

# Simulation of BSDEs with jumps by Wiener Chaos Expansion

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# Backward Stochastic Differential Equations with jumps

We consider the BSDE with jumps

$$Y_t = \xi + \int_t^T f(s, Y_s, Z_s, U_s) ds - \int_t^T Z_s dB_s - \int_{]t, T]} U_s d\tilde{N}_s, \quad 0 \leq t \leq T$$

$\mathcal{F}_T$  : natural filtration of the Brownian motion  $B$  and the compensated Poisson process  $\tilde{N}_t := N_t - \kappa t, t \geq 0$ .

Assume

- $f$  is Lipschitz in space, unif. in time,
- $\xi \in \mathbb{D}^{1,2}$

then  $Z_t = \mathbb{E}(D_t^{(0)} Y_t | \mathcal{F}_{t^-})$  and  $U_t = \mathbb{E}(D_t^{(1)} Y_t | \mathcal{F}_{t^-})$ .

# Discretization of BSDEs with jumps

- **Dynamic programming equation** Bouchard-Elie (2008)
- **tree method** Lejay-Mordecki-Torres (2014)

We propose here to use a Picard's iterations and chaos expansions, extending the paper Briand-Labart (2014) to the case of jumps.

## Idea of the algorithm

$(Y^0, Z^0, U^0) = (0, 0, 0)$  and for  $q \geq 0$

$$Y_t^{q+1} = \xi + \int_t^T f(s, Y_s^q, Z_s^q, U_s^q) ds - \int_t^T Z_s^{q+1} \cdot dB_s - \int_{]t, T]} U_s^{q+1} d\tilde{N}_s, \quad 0 \leq t \leq T.$$

$$\begin{aligned} Y_t^{q+1} &= \mathbb{E} \left( \xi + \int_t^T f(s, Y_s^q, Z_s^q, U_s^q) ds \mid \mathcal{F}_t \right), \\ &= \mathbb{E} \left( \underbrace{\xi + \int_0^T f(s, Y_s^q, Z_s^q, U_s^q) ds}_{F^q} \mid \mathcal{F}_t \right) - \int_0^t f(s, Y_s^q, Z_s^q, U_s^q) ds \end{aligned}$$

## Idea of the algorithm

We have

$$Y_t^{q+1} = \mathbb{E}(F^q | \mathcal{F}_t) - \int_0^t f(s, Y_s^q, Z_s^q, U_s^q) ds,$$

$$Z_t^{q+1} = \mathbb{E}\left(D_t^{(0)} F^q | \mathcal{F}_{t-}\right),$$

$$U_t^{q+1} = \mathbb{E}\left(D_t^{(1)} F^q | \mathcal{F}_{t-}\right),$$

$\mathbb{E}(F^q | \mathcal{F}_t)$  and  $\mathbb{E}\left(D_t^{(0)} F^q | \mathcal{F}_{t-}\right)$  and  $\mathbb{E}\left(D_t^{(1)} F^q | \mathcal{F}_{t-}\right)$  are computed thanks to the chaos decomposition of  $F^q$ .

**$F^q$  does not depend on  $t$  : only one chaos decomposition per Picard iteration**

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## Chaos Expansion

If  $F \in L^2(\mathcal{F}_T)$ ,

$$F = \mathbb{E}(F) + \sum_{k=1}^{\infty} \sum_{\mathbf{i}_k \in \{0,1\}^k} L_k^{\mathbf{i}_k}(f_{\mathbf{i}_k})$$

where

$$L_k^{i_1, \dots, i_k}(f) = \int_0^T \left( \int_0^{t_k^-} \dots \left( \int_0^{t_2^-} f(t_1, \dots, t_k) dG_{i_1}(t_1) \right) \dots dG_{i_{k-1}}(t_{k-1}) \right) dG_{i_k}(t_k).$$

and  $G_0(t) = B_t$  and  $G_1(t) = N_t - \kappa t$ .

# Chaos Expansion

$$F = \mathbb{E}[F] + \sum_{k=1}^{\infty} \sum_{l=0}^k \sum_{\mathbf{k}_l \in \mathbb{N}^l} \sum_{\mathbf{j}_{k-l} \in \mathbb{N}^{k-l}} d_{\mathbf{k}_l, \mathbf{j}_{k-l}} L_l^{0, \dots, 0}(\tilde{e}[k_1, \dots, k_l]) L_{k-l}^{1, \dots, 1}(\tilde{e}[j_1, \dots, j_{k-l}]),$$

- $(\tilde{e}[k_1, \dots, k_m])_{k_m \in \mathbb{N}}$  is an orthogonal basis of  $(\tilde{L}^2)^{\otimes m}([0, T])$ , the subspace of symmetric functions from  $(L^2)^{\otimes m}([0, T])$ .
- $(d_{\mathbf{k}_l, \mathbf{j}_{k-l}})$  coefficients ensuing from the chaos decomposition of  $F$ .

## Hermite and Charlier polynomials

If we choose  $e_i := \frac{1}{\sqrt{h}} \mathbf{1}_{] \bar{t}_{i-1}, \bar{t}_i ]}$  where  $\bar{t}_i = ih$  and  $h := \frac{T}{N}$ , we obtain <sup>1</sup>

$$L_k^{0, \dots, 0} (e_1^{\otimes n_1^B} \circ \dots \circ e_N^{\otimes n_N^B}) = \frac{n^B!}{|n^B|!} \prod_{i=1}^N K_{n_i^B} \left( \frac{B_{\bar{t}_i} - B_{\bar{t}_{i-1}}}{\sqrt{h}} \right),$$

$(K_m)_m$  are the Hermite polynomials (defined by  $e^{xt - \frac{t^2}{2}} = \sum_{m \geq 0} K_m(x) t^m$ ),

$$L_k^{1, \dots, 1} (e_1^{\otimes n_1^P} \circ \dots \circ e_N^{\otimes n_N^P}) = \frac{1}{|n^P|! h^{\frac{|n^P|}{2}}} \prod_{i=1}^N C_{n_i^P} (N_{t_i} - N_{t_{i-1}}, \kappa h)$$

where  $(C_m)_m$  are the Charlier polynomials (defined by  $C_0(x, t) = 1$ ,  $C_1(x, t) = x - t$  and  $C_{m+1}(x, t) = (x - m - t)C_m(x, t) - mtC_{m-1}(x, t)$ .)

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1.  $n^B = (n_1^B, \dots, n_N^B)$  s.t.  $|n^B| = k$ .

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## Approximation of $F$

- we consider a finite number of  $p$  chaos
- we consider the  $N$  first functions  $(e_1, \dots, e_N)$  of the basis  $(e_i)_i$

$$\begin{aligned}
 F &\sim \mathcal{C}_p^N(F) = \mathbb{E}[F] \\
 &+ \sum_{k=1}^p \sum_{l=0}^k \sum_{\mathbf{k}_l \in \{1, \dots, N\}^l} \sum_{\mathbf{j}_{k-l} \in \{1, \dots, N\}^{k-l}} d_{\mathbf{k}_l, \mathbf{j}_{k-l}} L_l^{0, \dots, 0}(\tilde{e}[k_1, \dots, k_l]) L_{k-l}^{1, \dots, 1}(\tilde{e}[j_1, \dots, j_{k-l}]).
 \end{aligned}$$

## Approximation of $F$

$$F \sim \mathcal{C}_p^N(F) = d_0 + \sum_{k=1}^p \sum_{|n|=k} d_k^n \prod_{i=1}^N K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h)$$

where  $n = (n^B, n^P)$ ,  $d_0 = \mathbb{E}(F)$ ,  $G_i := \frac{\Delta B_i}{\sqrt{h}}$ ,  $Q_i := \Delta N_i$  and

$$d_k^n := \frac{n^B!}{n^P!(\kappa h)^{|n^P|}} \mathbb{E} \left( F \prod_{i=1}^N K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h) \right).$$

## Approximation of $F - p = 2$

$$\begin{aligned} \mathcal{C}_2^N(F) = & d_0 + \sum_{j=1}^N \left( d_1^{j,B} K_1(G_j) + d_1^{j,P} C_1(Q_j, \kappa h) \right) + \sum_{j=1}^N \left( d_2^{j,B} K_2(G_j) + d_2^{j,P} C_2(Q_j, \kappa h) \right) \\ & + \sum_{j=1}^N \sum_{i=1}^{j-1} \left( d_2^{i,j,B} K_1(G_i) K_1(G_j) + d_2^{i,j,P} C_1(Q_i, \kappa h) C_1(Q_j, \kappa h) \right) \\ & + \sum_{i=1}^N \sum_{j=1}^N d_2^{i,j,B,P} K_1(G_i) C_1(Q_j, \kappa h) \end{aligned}$$

where  $d_1^{j,B} = \mathbb{E}(FK_1(G_j))$ ,  $d_1^{j,P} = \frac{1}{\kappa h} \mathbb{E}(FC_1(Q_j, \kappa h))$ ,  $d_2^{j,B} = 2\mathbb{E}(FK_2(G_j))$ ,  
 $d_2^{j,P} = \frac{1}{2(\kappa h)^2} \mathbb{E}(FC_2(Q_j, \kappa h))$ ,  $d_2^{i,j,B} = \mathbb{E}(FK_1(G_i) K_1(G_j))$ ,  
 $d_2^{i,j,P} = \frac{1}{(\kappa h)^2} \mathbb{E}(FC_1(Q_i, \kappa h) C_1(Q_j, \kappa h))$ ,  $d_2^{i,j,B,P} = \frac{1}{\kappa h} \mathbb{E}(FK_1(G_i) C_1(Q_j, \kappa h))$ .

## Approximation of conditional expectations

$$\mathcal{C}_p^N(F) = d_0 + \sum_{k=1}^p \sum_{|n|=k} d_k^n \prod_{i=1}^N K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h)$$

Let  $r$  be an integer in  $\{1, \dots, N\}$ . On  $\{n_{r+1}^B + \dots + n_N^B = n_{r+1}^P + \dots + n_N^P = 0\}$  we have

$$\mathbb{E}_{t_r} \left( \prod_{i=1}^N K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h) \right) = \prod_{i \leq r} K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h)$$

$$D_{t_r}^{(0)} \mathbb{E}_{t_r} \left( \prod_{i=1}^N K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h) \right) = h^{-1/2} K_{n_r^B-1}(G_r) C_{n_r^P}(Q_r, \kappa h) \prod_{i < r} K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h),$$

$$D_{t_r}^{(1)} \mathbb{E}_{t_r} \left( \prod_{i=1}^N K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h) \right) = n_r^P K_{n_r^B}(G_r) C_{n_r^P-1}(Q_r, \kappa h) \prod_{i < r} K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h),$$



## Approximation of the expectations

- Starting from  $M$  trajectories of the BM  $B$  and the Poisson process  $N$ , we get  $M$  samples of  $F$
- We compute

$$\mathbb{E}[F] \simeq \hat{d}_0 := \frac{1}{M} \sum_{m=1}^M F^m$$

$$\hat{d}_k^n := \frac{n^{B!}}{n^{P!}(\kappa h)^{|n^P|} M} \sum_{m=1}^M \left( F^m \prod_{i=1}^N K_{n_i^B}(G_i^m) C_{n_i^P}(Q_i^m, \kappa h) \right)$$

$$\mathcal{E}_p^{N,M}(F) = \hat{d}_0 + \sum_{k=1}^p \sum_{|n|=k} \hat{d}_k^n \prod_{1 \leq i \leq N} K_{n_i^B}(G_i) C_{n_i^P}(Q_i, \kappa h).$$

## Algorithm

Let  $(Y^{q,p,N,M}, Z^{q,p,N,M}, U^{q,p,N,M})$  be the approximation of  $(Y^q, Z^q, U^q)$

- $(Y^0, Z^0, U^0) = (0, 0, 0)$ ,  $F^{q,p,N,M} = \xi + \int_0^T f(s, \theta_s^{q,p,N,M}) ds$
- For  $i = 0, \dots, N$  and  $q \geq 0$

$$Y_{t_i}^{q+1,p,N,M} = \mathbb{E} \left( \mathcal{C}_p^{N,M} (F^{q,p,N,M}) \mid \mathcal{F}_{t_i} \right) - h \sum_{j=0}^{i-1} f(t_j, \theta_{t_j}^{q,p,N,M})$$

$$Z_{t_i}^{q+1,p,N,M} = D_{t_i}^{(0)} \mathbb{E} \left( \mathcal{C}_p^{N,M} (F^{q,p,N,M}) \mid \mathcal{F}_{t_i} \right)$$

$$U_{t_i}^{q+1,p,N,M} = D_{t_i}^{(1)} \mathbb{E} \left( \mathcal{C}_p^{N,M} (F^{q,p,N,M}) \mid \mathcal{F}_{t_i} \right)$$

Starting with  $M$  trajectories of  $B$  and  $N$ , the coefficients of the chaos expansions are computed by Monte-Carlo, and we obtain  $M$  trajectories of the process  $(Y^{q,p,N,M}, Z^{q,p,N,M}, U^{q,p,N,M})$ .

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## Scheme of the proof

We split the error between the exact solution  $(Y, Z, U)$  and the implementable approximation  $(Y^{q,p,N,M}, Z^{q,p,N,M}, U^{q,p,N,M})$  in four terms

- error between the exact solution and Picard's approximation  $(Y^q, Z^q, U^q)$
- error between Picard's iteration and Picard's iteration + truncation onto  $p$  chaos  $(Y^{q,p}, Z^{q,p}, U^{q,p})$
- error between Picard's iteration + truncation onto  $p$  chaos and Picard's iteration, truncation onto  $p$  chaos and  $N$  basis functions  $(Y^{q,p,N}, Z^{q,p,N}, U^{q,p,N})$
- error between Picard's iteration + truncation onto  $p$  chaos and  $N$  basis functions and the fully implementable scheme  $(Y^{q,p,N,M}, Z^{q,p,N,M}, U^{q,p,N,M})$

## Picard approximation

Picard's iterations :

$$Y_t^{q+1} = \xi + \int_t^T f(s, Y_s^q, Z_s^q, U_s^q) ds - \int_t^T Z_s^{q+1} dB_s - \int_{]t, T]} U_s^{q+1} d\tilde{N}_s, \quad 0 \leq t \leq T.$$

$$Y_t^{q+1} = \mathbb{E}\left(F^q \mid \mathcal{F}_t\right) - \int_0^t f(s, Y_s^q, Z_s^q, U_s^q) ds,$$

$$Z_t^{q+1} = \mathbb{E}\left(D_t^{(0)} F^q \mid \mathcal{F}_{t-}\right), \quad U_t^{q+1} = \mathbb{E}\left(D_t^{(1)} F^q \mid \mathcal{F}_{t-}\right).$$

where  $F^q := \xi + \int_0^T f(s, Y_s^q, Z_s^q, U_s^q) ds$ .

$(Y^q, Z^q, U^q)$  converges exponentially fast towards the solution  $(Y, Z, U)$ .

## Chaos approximation

$(Y^{q,p}, Z^{q,p}, U^{q,p})$  we use a chaos decomposition up to order  $p$ :

$$Y_t^{q+1,p} = \mathbb{E} \left[ \mathcal{C}_p(F^{q,p}) \mid \mathcal{F}_t \right] - \int_0^t f(s, Y_s^{q,p}, Z_s^{q,p}, U_s^{q,p}) ds,$$

$$Z_t^{q+1,p} = \mathbb{E} \left[ D_t^{(0)} \mathcal{C}_p(F^{q,p}) \mid \mathcal{F}_{t-} \right], \quad U_t^{q+1,p} = \mathbb{E} \left[ D_t^{(1)} \mathcal{C}_p(F^{q,p}) \mid \mathcal{F}_{t-} \right]$$

where  $F^{q,p} = \xi + \int_0^T f(s, Y_s^{q,p}, Z_s^{q,p}, U_s^{q,p}) ds$ .

Let  $1 \leq m \leq p+1$  and  $F \in \mathbb{D}^{m,2}$ . We have

$$\mathbb{E}[|F - \mathcal{C}_p(F)|^2] \leq \frac{\|F\|_{D^m}^2}{(p+2-m) \cdots (p+1)}.$$

.

## Truncation of the basis

We truncate the  $L^2(0, T)$  basis  $(e_i)_i$ , we keep the first  $N$  functions

$$Y_t^{q+1,p,N} = \mathbb{E}_t(\mathcal{C}_p^N(F^{q,p,N})) - \int_0^t f\left(s, Y_s^{q,p,N}, Z_s^{q,p,N}, U_s^{q,p,N}\right) ds,$$

$$Z_t^{q+1,p,N} = D_t^{(0)}(\mathbb{E}_t(\mathcal{C}_p^N(F^{q,p,N}))), \quad U_t^{q+1,p,N} = D_t^{(1)}(\mathbb{E}_t(\mathcal{C}_p^N(F^{q,p,N})))$$

where  $F^{q,p,N} := \xi + \int_0^T f(s, Y_s^{q,p,N}, Z_s^{q,p,N}, U_s^{q,p,N}) ds$ .

$$\mathbb{E}|(\mathcal{C}_p^N - \mathcal{C}_p)(F)|^2 \leq \overline{K}_p^F \left(\frac{T}{N}\right)^{2\beta_F} T(1+T)e^T.$$

## Monte Carlo approximation

We use Monte Carlo simulations to compute the coefficients of the chaos decomposition of  $F^{q,p,N}$

$$Y_t^{q+1,p,N,M} = \mathbb{E}_t(\mathcal{C}_p^{N,M}(F^{q,p,N,M})) - \int_0^t f(\theta_s^{q,p,N,M}) ds,$$

$$Z_t^{q+1,p,N,M} = D_t^{(0)}(\mathbb{E}_t(\mathcal{C}_p^{N,M}(F^{q,p,N,M}))), \quad U_t^{q+1,p,N,M} = D_t^{(1)}(\mathbb{E}_t(\mathcal{C}_p^{N,M}(F^{q,p,N,M})))$$

where  $F^{q,p,N,M} := \xi + \int_0^T f(\theta_s^{q,p,N,M}) ds$ .

$$\mathbb{E}(|(\mathcal{C}_p^N - \mathcal{C}_p^{N,M})(F)|^2) = \frac{1}{M} V_{p,N}(F).$$



## Convergence result

$$\mathcal{E} = \mathbb{E} \left[ \sup_{0 \leq t \leq T} |Y_t - Y_t^{q,p,N,M}|^2 + \int_0^T |Z_t - Z_t^{q,p,N,M}|^2 dt + \kappa \int_0^T |U_t - U_t^{q,p,N,M}|^2 dt \right]$$

### Main result

Let  $k$  be an integer s.t.  $k \leq p$ . Assume that  $\xi$  is regular enough and  $f \in C_b^{0,p+q+1,p+q+1,p+q+1}$ . We have

$$\mathcal{E} \leq \frac{A_0}{2^q} + \frac{A_1(q, k)}{(p+2-k) \cdots (p+1)} + A_2(q, p) \left( \frac{T}{N} \right)^{2\beta_\xi \wedge 1} + \frac{A_3(q, p, N)}{M}.$$

If  $f \in C_b^{0,\infty,\infty,\infty}$ , we get

$$\lim_{q \rightarrow \infty} \lim_{p \rightarrow \infty} \lim_{N \rightarrow \infty} \lim_{M \rightarrow \infty} \|(Y - Y^{q,p,N,M}, Z - Z^{q,p,N,M}, U - U^{q,p,N,M})\|_{L^2}^2 = 0.$$

## Convergence result - hypotheses

Strong assumptions on  $\xi$  are needed

- $\forall j, m \in \mathbb{N}^*$ ,

$$\|\xi\|_{m,j}^j := \sum_{1 \leq l \leq m} \sum_{\mathbf{i}_l \in \{0,1\}^l} \text{ess sup}_{(t_1, \dots, t_l) \in [0, T]^l} \mathbb{E}[|D_{t_1, \dots, t_l}^{\mathbf{i}_l} \xi|^j] < \infty$$

- There exists  $\beta_\xi > 0$  such that

$$\text{ess sup}_{t_1, \dots, t_0} \text{ess sup}_{s_{i+1}, \dots, s_{i+l_1}} \mathbb{E}[|D_{t_1, \dots, t_0}^\alpha (D_{t_i, s_{i+1}, \dots, s_{i+l_1}}^\gamma \xi - D_{s_i, \dots, s_{i+l_1}}^\gamma \xi)|^j] \leq k_l^\xi(j) |t_i - s_i|^{j\beta_\xi}.$$

## Main difference with the Brownian case : moments of chaos

In the Brownian case, if  $\xi = \sum_{n=1}^{\infty} I_n(f_n)$ , the hypercontractivity property of the Ornstein-Uhlenbeck semigroup implies that it holds for  $q > 2$  that

$$\left\| \sum_{n=0}^p I_n(f_n) \right\|_{L_q} \leq (1 + p(q-1)^{p/2}) \|\xi\|_{L_q}$$

Hypercontractivity does not hold for the Poisson process. To compute  $\mathbb{E}(\prod_{i=1}^l I_{n_i}(f_i))$  we adapt a recent result from Last et al (2014).

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## Example with benchmark

$$dY_t = -(\alpha Y_t + \beta Z_t + \gamma U_t) dt + Z_t dB_t + U_t d\tilde{N}_t,$$

$$\xi = \exp(aT + bB_T + cN_T).$$

The explicit solution is given by

$$Y_t = e^{aT + bB_t + cN_t} e^{(\alpha + \frac{(b+\beta)^2 - \beta^2}{2})(T-t) + (e^c - 1)(\kappa + \gamma)(T-t)},$$

$$Z_t = \mathbb{E}_{t-} (D_t^0 Y_t) = bY_{t-}, \quad U_t = \mathbb{E}_{t-} (D_t^1 Y_t) = (e^c - 1)Y_{t-}$$

We choose  $\alpha = \beta = 0.3$ ,  $\gamma = 0.2$ ,  $a = -0.1$ ,  $b = 0.1$ ,  $c = 0.2$ ,  $\kappa = 3$  and  $T = 2$ ,  
 $M = 2 \times 10^5$ ,  $p = 2$ ,  $N = 50$  and  $q = 5$ .

# Trajectory

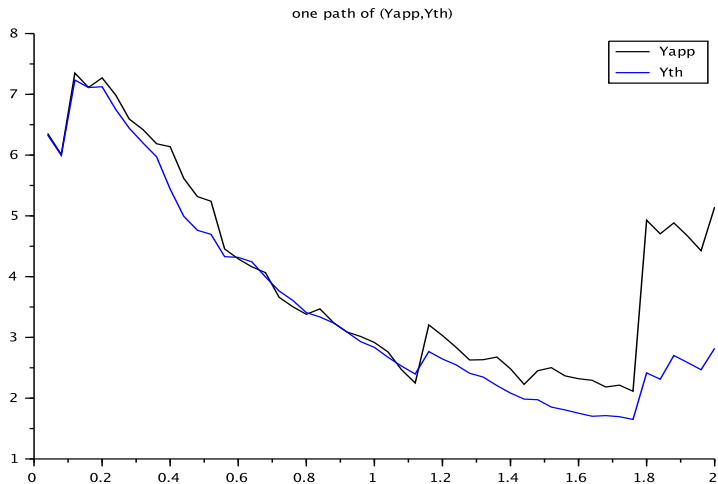


FIGURE – One path of  $(Y^{q,p,N,M}, Y)$

## Complexity - CPU time

The complexity of the algorithm is in  $q \times M \times p \times (N \times d)^{p+1}$ .

M	$10^3$	$5 \times 10^3$	$10^4$	$5 \times 10^4$	$10^5$	$2 \times 10^5$
CPU time (in s)	1.00	4.98	10.16	52.23	116.67	222.58

TABLE – CPU time w.r.t.  $M$  when  $p = 2$ ,  $N = 50$ ,  $q = 5$

## Conclusion

- The algorithm is very fast and can be applied in high dimensions :
  - there is no space discretization
  - we manage to compute conditional expectations and their derivatives very quickly
- It can be used for non Markovian BSDEs