cdot, \mu) \in C^2(\mathbb{R}^d)$.

If $\Phi \in C_b^{2,2,1}(\mathcal{M}_{\lambda^p}(\mathbb{R}^d \times \mathbb{R}^d))$ and $\Phi \geq 0$, then we say $\Phi \in C_{b^+}^{2,2,1}(\mathbb{R}^d \times \mathcal{M}_{\lambda^p}(\mathbb{R}^d))$.

DEFINITION 2.6. The function $\Phi \in C(\mathbb{R}^d \times \mathcal{M}_{\lambda^p}(\mathbb{R}^d))$, if $\Phi \in C^{2,2}(\mathbb{R}^d \times \mathcal{M}_{\lambda^p}(\mathbb{R}^d))$ and for every compact set $K \subseteq \mathbb{R}^d \times \mathcal{M}_{\lambda^p}(\mathbb{R}^d)$,

$$\sup_{(x,\mu) \in K} \int_{\mathbb{R}^d} (\|\partial_y \partial_\mu \Phi(x, \mu)(y)\|^2 + |\partial_\mu \Phi(x, \mu)(y)|^2) \mu(dy) < \infty.$$

If $\Phi \in C(\mathbb{R}^d \times \mathcal{M}_{\lambda^p}(\mathbb{R}^d))$ and $\Phi \geq 0$, then we say that $\Phi \in C_+(\mathbb{R}^d \times \mathcal{M}_{\lambda^p}(\mathbb{R}^d))$.

For (1.1), we make the following assumptions.

ASSUMPTION 2.7. Functions b, σ are continuous with respect to $(x, \mu) \in \mathbb{R}^d \times \mathcal{M}_{\lambda^2}(\mathbb{R}^d)$, and there is a constant $L_1 > 0$ such that

$$|b(x, \mu)|^2 + \|\sigma(x, \mu)\|^2 \leq L_1(1 + |x|^2 + \|\mu\|_{\lambda^2}^2).$$

ASSUMPTION 2.8. There is a constant $L_2 > 0$ such that

$$2\langle x - y, b(x, \mu) - b(y, \mu) \rangle + \|\sigma(x, \mu) - \sigma(y, \mu)\|^2 \leq L_2(|x - y|^2 + \rho(\mu, \mu)^2).$$

ASSUMPTION 2.9. There exists a function $v(\cdot, \cdot) : \mathbb{R}^d \times \mathcal{M}_{\lambda^p}(\mathbb{R}^d) \rightarrow \mathbb{R}$ such that:

- (i) $v \in C_+(\mathbb{R}^d \times \mathcal{M}_{\lambda^2}(\mathbb{R}^d))$;
- (ii) $\int_{\mathbb{R}^d} (L^\mu v(x, \mu) + \gamma v(x, \mu)) \mu(dx) \leq 0$;
- (iii) for some $p \geq 1, a_1 \int_{\mathbb{R}^d} |x|^p \mu(dx) \leq \int_{\mathbb{R}^d} v(x, \mu) \mu(dx) \leq a_2 \int_{\mathbb{R}^d} |x|^p \mu(dx)$.

By the classical result of Wang [19], under Assumptions 2.7–2.9, there exists a unique strong solution $X_t^{x_0}$, with initial value x_0 , to (1.1), and for $p \geq 2, \mathbb{E} \sup_{0 \leq t \leq T} |X_t^{x_0}|^p < \infty$. Let $C^2(\mathbb{R}^d \times \mathcal{M}_{\lambda^2}(\mathbb{R}^d); \mathbb{R}^+)$ denote the space of nonnegative functions which are continuous and twice differentiable. For $V \in C^2(\mathbb{R}^d \times \mathcal{M}_{\lambda^2}(\mathbb{R}^d); \mathbb{R}^+)$, we have the following generator of (1.1):

$$\begin{aligned} L^\mu V(x, \mu) &= (b^i \partial_{x_i})(x, \mu) + \frac{1}{2}((\sigma \sigma^*)^{ij} \partial_{x_i x_j}^2)(x, \mu) + \int_{\mathbb{R}^d} b^i(y, \mu) (\partial_\mu V)_i(x, \mu)(y) \mu(dy) \\ &+ \frac{1}{2} \int_{\mathbb{R}^d} (\sigma \sigma^*)^{ij}(y, \mu) \partial_{y_i} (\partial_\mu V)_j(y) \mu(dy). \end{aligned}$$

REMARK 2.10. In fact, the strong solution to (1.1) defines a Markov process [19]. Let $p(t, x_0, dz)$ be the transition probability distribution to process $X_t^{x_0}$ and $p(t, x_0, \Gamma)$ be the probability for the event $\{X_t^{x_0} \in \Gamma\}$ with the initial value x_0 , that is,

$$p(t, x_0, \Gamma) = \int_{\Gamma} p(t, x_0, dz), \quad \Gamma \in \mathcal{B}(\mathbb{R}^d).$$

DEFINITION 2.11. The process $X_t^{x_0}$ with initial value x_0 is called stable in distribution if there exists a probability measure $\Pi(\cdot)$ such that for any initial value x_0 , its transition probability $p(t, x_0, dz)$ weakly converges to $\Pi(\cdot)$, as $t \rightarrow \infty$. Equation (1.1) is said to be stable in distribution if $X_t^{x_0}$ is stable in distribution.

To study the stability in distribution, we need the following assumption. First, for a given function $U \in C^2(\mathbb{R}^d; \mathbb{R})$, we define the operator

$$L(x, y, \mu, \nu)U(x - y) = [b(x, \mu) - b(y, \nu)]U_x(x - y) + \frac{1}{2}Tr[(\sigma(x, \mu) - \sigma(y, \nu))^* U_{xx}(x - y)(\sigma(x, \mu) - \sigma(y, \nu))].$$

ASSUMPTION 2.12. There exist a function $U \in C^2(\mathbb{R}^d; \mathbb{R}_+)$ and a constant $K > 0$, such that for any two solutions $(X_t^{x_0})_{t \geq 0}$ and $(X_t^{y_0})_{t \geq 0}$ with its distributions $\mathcal{L}(X_t^{x_0}) = \mu_t$ and $\mathcal{L}(X_t^{y_0}) = \nu_t$, and for all couplings $\pi \in \Pi(\mu_t, \nu_t)$,

$$\int_{\mathbb{R}^d \times \mathbb{R}^d} L(x, y, \mu_t, \nu_t)U(x - y)\pi(dx, dy) \leq -K \int_{\mathbb{R}^d \times \mathbb{R}^d} U(x - y)\pi(dx, dy).$$

3. Stability analysis

3.1. Exponential stability This section gives the exponential stability in the p th moment and in a.s. sense.

DEFINITION 3.1. Let $p \geq 1$. The solution $X_t^{x_0}$ of (1.1) is said to be p th moment exponentially stable if there is a pair of constants $\gamma > 0$ and $C > 0$ such that

$$\mathbb{E}|X_t^{x_0}|^p \leq C|x_0|^p e^{-\gamma t}, \quad t \geq 0.$$

Further, it is said to be a.s. exponentially stable if

$$\limsup_{t \rightarrow \infty} \frac{\log|X_t^{x_0}|}{t} \leq -\gamma, \quad \text{a.s.}$$

For this, we further assume that for some constant $N > 0$ and $p \geq 1$,

$$|b(x, \mu)|^p + \|\sigma(x, \mu)\|^p \leq N(|x|^p + \int_{\mathbb{R}^d} |x|^p \mu(dx)). \tag{3.1}$$

THEOREM 3.2. Assume that Assumptions 2.7–2.9 hold. For every $x_0 \in \mathbb{R}^d$, $X_t^{x_0}$ is p th moment exponentially stable and a.s. exponentially stable. Furthermore, for every $\epsilon > 0$, there exists an $R > 0$ such that for all $t \geq 0$, $\mathbb{P}\{|X_t^{x_0}| \geq R\} < \epsilon$.

PROOF. For $x_0 \in \mathbb{R}^d$, let $X_t^{x_0}$ be the solution of (1.1), for positive integer k , define the stopping times

$$\rho_k = \inf\{t > 0 \mid |X_t^{x_0}| \geq k\},$$

then obviously, $\rho_k \rightarrow \infty$, a.s. as $k \rightarrow \infty$. Then for the stopped processes $(X_{t \wedge \rho_k}^{x_0})_{t \geq 0}$, function v and distribution processes $\mathcal{L}(X_t^{x_0})_{t \geq 0}$, by Itô's formula [9],

$$\begin{aligned} & e^{\gamma(t \wedge \rho_k)} v(X_{t \wedge \rho_k}^{x_0}, \mathcal{L}(X_t^{x_0})) - v(x_0, \delta_{x_0}) \\ &= \int_0^t \gamma e^{\gamma(s \wedge \rho_k)} v(X_{s \wedge \rho_k}^{x_0}, \mathcal{L}(X_s^{x_0})) ds \\ &+ \int_0^t e^{\gamma(s \wedge \rho_k)} (b^i \partial_{x_i} v)(X_{s \wedge \rho_k}^{x_0}, \mathcal{L}(X_s^{x_0})) ds \\ &+ \frac{1}{2} \int_0^t e^{\gamma(s \wedge \rho_k)} ((\sigma \sigma^*)^{ij} \partial_{x_i x_j}^2 v)(X_{s \wedge \rho_k}^{x_0}, \mathcal{L}(X_s^{x_0})) ds \\ &+ \int_0^t e^{\gamma(s \wedge \rho_k)} (\partial_{x_i} v \sigma^{ij})(X_{s \wedge \rho_k}^{x_0}, \mathcal{L}(X_s^{x_0})) dW_s^j \\ &+ \int_0^t \int_{\mathbb{R}^d} e^{\gamma(s \wedge \rho_k)} ((b^i \partial_{x_i} v)(X_{s \wedge \rho_k}^{x_0}, \mathcal{L}(X_s^{x_0}))(y) \mathcal{L}(X_s^{x_0})(dy) ds \\ &+ \frac{1}{2} \int_0^t \int_{\mathbb{R}^d} e^{\gamma(s \wedge \rho_k)} (\sigma \sigma^*)^{ij} (X_{s \wedge \rho_k}^{x_0}, \mathcal{L}(X_s^{x_0}))(y) \mathcal{L}(X_s^{x_0})(dy) ds. \end{aligned}$$

Then taking expectation, by Assumption 2.9,

$$\mathbb{E}[e^{\gamma(t \wedge \rho_k)} v(X_{t \wedge \rho_k}^{x_0}, \mathcal{L}(X_t^{x_0}))] - v(x_0, \delta_{x_0}) \leq 0.$$

Let $k \rightarrow \infty$ and together with the Fatou lemma [7],

$$\mathbb{E}[e^{\gamma t} v(X_t, \mathcal{L}(X_t^{x_0}))] \leq v(x_0, \delta_{x_0}) \leq 0.$$

Furthermore, by Assumption 2.7,

$$a_1 \mathbb{E}|X_t^{x_0}|^p \leq \mathbb{E}v(X_t, \mathcal{L}(X_t^{x_0})) \leq e^{-\gamma t} v(x_0, \delta_{x_0}) \leq a_2 e^{-\gamma t} |x_0|^p.$$

Thus,

$$\mathbb{E}|X_t^{x_0}|^p \leq \frac{a_2}{a_1} e^{-\gamma t} |x_0|^p.$$

Then by Chebyshev's inequality [7], for $R > 0$,

$$\mathbb{P}\{|X_t^{x_0}| \geq R\} \leq \frac{\mathbb{E}|X_t^{x_0}|^p}{R^p}.$$

Noticing that from (1.1),

$$X_{t+s}^{x_0} = X_t^{x_0} + \int_t^{t+s} b(X_u^{x_0}, \mathcal{L}(X_u^{x_0})) du + \int_t^{t+s} \sigma(X_u^{x_0}, \mathcal{L}(X_u^{x_0})) dW_u,$$

and for $p \geq 1$, $\tau > 0$, by (3.1),

$$\begin{aligned}
 \mathbb{E} \sup_{0 \leq s \leq \tau} |X_{t+s}^{x_0}|^p &\leq C_p \mathbb{E} |X_t^{x_0}|^p + C_p \mathbb{E} \sup_{0 \leq s \leq \tau} \left| \int_t^{t+s} b(X_u^{x_0}, \mathcal{L}(X_u^{x_0})) du \right|^p \\
 &\quad + C_p \mathbb{E} \sup_{0 \leq s \leq \tau} \left| \int_t^{t+s} \sigma(X_u^{x_0}, \mathcal{L}(X_u^{x_0})) dW_u \right|^p \\
 &\leq C_p \mathbb{E} |X_t^{x_0}|^p + C_{p,\tau} \mathbb{E} \int_t^{t+\tau} |b(X_u^{x_0}, \mathcal{L}(X_u^{x_0}))|^p du \\
 &\quad + C_p \mathbb{E} \int_t^{t+\tau} |\sigma(X_u^{x_0}, \mathcal{L}(X_u^{x_0}))|^p du \\
 &\leq C_p \mathbb{E} |X_t^{x_0}|^p + C_{p,\tau,N} \mathbb{E} \int_t^{t+\tau} \left(|X_u^{x_0}|^p + \int_{\mathbb{R}^d} |x|^p \mathcal{L}(X_u^{x_0})(dx) \right) du \\
 &\leq C_p \mathbb{E} |X_t^{x_0}|^p + C_{p,\tau,N} \int_t^{t+\tau} \mathbb{E} |X_u^{x_0}|^p du \\
 &\leq C_{p,x_0} e^{-\gamma t} + C_{p,\tau,x_0,N} \int_t^{t+\tau} e^{-\gamma u} du \leq C_{p,\tau,x_0,\gamma,N} e^{-\gamma t}.
 \end{aligned}$$

Then for $n = 1, 2, \dots$,

$$\mathbb{E} \sup_{n\tau \leq t \leq (n+1)\tau} |X_t^{x_0}|^p \leq C_{p,\tau,x_0,\gamma,N} e^{-\gamma n\tau},$$

thus, for $\epsilon \in (0, \gamma)$ and $n \in \mathbb{N}$, by Chebychev’s inequality,

$$\mathbb{P}\left(\omega : \sup_{n\tau \leq t \leq (n+1)\tau} |X_t^{x_0}|^p > e^{-(\gamma-\epsilon)n\tau}\right) \leq C_{p,\tau,x_0,\gamma,N} e^{-\epsilon n\tau}.$$

By the Borel–Cantelli lemma [11], there exists a random constant $n_0(\omega)$ such that for almost all $\omega \in \Omega$, for $n > n_0(\omega)$,

$$\sup_{n\tau \leq t \leq (n+1)\tau} |X_t^{x_0}|^p \leq C_{p,\tau,x_0,\gamma,N} e^{-(\gamma-\epsilon)n\tau}, \quad \text{a.s.}$$

Thus, for any $n\tau \leq t \leq (n+1)\tau$,

$$\frac{\log |X_t^{x_0}|}{t} = \frac{\log |X_t^{x_0}|^p}{pt} \leq \frac{\log \sup_{n\tau \leq t \leq (n+1)\tau} |X_t^{x_0}|^p}{pn\tau} \leq -\frac{\gamma - \epsilon}{p}, \quad \text{a.s.},$$

and

$$\limsup_{t \rightarrow \infty} \frac{\log |X_t^{x_0}|}{t} \leq -\frac{\gamma - \epsilon}{p}, \quad \text{a.s.}$$

Now letting $\epsilon \rightarrow 0$, the proof is complete. □

REMARK 3.3. From Theorem 3.2, the transition probability family $\{p(t, x_0, dz) \mid t \geq 0\}$ is tight, that is, for $\epsilon > 0$, there exists a compact set $\mathcal{K} = \mathcal{K}(x_0, \epsilon)$ such that

$$\mathbb{P}(t, x_0, \mathcal{K}) \geq 1 - \epsilon.$$

3.2. Stability in distribution Next, we consider the stability in distribution. For this, we need to consider the difference between two solutions with different initial values, that is,

$$\begin{aligned}
 X_t^{x_0} - X_t^{y_0} &= x_0 - y_0 + \int_0^t [b(X_s^{x_0}, \mathcal{L}(X_s^{x_0})) - b(X_s^{y_0}, \mathcal{L}(X_s^{y_0}))] ds \\
 &\quad + \int_0^t [\sigma(X_s^{x_0}, \mathcal{L}(X_s^{x_0})) - \sigma(X_s^{y_0}, \mathcal{L}(X_s^{y_0}))] dW_s.
 \end{aligned}$$

We need two more notation. Let \mathcal{H} be the set consisting of nondecreasing functions $K : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ such that $K(0) = 0$, and \mathcal{H}_∞ be the set of functions $K \in \mathcal{H}$ such that $K(x) \rightarrow \infty$ as $x \rightarrow \infty$.

LEMMA 3.4. *If there exists a function $U \in C^2(\mathbb{R}^d; \mathbb{R}_+)$ satisfying $U(0) = 0$ and a function $\alpha_1 \in \mathcal{H}_\infty$ such that*

$$\alpha_1(|x|) \leq U(x) \quad \text{for } x \in \mathbb{R}^d,$$

then for every $\epsilon > 0$ and compact set \mathcal{K} on \mathbb{R}^d , there exists $T = T(\mathcal{K}, \epsilon) > 0$ such that

$$\mathbb{P}\{\|X_t^{x_0} - X_t^{y_0}\| > \epsilon\} < 1 - \epsilon, \quad t \geq T, \quad x_0, y_0 \in \mathcal{K}.$$

For the convenience of presentation in the following, we rewrite (1.1) as

$$X_t^{x_0} = x_0 + \int_0^t \tilde{b}(u, X_u^{x_0}) du + \int_0^t \tilde{\sigma}(u, X_u^{x_0}) dW_u, \quad t \geq 0, \tag{3.2}$$

where $\tilde{b}(u, X_u^{x_0}) = b(X_u^{x_0}, \mathcal{L}(X_u^{x_0}))$ and $\tilde{\sigma}(u, X_u^{x_0}) = \sigma(X_u^{x_0}, \mathcal{L}(X_u^{x_0}))$. Since (1.1) has a unique strong solution $(X_t^{x_0})_{t \geq 0}$ with the initial distribution δ_{x_0} , the distribution of process $(X_t^{x_0})_{t \geq 0}$ is known, and (3.2) is a classic SDE. Then, the solution of (3.2) is a strong Markov process [5, Lemma 5.3].

PROOF OF LEMMA 3.4. For $\epsilon > 0$, by the continuity of function U with $U(0) = 0$, we choose $\alpha \in (0, \epsilon)$ small enough such that

$$\frac{\sup_{|x| \leq \alpha} U(x)}{\mu_1(\epsilon)} < \frac{\epsilon}{2}.$$

Let \mathcal{K} be a compact set on \mathbb{R}^d and for fixed $x_0, y_0 \in \mathcal{K}$ and $\beta > \alpha$, we define two stopping times

$$\begin{aligned}
 \tau_\alpha &= \inf\{t \geq 0 \mid |X_t^{x_0} - X_t^{y_0}| \leq \alpha\}, \\
 \tau_\beta &= \inf\{t \geq 0 \mid |X_t^{x_0} - X_t^{y_0}| \geq \beta\}.
 \end{aligned}$$

By Itô’s formula for the stopped process $U(X_{\tau_\beta \wedge t}^{x_0} - X_{\tau_\beta \wedge t}^{y_0})$ and Assumption 2.12,

$$\begin{aligned} \mathbb{E}U(X_{\tau_\beta \wedge t}^{x_0} - X_{\tau_\beta \wedge t}^{y_0}) &\leq U(x_0 - y_0) - K \int_0^{\tau_\beta \wedge t} U(X_s^{x_0} - X_s^{y_0}) ds \\ &\quad + \mathbb{E} \int_0^{\tau_\beta \wedge t} U_x(X_s^{x_0} - X_s^{y_0})(\tilde{\sigma}(s, X_s^{x_0}) - \tilde{\sigma}(s, X_s^{y_0})) dW_s \\ &= U(x_0 - y_0) - K \int_0^{\tau_\beta \wedge t} U(X_s^{x_0} - X_s^{y_0}) ds. \end{aligned}$$

Then,

$$\alpha_1(\beta)\mathbb{P}\{\tau_\beta \leq t\} \leq U(x_0 - y_0),$$

that is,

$$\mathbb{P}\{\tau_\beta \leq t\} \leq \frac{U(x_0 - y_0)}{\alpha_1(\beta)}.$$

Notice that for all $x_0, y_0 \in \mathcal{K}$ and $U(x_0 - y_0)$ bounded, there exists $\beta = \beta(\mathcal{K}, \epsilon) > 0$ such that

$$\mathbb{P}\{\tau_\beta < \infty\} \leq \frac{\epsilon}{4}.$$

Fix the β and let $t_\alpha = \tau_\alpha \wedge \tau_\beta \wedge t$, then similar discussion yields

$$\begin{aligned} \mathbb{E}U(X_{t_\alpha}^{x_0} - X_{t_\alpha}^{y_0}) &\leq U(x_0 - y_0) - K\mathbb{E} \int_0^{t_\alpha} U(X_s^{x_0} - X_s^{y_0}) ds \\ &\leq U(x_0 - y_0) - K\mathbb{E} \int_0^{t_\alpha} \alpha_1(|X_s^{x_0} - X_s^{y_0}|) ds \\ &\leq U(x_0 - y_0) - K\alpha_1(\alpha)\mathbb{E}(\tau_\alpha \wedge \tau_\beta \wedge t), \end{aligned}$$

which implies that

$$\mathbb{P}\{\tau_\alpha \wedge \tau_\beta \geq t\} \leq \frac{U(x_0 - y_0)}{K\alpha_1(\alpha)t}.$$

Moreover, this implies that for a given $\epsilon \in (0, 1)$, there exists $T = T(\mathcal{K}, \epsilon) > 0$ such that

$$\mathbb{P}\{\tau_\alpha \wedge \tau_\beta \leq T\} > 1 - \frac{\epsilon}{4}.$$

Thus,

$$\begin{aligned} 1 - \frac{\epsilon}{4} &< \mathbb{P}\{\tau_\alpha \wedge \tau_\beta \leq T\} \leq \mathbb{P}\{\tau_\alpha \leq T\} + \mathbb{P}\{\tau_\beta \leq T\} \\ &\leq \mathbb{P}\{\tau_\alpha \leq T\} + \mathbb{P}\{\tau_\beta \leq \infty\} \\ &\leq \mathbb{P}\{\tau_\alpha \leq T\} + \frac{\epsilon}{4} \end{aligned}$$

and

$$\mathbb{P}\{\tau_\alpha \leq T\} \geq 1 - \frac{\epsilon}{2}.$$

Now we define the stopping time

$$\sigma = \inf\{t \geq \tau_\alpha \wedge T \mid |X_t^{x_0} - X_t^{y_0}| \geq \epsilon\}.$$

Let $t > T$, then

$$\begin{aligned} \mathbb{P}(\tau_\alpha \leq T \cap \sigma \leq t)\mu_1(\epsilon) &\leq \mathbb{E}(I_{\tau_\alpha \leq T, \sigma \leq t} U(X_{t \wedge \sigma}^{x_0} - X_{t \wedge \sigma}^{y_0})) \\ &\leq \mathbb{E}(I_{\tau_\alpha \leq T} U(X_{t \wedge \tau_\alpha}^{x_0} - X_{t \wedge \tau_\alpha}^{y_0})) \\ &\leq \mathbb{E}(I_{\tau_\alpha \leq T} U(X_{\tau_\alpha}^{x_0} - X_{\tau_\alpha}^{y_0})) \leq \mathbb{P}(\tau_\alpha \leq T) \sup_{|x| \leq \alpha} U(x). \end{aligned}$$

Thus,

$$\mathbb{P}(\{\tau_\alpha \leq T\} \cap \{\sigma \leq t\}) \leq \frac{\epsilon}{2}$$

and

$$\mathbb{P}\{\sigma \leq t\} \leq \mathbb{P}(\{\tau_\alpha \leq T\} \cap \{\sigma \leq t\}) + \mathbb{P}\{\tau_\alpha > T\} < \epsilon.$$

Let $t \rightarrow \infty$, then

$$\mathbb{P}\{\sigma < \infty\} \leq \epsilon.$$

This indicates that for all $x_0, y_0 \in \mathcal{K}$, $t \geq T$,

$$\mathbb{P}\{|X_t^{x_0} - X_t^{y_0}| < \epsilon\} \geq 1 - \epsilon.$$

This completes the proof. □

LEMMA 3.5. For every compact set \mathcal{K} ,

$$\lim_{t \rightarrow \infty} \rho(p(t, x_0, \cdot), p(t, y_0, \cdot)) = 0, \quad x_0, y_0 \in \mathcal{K}.$$

PROOF. We only need to show that there exists $T > 0$, such that for all $\epsilon > 0$ and $x_0, y_0 \in \mathcal{K}$,

$$\rho(p(t, x_0, \cdot), p(t, y_0, \cdot)) \leq \epsilon, \quad t \geq T.$$

It is equivalent to show that

$$\sup_{\phi \in C_\lambda(\mathbb{R}^d)} |\mathbb{E}\phi(X_t^{x_0}) - \mathbb{E}\phi(X_t^{y_0})| \leq \epsilon, \quad t \geq T.$$

However, notice that for every $\phi \in C_\lambda(\mathbb{R}^d)$,

$$|\mathbb{E}\phi(X_t^{x_0}) - \mathbb{E}\phi(X_t^{y_0})| \leq \mathbb{E}[2 \wedge |X_t^{x_0} - X_t^{y_0}|].$$

By Lemma 3.4, there exists a $T_1 > 0$ such that

$$\mathbb{E}[2 \wedge |X_t^{x_0} - X_t^{y_0}|] < \epsilon, \quad t \geq T_1.$$

Due to the arbitrariness of $\phi \in C_\lambda(\mathbb{R}^d)$,

$$\sup_{\phi \in C_\lambda(\mathbb{R}^d)} |\mathbb{E}\phi(X_t^{x_0}) - \mathbb{E}\phi(X_t^{y_0})| \leq \epsilon, \quad t \geq T_1.$$

The proof is now complete. \square

LEMMA 3.6. *Under the assumptions of Theorem 3.2 and Lemma 3.4, for $x_0 \in \mathbb{R}^d$, $\{p(t, x_0, \cdot), t \geq 0\}$ is a Cauchy sequence.*

PROOF. We need to show that for every $x_0 \in \mathbb{R}^d$ and $\epsilon > 0$, there exists $T > 0$ such that for $t \geq T$ and $s > 0$,

$$\rho(p(t+s, x_0, \cdot), p(t, x_0, \cdot)) \leq \epsilon,$$

which is equivalent that for every $\phi \in C_\lambda(\mathbb{R}^d)$,

$$\sup_{\phi \in C_\lambda(\mathbb{R}^d)} |\mathbb{E}\phi(X_{t+s}^{x_0}) - \mathbb{E}\phi(X_t^{x_0})| \leq \epsilon, \quad t \geq T, s > 0.$$

By Lemma 3.2, there exists a compact set \mathcal{K} on \mathbb{R}^d such that for $\epsilon > 0$,

$$p(t, x_0, \mathcal{K}) > 1 - \frac{\epsilon}{8}.$$

Furthermore, by the strong Markov property of $X_t^{x_0}$, for $\phi \in C_\lambda(\mathbb{R}^d)$ and $t, s > 0$,

$$\begin{aligned} |\mathbb{E}\phi(X_{t+s}^{x_0}) - \mathbb{E}\phi(X_t^{x_0})| &= |\mathbb{E}[\mathbb{E}(\phi(X_{t+s}^{x_0})|\mathcal{F}_s)] - \mathbb{E}\phi(X_t^{x_0})| \\ &= |\mathbb{E}[\mathbb{E}\phi(X_t^{x_s, X_s^{x_0}})] - \mathbb{E}\phi(X_t^{x_0})| \\ &= \left| \int_{\mathbb{R}^d} \mathbb{E}\phi(X_t^z) p(s, x_0, dz) - \mathbb{E}\phi(X_t^{x_0}) \right| \\ &\leq \int_{\mathbb{R}^d} \mathbb{E}|\phi(X_t^z) - \phi(X_t^{x_0})| p(s, x_0, dz) \\ &= \int_{\mathcal{K}} \mathbb{E}|\phi(X_t^z) - \phi(X_t^{x_0})| p(s, x_0, dz) \\ &\quad + \int_{\mathbb{R}^d - \mathcal{K}} \mathbb{E}|\phi(X_t^z) - \phi(X_t^{x_0})| p(s, x_0, dz) \\ &\leq \int_{\mathcal{K}} \mathbb{E}|\phi(X_t^z) - \phi(X_t^{x_0})| p(s, x_0, dz) + \frac{\epsilon}{4}. \end{aligned}$$

By Lemma 3.4, there exists $T > 0$ such that for every $\epsilon > 0$,

$$\mathbb{E}|\phi(X_t^z) - \phi(X_t^{x_0})| \leq \mathbb{E}[2 \wedge |X_t^z - X_t^{x_0}|] \leq \frac{3\epsilon}{4}, \quad t \geq T.$$

Thus,

$$|\mathbb{E}\phi(X_{t+s}^{x_0}) - \mathbb{E}\phi(X_t^{x_0})| \leq \epsilon, \quad t \geq T, s > 0,$$

which completes the proof. \square

THEOREM 3.7. *Under assumptions of Theorem 3.2 and Lemma 3.4, (1.1) is stable in distribution.*

PROOF. By Definition 2.11, we need to show that there exists a probability measure $\pi(\cdot)$ such that for every $x_0 \in \mathbb{R}^d$, the transition probability family $\{p(t, x_0, \cdot) : t \geq 0\}$ weakly converges to $\pi(\cdot)$. In fact, we show that for every $x \in \mathbb{R}^d$,

$$\lim_{t \rightarrow \infty} \rho(p(t, x_0, \cdot), \pi(\cdot)) = 0.$$

By Lemma 3.6, $\{p(t, 0, \cdot) : t \geq 0\}$ is a Cauchy sequence in $\mathcal{P}(\mathbb{R}^d)$ with the metric ρ . Since $\mathcal{P}(\mathbb{R}^d)$ is a complete metric space, there exists a probability measure $\pi(\cdot) \in \mathcal{P}(\mathbb{R}^d)$ such that

$$\lim_{t \rightarrow \infty} \rho(p(t, x, \cdot), \pi(\cdot)) = 0.$$

By a triangle inequality,

$$\begin{aligned} \lim_{t \rightarrow \infty} \rho(p(t, x, \cdot), \pi(\cdot)) &\leq \lim_{t \rightarrow \infty} \rho(p(t, x, \cdot), p(t, 0, \cdot)) + \lim_{t \rightarrow \infty} \rho(p(t, 0, \cdot), \pi(\cdot)) \\ &= 0. \end{aligned}$$

The proof is complete. □

4. Conclusions

In the study, we first prove the p th moment exponential stability and a.s. exponential stability of the solution of (1.1) by using the distribution-dependent Itô's formula, and then obtain the tightness of the transition probability family corresponding to the solution of (1.1). Based on this, we introduce a distribution-dependent operator, that is, Assumption 2.12, and combined with the method of Yuan and Mao [21], we get that when the time is long enough, the transition probability family tends to a unique probability measure, that is, the solution of (1.1) is asymptotically stable in distribution. It would be valuable to use a similar method to analyse the long time behaviour of (1.1) with jump noise.

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References

- [1] K. Bahlali, M. A. Mezerdi and B. Mezerdi, "Stability of McKean–Vlasov stochastic differential equations and applications", *Stoch. Dyn.* **20** (2020) Article ID: 2050007; doi:10.1142/S0219493720500070.
- [2] J. H. Bao, Z. T. Hou and C. G. Yuan, "Stability in distribution of neutral stochastic differential delay equations with Markovian switching", *Stat. Probab. Lett.* **79** (2009) 1663–1673; doi:10.1016/j.spl.2009.04.006.

- [3] H. Brezis, *Functional analysis, Sobolev spaces and partial differential equations* (Springer, New York, 2010).
- [4] P. Cardaliaguet, *Notes on mean field games (from P. L. Lion's lectures at College de France)*. <https://www.ceremade.dauphine.fr/cardalia/MFG100629.pdf>.
- [5] X. J. Ding and H. J. Qiao, “Stability for stochastic McKean–Vlasov equations with non-Lipschitz coefficients”, *SIAM J. Control Optim.* **59** (2021) Article ID: 19M1289418; doi:10.1137/19M1289418.
- [6] N. H. Du, N. H. Dang and N. T. Dieu, “On stability in distribution of stochastic differential delay equations with Markovian switching”, *Syst. Control Lett.* **65** (2014) 43–49; doi:10.1016/j.sysconle.2013.12.006.
- [7] S. N. Ethier and T. G. Kurtz, *Markov processes: characterization and convergence* (John Wiley & Sons, NJ, 1986).
- [8] C. Fei, W. Y. Fei, S. N. Deng and X. R. Mao, “Asymptotic stability in distribution of highly nonlinear stochastic differential equations with G -Brownian motion”, *Qual. Theory Dyn. Syst.* **22** (2023) Article ID: 57; doi:10.1007/s12346-023-00760-9.
- [9] W. R. P. Hammersley, D. Siska and L. Szpruch, “McKean–Vlasov SDEs under measure dependent Lyapunov conditions”, *Ann. Inst. Henri Poincaré Probab. Stat.* **57** (2021) 1032–1057; doi:10.1214/20-AIHP1106.
- [10] W. Hong, S. H. Li and W. Liu, “Large deviation principle for McKean–Vlasov quasilinear stochastic evolution equations”, *Appl. Math. Optim.* **84** (2021) 1119–1147; doi:10.1007/s00245-021-09796-2.
- [11] O. Kallenberg, *Foundations of modern probability* (Springer, New York, 2000).
- [12] R. Khasminskii, *Stochastic stability of differential equations* (Springer, Berlin–Heidelberg, 2011).
- [13] Z. X. Liu and J. Ma, “Existence, uniqueness and ergodicity for McKean–Vlasov SDEs under distribution-dependent Lyapunov conditions”, Preprint, 2023, [arXiv:2309.05411](https://arxiv.org/abs/2309.05411).
- [14] G. Y. Lv and Y. Q. Shan, “Long time behavior of stochastic McKean–Vlasov equations”, *Appl. Math. Lett.* **128** (2022) Article ID: 107879; doi:10.1016/j.aml.2021.107879.
- [15] H. P. McKean, “A class of Markov processes associated with nonlinear parabolic equations”, *Proc. Natl. Acad. Sci. USA* **56** (1966) 1907–1911; <https://www.jstor.org/stable/57643>.
- [16] S. G. Peng, “ G -Brownian motion and dynamic risk measure under volatility uncertainty”, Preprint, 2007, [arXiv:0711.2834](https://arxiv.org/abs/0711.2834).
- [17] D. Reis, G. Salkeld and W. Tugaut, “Freidlin–Wentzell LDPs in path space for McKean–Vlasov equations and the functional iterated logarithm law”, *Ann. Appl. Probab.* **29** (2019) 1487–1540; <https://www.jstor.org/stable/26729307>.
- [18] A. A. Vlasov, “The vibrational properties of an electron gas”, *Sov. Phys.* **10** (1968) 721–733; doi:10.1070/PU1968v010n06ABEH003709.
- [19] F. Y. Wang, “Distribution dependent SDEs for Landau type equations”, *Stoch. Process. Appl.* **128** (2018) 596–621; doi:10.1016/j.spa.2017.05.006.
- [20] H. Wu, J. H. Hu, S. B. Gao and C. G. Yuan, “Stabilization of stochastic McKean–Vlasov equations with feedback control based on discrete-time state observation”, *SIAM J. Control Optim.* **60** (2022) 2884–2901; doi:10.1137/21M1454997.
- [21] C. G. Yuan and X. R. Mao, “Asymptotic stability in distribution of stochastic differential equations with Markovian switching”, *Stoch. Process. Appl.* **103** (2003) 277–291; doi:10.1016/S0304-4149(02)00230-2.
- [22] C. G. Yuan, J. Z. Zou and X. R. Mao, “Stability in distribution of stochastic differential delay equations with Markovian switching”, *Syst. Control Lett.* **50** (2003) 195–207; doi:10.1016/S0167-6911(03)00154-3.