

Stochastic PDEs on networks with non-local boundary conditions and application to finance

F. Cordoni, University of Verona - HPA s.r.l. 

December 20, 2017,
Opening conference VPSMS, Verona

Bibliography

- [1] F. C. and L. Di Persio, *Gaussian estimates on networks with dynamic stochastic boundary conditions*, Infinite Dimensional Analysis, Quantum Probability and Related Topics, 20, (2017): 1750001;
- [2] F. C. and L. Di Persio, *Stochastic reaction–diffusion equations on networks with dynamic time–delayed boundary conditions*, Journal of Mathematical Analysis and Applications, (2017), 1, 583-603.

Outline

Main motivations

Notation

Non-local Kirchhoff condition

The perturbed non-linear stochastic problem

Time-Delayed Kirchhoff condition

The perturbed non-linear stochastic problem

Application to optimal control

Financial applications

Main motivations

Notation

Non-local Kirchhoff condition

The perturbed non-linear stochastic problem

Time-Delayed Kirchhoff condition

The perturbed non-linear stochastic problem

Application to optimal control

Financial applications

Main motivations

- (i) quantum mechanics;
- (ii) electrical circuits;
- (iii) traffic flow;
- (iv) neurobiology;
- (v) smart grid optimization;
- (vi) system of interconnected banks.

Main motivations

Notation

Non-local Kirchhoff condition

The perturbed non-linear stochastic problem

Time-Delayed Kirchhoff condition

The perturbed non-linear stochastic problem

Application to optimal control

Financial applications

Notation

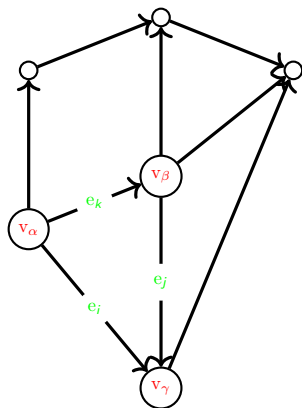
Let us consider a graph \mathbb{G} with:

$n \in \mathbb{N}$ vertices $V = \{v_1, \dots, v_n\}$

$m \in \mathbb{N}$ edges $E = \{e_1, \dots, e_m\}$

Greek letters for vertices $v_\alpha, v_\beta, v_\gamma$

Latin letters for edges e_i, e_j, e_k



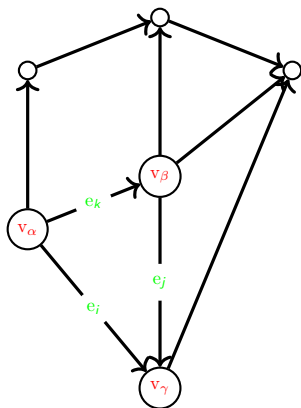
Notation

Incidence matrix

$$\mathcal{I} = (\iota_{ve}), \quad \iota_{ve} = \begin{cases} 1 & \cdot \xrightarrow{e} v, \\ -1 & v \xrightarrow{e} \cdot, \\ 0 & \text{otherwise;} \end{cases}$$

Adjacency matrix

$$\mathcal{A} = (a_{vw}), \quad a_{vw} = \begin{cases} 1 & v \xrightarrow{e} w, \\ 1 & w \xrightarrow{e} v, \\ 0 & \text{otherwise;} \end{cases}$$



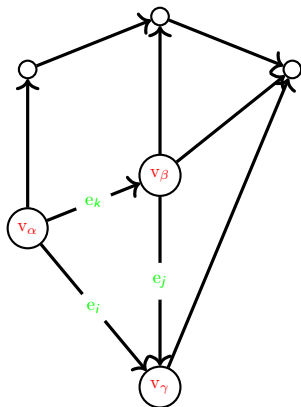
Notation

Incidence matrix

$$\mathcal{I} = (\iota_{ve}), \quad \iota_{ve} = \begin{cases} 1 & \cdot \xrightarrow{e} v, \\ -1 & v \xrightarrow{e} \cdot, \\ 0 & \text{otherwise;} \end{cases}$$

Adjacency matrix

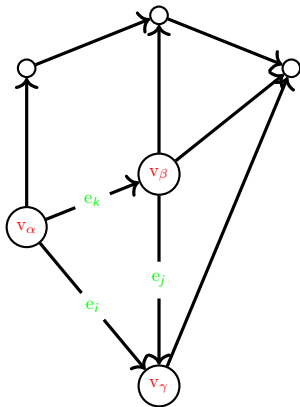
$$\mathcal{A} = (a_{vw}), \quad a_{vw} = \begin{cases} \gamma(e) & v \xrightarrow{e} w, \\ \gamma(e) & w \xrightarrow{e} v, \\ 0 & \text{otherwise;} \end{cases}$$



Consider a diffusion equation on the graph \mathbb{G}

$$\dot{u}_j(t, x) = \Delta u_j(t, x),$$

$u_j(t, x)$, on the edge e_j ,



Main aim

Write the diffusion equation as an abstract operatorial problem

Main aim

Write the diffusion equation as an abstract operatorial problem

Boundary conditions?

Continuity in the nodes

$$u_j(t, v_\alpha) = u_i(t, v_\alpha) =: d_\alpha^u(t), \quad i, j \in \Gamma(v_\alpha),$$

Continuity in the nodes

$$u_j(t, \mathbf{v}_\alpha) = u_i(t, \mathbf{v}_\alpha) =: d_\alpha^u(t), \quad i, j \in \Gamma(\mathbf{v}_\alpha),$$

Kirchhoff condition

$$\sum_{j \in \Gamma(\mathbf{v}_\alpha)} \iota_{\alpha j} u_j'(t, \mathbf{v}_\alpha) = 0.$$

Main motivations

Notation

Non-local Kirchhoff condition

The perturbed non-linear stochastic problem

Time-Delayed Kirchhoff condition

The perturbed non-linear stochastic problem

Application to optimal control

Financial applications

Reaction–diffusion equation

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = \sum_{i=1}^m (c_{ij} u_i')' (t, x) + \sum_{i=1}^m p_{ij} u_i(t, x), \\ u_j(0, x) = u_j^0(x), \end{array} \right.$$

Continuity condition

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = \sum_{i=1}^m (c_{ij} u_i')'(t, x) + \sum_{i=1}^m p_{ij} u_i(t, x), \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d_\alpha^u(t), \\ \\ u_j(0, x) = u_j^0(x), \end{array} \right.$$

Generalized non-local Kirchhoff condition

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = \sum_{i=1}^m (c_{ij} u_i')'(t, x) + \sum_{i=1}^m p_{ij} u_i(t, x), \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d_\alpha^u(t), \\ \sum_{\beta=1}^n b_{\alpha\beta} d_\beta^u(t) = \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{\alpha i} u_j'(t, v_\alpha), \quad \alpha = n_0 + 1, \dots, n, \\ u_j(0, x) = u_j^0(x), \end{array} \right.$$

Dynamic non-local Kirchhoff condition

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = \sum_{i=1}^m (c_{ij} u_i')'(t, x) + \sum_{i=1}^m p_{ij} u_i(t, x), \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d_\alpha^u(t), \\ \sum_{\beta=1}^n b_{\alpha\beta} d_\beta^u(t) = \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{\alpha i} u_j'(t, v_\alpha), \quad \alpha = n_0 + 1, \dots, n, \\ \dot{d}_\alpha^u(t) = - \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{\alpha i} u_j'(t, v_\alpha) + \sum_{\beta=1}^n b_{\alpha\beta} d_\beta^u(t), \quad \alpha = 1, \dots, n_0, \\ u_j(0, x) = u_j^0(x), \\ d_\alpha^u(0) = d_\alpha^0, \quad \alpha = 1, \dots, n_0, \end{array} \right.$$

The abstract setting

$$X^2 := (L^2([0, 1]))^m, \quad \mathbb{R}^n,$$

$$\mathcal{X}^2 := X^2 \times \mathbb{R}^n,$$

$$\left\langle \begin{pmatrix} u \\ d^u \end{pmatrix}, \begin{pmatrix} v \\ d^v \end{pmatrix} \right\rangle_{\mathcal{X}^2} := \sum_{j=1}^m \int_0^1 u_j(x) v_j(x) dx + \sum_{\alpha=1}^n d_\alpha^u d_\alpha^v,$$

The differential operator

$$Au = \begin{pmatrix} (c_{1,1}u_1')' + p_{1,1}u_1 & \dots & (c_{1,m}u_1')' + p_{1,m}u_m \\ \vdots & \ddots & \vdots \\ (c_{m,1}u_1')' + p_{m,1}u_1 & \dots & (c_{m,m}u_m')' + p_{m,m}u_m \end{pmatrix},$$

with domain

$$D(A) = \left\{ u \in (H^2(0,1))^m : \exists d^u(t) \in \mathbb{R}^n \text{ s.t. } (\Phi^+)^T d^u(t) = u(0), \right. \\ \left. (\Phi^-)^T d^u(t) = u(1), \Phi_\delta^+ u'(0) - \Phi_\delta^- u'(1) = B_2 d^u(t) \right\}.$$

Operator matrix

$$\mathcal{A} = \begin{pmatrix} A & 0 \\ C & B_1 \end{pmatrix},$$

with

$$D(\mathcal{A}) = \left\{ \begin{pmatrix} u \\ d^u \end{pmatrix} \in D(A) \times \mathbb{R}^n : u_i(\mathbf{v}_\alpha) = d_\alpha^u, \quad \forall i \in \Gamma(\mathbf{v}_\alpha), \alpha = 1, \dots, n \right\}.$$

Operator matrix

$$\mathcal{A} = \begin{pmatrix} A & 0 \\ C & B_1 \end{pmatrix},$$

with

$$D(\mathcal{A}) = \left\{ \begin{pmatrix} u \\ d^u \end{pmatrix} \in D(A) \times \mathbb{R}^n : u_i(\mathbf{v}_\alpha) = d_\alpha^u, \quad \forall i \in \Gamma(\mathbf{v}_\alpha), \alpha = 1, \dots, n \right\}.$$

$C : D(C) := D(A) \rightarrow \mathbb{R}^n$ the **feedback operator**

$$Cu := \left(- \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{1i} u_j'(\mathbf{v}_1), \dots, - \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{n_0 i} u_j'(\mathbf{v}_{n_0}), 0, \dots, 0 \right)^T,$$

The abstract equation

$$\begin{cases} \dot{\mathbf{u}}(t) = \mathcal{A} \mathbf{u}(t), & t \geq 0, \\ \mathbf{u}(0) = \mathbf{u}_0 \in \mathcal{X}^2. \end{cases}$$

The abstract equation

$$\begin{cases} \dot{\mathbf{u}}(t) = \mathcal{A} \mathbf{u}(t), & t \geq 0, \\ \mathbf{u}(0) = \mathbf{u}_0 \in \mathcal{X}^2. \end{cases}$$

Does \mathcal{A} generate a C_0 -semigroup?

Define the **sesquilinear form**

$$\alpha(\mathbf{u}, \mathbf{v}) := \langle Cu', v' \rangle_2 - \langle Pu, v \rangle_2 - \langle B_1 d^u, d^v \rangle_n - \langle B_2 d^u, d^v \rangle_n.$$

Define the **sesquilinear form**

$$\mathfrak{a}(\mathbf{u}, \mathbf{v}) := \langle C\mathbf{u}', \mathbf{v}' \rangle_2 - \langle P\mathbf{u}, \mathbf{v} \rangle_2 - \langle B_1 d^{\mathbf{u}}, d^{\mathbf{v}} \rangle_n - \langle B_2 d^{\mathbf{u}}, d^{\mathbf{v}} \rangle_n.$$

Proposition

The operator associated with the form \mathfrak{a} is the operator $(\mathcal{A}, D(\mathcal{A}))$. Also $(\mathcal{A}, D(\mathcal{A}))$ generates an analytic and compact C_0 -semigroup $\mathcal{T}(t)$ on \mathcal{X}^2 .

Gaussian upper bound

Theorem

The semigroup $\mathcal{T}(t)$, acting on the space \mathcal{X}^2 and associated to \mathbf{a} , is ultracontractive, namely there exists a constant $M > 0$ such that

$$\|\mathcal{T}(t)\mathbf{u}\|_{\mathcal{X}^\infty} \leq Mt^{-\frac{1}{4}}\|\mathbf{u}\|_{\mathcal{X}^2}, \quad t \in [0, T], \mathbf{u} \in \mathcal{X}^2.$$

Gaussian upper bound

Theorem

The semigroup $\mathcal{T}(t)$, acting on the space \mathcal{X}^2 and associated to \mathfrak{a} , is ultracontractive, namely there exists a constant $M > 0$ such that

$$\|\mathcal{T}(t)\mathbf{u}\|_{\mathcal{X}^\infty} \leq Mt^{-\frac{1}{4}}\|\mathbf{u}\|_{\mathcal{X}^2}, \quad t \in [0, T], \mathbf{u} \in \mathcal{X}^2.$$

Theorem

The semigroup $\mathcal{T}(t)$ has an integral kernel K_t

$$[\mathcal{T}(t)g](x) = \int_{\Omega} K_t(x, y)g(y)\mu(dy).$$

It holds the Gaussian upper bound

$$0 \leq K_t(x, y) \leq c_\delta t^{-\frac{1}{2}} e^{-\frac{|x-y|^2}{\sigma t}}.$$

Proposition

For any $t \geq 0$, the semigroup $\mathcal{T}(t) \in \mathcal{L}_2(\mathcal{X}^2)$, moreover there exists $M > 0$ such that

$$|\mathcal{T}(t)|_{HS} \leq Mt^{-\frac{1}{4}}.$$

The perturbed non-linear stochastic problem

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = \sum_{i=1}^m (c_{ij} u_i')'(t, x) + \sum_{i=1}^m p_{ij} u_i(t, x) \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d_\alpha^u(t), \\ \sum_{\beta=1}^n b_{\alpha\beta} d_\beta^u(t) = \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{\alpha i} u_j'(t, v_\alpha), \\ \dot{d}_\alpha^u(t) = - \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{\alpha i} u_j'(t, v_\beta) + \sum_{\beta=1}^n b_{\alpha\beta} d_\beta^u(t) \\ u_j(0, x) = u_j^0(x), \\ d_\alpha^u(0) = d_\alpha^0, \end{array} \right. ,$$

The perturbed non-linear stochastic problem

$$\left\{ \begin{aligned}
 \dot{u}_j(t, x) &= \sum_{i=1}^m (c_{ij} u_i')'(t, x) + \sum_{i=1}^m p_{ij} u_i(t, x) + \\
 &\quad + f_j(t, x, u_j(t, x)) \quad , \\
 u_j(t, v_\alpha) &= u_l(t, v_\alpha) =: d_\alpha^u(t) , \\
 \sum_{\beta=1}^n b_{\alpha\beta} d_\beta^u(t) &= \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{\alpha i} u_j'(t, v_\alpha) , \\
 \dot{d}_\alpha^u(t) &= - \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{\alpha i} u_j'(t, v_\beta) + \sum_{\beta=1}^n b_{\alpha\beta} d_\beta^u(t) \quad , \\
 u_j(0, x) &= u_j^0(x) , \\
 d_\alpha^u(0) &= d_\alpha^0 ,
 \end{aligned} \right.$$

The perturbed non-linear stochastic problem

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = \sum_{i=1}^m (c_{ij} u_i')'(t, x) + \sum_{i=1}^m p_{ij} u_i(t, x) + \\ \quad + f_j(t, x, u_j(t, x)) + g_j(t, x, u_j(t, x)) \dot{W}_j^1(t, x), \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d_\alpha^u(t), \\ \sum_{\beta=1}^n b_{\alpha\beta} d_\beta^u(t) = \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{\alpha i} u_j'(t, v_\alpha), \\ \dot{d}_\alpha^u(t) = - \sum_{i,j=1}^m \sum_{\beta=1}^n \delta_{\beta j}^{\alpha i} u_j'(t, v_\beta) + \sum_{\beta=1}^n b_{\alpha\beta} d_\beta^u(t) + \tilde{g}_\alpha(t, d_\alpha^u(t)) \dot{W}_\alpha^2(t, v_\alpha), \\ u_j(0, x) = u_j^0(x), \\ d_\alpha^u(0) = d_\alpha^0, \end{array} \right.$$

The abstract equation

$$\begin{cases} d\mathbf{u}(t) = [\mathcal{A}\mathbf{u}(t) + F(t, \mathbf{u}(t))] dt + G(t, \mathbf{u}(t))dW(t), & t \geq 0, \\ \mathbf{u}(0) = \mathbf{u}_0 \in \mathcal{X}^2, \end{cases}$$

Theorem

There exists a unique mild solution in the sense that

$$\mathbf{u}(t) = \mathcal{T}(t)\mathbf{u}_0 + \int_0^t \mathcal{T}(t-s)F(s, \mathbf{u}(s))ds + \int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$

Proof.



Theorem

There exists a unique mild solution in the sense that

$$\mathbf{u}(t) = \mathcal{T}(t)\mathbf{u}_0 + \int_0^t \mathcal{T}(t-s)F(s, \mathbf{u}(s))ds + \int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$

Proof.

Main difficulty: treat the stochastic convolution

$$\int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$



Theorem

There exists a unique mild solution in the sense that

$$\mathbf{u}(t) = \mathcal{T}(t)\mathbf{u}_0 + \int_0^t \mathcal{T}(t-s)F(s, \mathbf{u}(s))ds + \int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$

Proof.

Main difficulty: treat the stochastic convolution

$$\int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$

Standard assumption $G(s, \mathbf{u}(s)) \in \mathcal{L}_2(\mathcal{X}^2)$



Theorem

There exists a unique mild solution in the sense that

$$\mathbf{u}(t) = \mathcal{T}(t)\mathbf{u}_0 + \int_0^t \mathcal{T}(t-s)F(s, \mathbf{u}(s))ds + \int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$

Proof.

Main difficulty to treat the stochastic convolution

$$\int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$

We only require $G(s, \mathbf{u}(s)) \in \mathcal{L}(\mathcal{X}^2)$



proof continued...

Recall propositions above:

\mathcal{A} generates an analytic C_0 -semigroup and

$$|\mathcal{T}(t)|_{HS} \leq Mt^{-\frac{1}{4}}.$$

proof continued...

Recall propositions above:

\mathcal{A} generates an analytic C_0 -semigroup and

$$|\mathcal{T}(t)|_{HS} \leq Mt^{-\frac{1}{4}}.$$

$$\mathcal{T}(t)G(t, \mathbf{u}(t)) \in \mathcal{L}_2(\mathcal{X}^2):$$

$$|\mathcal{T}(t)G(t, \mathbf{u}(t))|_{\mathcal{L}_2(\mathcal{X}^2)} \leq Ct^{-\frac{1}{4}}(1 + |\mathbf{u}|).$$

Main motivations

Notation

Non-local Kirchhoff condition

The perturbed non-linear stochastic problem

Time-Delayed Kirchhoff condition

The perturbed non-linear stochastic problem

Application to optimal control

Financial applications

Reaction–diffusion equation

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = (c_j u_j')'(t, x), \\ u_j(0, x) = u_j^0(x), \end{array} \right.$$

Continuity condition

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = (c_j u_j')'(t, x), \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d^\alpha(t), \\ u_j(0, x) = u_j^0(x), \end{array} \right.$$

Dynamic time-delayed Kirchhoff condition

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = (c_j u_j')'(t, x), \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d^\alpha(t), \\ \dot{d}^\alpha(t) = -\sum_{j=1}^m \phi_{j\alpha} u_j'(t, v_\alpha) + b_\alpha d^\alpha(t) + \int_{-r}^0 d^\alpha(t + \theta) \mu(d\theta), \\ u_j(0, x) = u_j^0(x), \\ d^\alpha(0) = d_\alpha^0, \end{array} \right.$$

Dynamic time–delayed Kirchhoff condition

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = (c_j u_j')'(t, x), \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d^\alpha(t), \\ \dot{d}^\alpha(t) = -\sum_{j=1}^m \phi_{j\alpha} u_j'(t, v_\alpha) + b_\alpha d^\alpha(t) + \int_{-r}^0 d^\alpha(t + \theta) \mu(d\theta), \\ u_j(0, x) = u_j^0(x), \\ d^\alpha(0) = d_\alpha^0, \\ d^\alpha(\theta) = \eta_\alpha^0(\theta). \end{array} \right.$$

The abstract setting

$$\begin{aligned} X^2 &:= (L^2([0, 1]))^m, & Z^2 &:= L^2([-r, 0]; \mathbb{R}^n), \\ \mathcal{X}^2 &:= X^2 \times \mathbb{R}^n, & \mathcal{E}^2 &:= \mathcal{X}^2 \times Z^2, \end{aligned}$$

The abstract setting

$$\begin{aligned} \mathcal{X}^2 &:= (L^2([0, 1]))^m, & Z^2 &:= L^2([-r, 0]; \mathbb{R}^n), \\ \mathcal{X}^2 &:= \mathcal{X}^2 \times \mathbb{R}^n, & \mathcal{E}^2 &:= \mathcal{X}^2 \times Z^2, \end{aligned}$$

Consider the process $d : [-r, T] \rightarrow \mathbb{R}^n$ and define the **segment**

$$d_t : [-r, 0] \rightarrow \mathbb{R}^n, \quad [-r, 0] \ni \theta \mapsto d_t(\theta) := d(t + \theta) \in \mathbb{R}^n.$$

The abstract PDE

$$\begin{cases} \dot{u}(t) = A_m u(t), & t \in [0, T], \\ \dot{d}(t) = C u(t) + \Phi d_t + \tilde{B} d(t), & t \in [0, T], \\ \dot{d}_t = A_\theta d_t, & t \in [0, T], \\ Lu(t) = d(t), \\ u(0) = u_0 \in X^2, \quad d_0 = \eta \in Z^2, \quad d(0) = d^0 \in \mathbb{R}^n, \end{cases}$$

The abstract PDE

$$A_m u(t, x) = \begin{pmatrix} \frac{\partial}{\partial x} (c_j(x) \frac{\partial}{\partial x} u_1(t, x)) & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \frac{\partial}{\partial x} (c_m(x) \frac{\partial}{\partial x} u_m(t, x)) \end{pmatrix},$$

and such that $A_m : D(A_m) \subset X^2 \rightarrow X^2$, with domain

$$D(A) := \left\{ u \in (H^2([0, 1]))^m : \exists d \in \mathbb{R}^n : Lu = d \right\},$$

The abstract PDE

$L : (H^1([0, 1]))^m \rightarrow \mathbb{R}^n$ is the **boundary evaluation operator**

$$Lu(t, x) := (d^1(t), \dots, d^n(t))^T, \quad d^\alpha(t) := u_j(t, v_\alpha).$$

The abstract PDE

$L : (H^1([0, 1]))^m \rightarrow \mathbb{R}^n$ is the **boundary evaluation operator**

$$Lu(t, x) := (d^1(t), \dots, d^n(t))^T, \quad d^\alpha(t) := u_j(t, v_\alpha).$$

$C : D(A) \rightarrow \mathbb{R}^n$ is the **feedback operator**

$$Cu(t, x) := \left(-\sum_{j=1}^m \phi_{j1} u_j'(t, v_1), \dots, -\sum_{j=1}^m \phi_{jn} u_j'(t, v_n) \right)^T.$$

The abstract PDE

$\Phi : H^1([-r, 0]; \mathbb{R}^n) \rightarrow \mathbb{R}^n$ is the **delay operator**

$$\Phi d_t = \int_{-r}^0 d^\alpha(t + \theta) \mu(d\theta).$$

The abstract PDE

$\Phi : H^1([-r, 0]; \mathbb{R}^n) \rightarrow \mathbb{R}^n$ is the **delay operator**

$$\Phi d_t = \int_{-r}^0 d^\alpha(t + \theta) \mu(d\theta).$$

$A_\theta : D(A_\theta) \subset Z^2 \rightarrow Z^2$

$$A_\theta \eta := \frac{\partial}{\partial \theta} \eta(\theta), \quad D(A_\theta) = \{\eta \in H^1([-r, 0]; \mathbb{R}^n) : \eta(0) = d^0\},$$

The abstract equation

$$\begin{cases} \dot{\mathbf{u}}(t) = \mathcal{A}\mathbf{u}(t), & t \in [0, T], \\ \mathbf{u}(0) = \mathbf{u}_0 \in \mathcal{E}^2, \end{cases}$$

\mathcal{A} is defined as

$$\mathcal{A} := \begin{pmatrix} A_m & 0 & 0 \\ C & B & \Phi \\ 0 & 0 & A_\theta \end{pmatrix},$$

with domain $D(\mathcal{A}) := D(A_m) \times D(A_\theta)$.

The abstract equation

$$\begin{cases} \dot{\mathbf{u}}(t) = \mathcal{A}\mathbf{u}(t), & t \in [0, T], \\ \mathbf{u}(0) = \mathbf{u}_0 \in \mathcal{E}^2, \end{cases}$$

\mathcal{A} is defined as

$$\mathcal{A} := \begin{pmatrix} A_m & 0 & 0 \\ C & B & \Phi \\ 0 & 0 & A_\theta \end{pmatrix},$$

with domain $D(\mathcal{A}) := D(A_m) \times D(A_\theta)$.

Does \mathcal{A} generate a C_0 -semigroup?

On the infinitesimal generator

$$\mathcal{A} := \begin{pmatrix} A_m & 0 & 0 \\ C & B & \Phi \\ 0 & 0 & A_\theta \end{pmatrix},$$

On the infinitesimal generator

$$\mathcal{A}_0 := \begin{pmatrix} A_m & 0 & 0 \\ C & B & 0 \\ 0 & 0 & A_\theta \end{pmatrix},$$

On the infinitesimal generator

$$\mathcal{A}_0 := \begin{pmatrix} A_m & 0 & 0 \\ C & B & 0 \\ 0 & 0 & A_\theta \end{pmatrix},$$

On the infinitesimal generator

$$\mathcal{A}_0 := \begin{pmatrix} A_m & 0 & 0 \\ C & B & 0 \\ 0 & 0 & A_\theta \end{pmatrix},$$

$$A_\alpha := \begin{pmatrix} A_m & 0 \\ C & B \end{pmatrix},$$

On the infinitesimal generator

$$\mathcal{A}_0 := \begin{pmatrix} A_m & 0 & 0 \\ C & B & 0 \\ 0 & 0 & A_\theta \end{pmatrix},$$

$$A_\alpha := \begin{pmatrix} A_m & 0 \\ C & B \end{pmatrix},$$

$$\mathcal{A}_0 := \begin{pmatrix} A_\alpha & 0 \\ 0 & A_\theta \end{pmatrix}, \quad D(\mathcal{A}_0) = D(\mathcal{A}),$$

Theorem

The matrix operator $(\mathcal{A}_0, D(\mathcal{A}_0))$ generates a C_0 -semigroup given by

$$\mathcal{T}_0(t) = \left(\begin{array}{cc|cc} & & & \\ & \mathbf{T}_a(t) & & 0 \\ \hline & 0 & \mathbf{T}_t & \mathbf{T}_0(t) \end{array} \right),$$

Theorem

The matrix operator $(\mathcal{A}_0, D(\mathcal{A}_0))$ generates a C_0 -semigroup given by

$$\mathcal{T}_0(t) = \left(\begin{array}{c|c} T_\alpha(t) & \begin{matrix} 0 \\ 0 \end{matrix} \\ \hline 0 & T_t | T_0(t) \end{array} \right),$$

T_α is the C_0 -semigroup generated by $(A_\alpha, D(A_\alpha))$

Theorem

The matrix operator $(\mathcal{A}_0, D(\mathcal{A}_0))$ generates a C_0 -semigroup given by

$$\mathcal{T}_0(t) = \left(\begin{array}{c|c} T_\alpha(t) & \begin{matrix} 0 \\ 0 \end{matrix} \\ \hline 0 & T_t | T_0(t) \end{array} \right),$$

T_α is the C_0 -semigroup generated by $(A_\alpha, D(A_\alpha))$

$T_0(t)$ is the nilpotent left-shift semigroup

$$(T_0(t)\eta)(\theta) := \begin{cases} \eta(t + \theta) & t + \theta \leq 0, \\ 0 & t + \theta > 0, \end{cases}, \quad \eta \in Z^2,$$

Theorem

The matrix operator $(\mathcal{A}_0, D(\mathcal{A}_0))$ generates a C_0 -semigroup given by

$$\mathcal{T}_0(t) = \left(\begin{array}{c|c} T_\alpha(t) & \begin{matrix} 0 \\ 0 \end{matrix} \\ \hline 0 & T_t | T_0(t) \end{array} \right),$$

T_α is the C_0 -semigroup generated by $(A_\alpha, D(A_\alpha))$

$T_0(t)$ is the nilpotent left-shift semigroup

$$(T_0(t)\eta)(\theta) := \begin{cases} \eta(t+\theta) & t+\theta \leq 0, \\ 0 & t+\theta > 0, \end{cases}, \quad \eta \in Z^2,$$

$T_t : \mathbb{R}^n \rightarrow Z^2$ is defined by

$$(T_t d)(\theta) := \begin{cases} e^{(t+\theta)B} d & -t < \theta \leq 0, \\ 0 & -r \leq \theta \leq -t, \end{cases}, \quad d \in \mathbb{R}^n,$$

$e^{(t+\theta)B}$ being the semigroup generated by the finite dimensional $n \times n$ matrix B .

The Miyadera-Voigt perturbation theorem

Theorem

Let $(G, D(G))$ be the generator of a C_0 semigroup $(S(t))_{t \geq 0}$. Assume that there exist constants $t_0 > 0$ and $0 \leq q \leq 1$, such that

$$\int_0^{t_0} \|KS(t)x\| dt \leq q\|x\|, \quad \forall x \in D(G).$$

Then $(G + K, D(G))$ generates a strongly continuous semigroup $(U(t))_{t \geq 0}$ on X , which satisfies

$$U(t)x = S(t)x + \int_0^t S(t-s)KU(s)x ds,$$

and

$$\int_0^{t_0} \|KU(t)x\| dt \leq \frac{q}{1-q}\|x\|, \quad \forall x \in D(G), t \geq 0.$$

$$\mathcal{A}_1 := \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & \Phi \\ 0 & 0 & 0 \end{pmatrix},$$

$$\mathcal{A} = \mathcal{A}_0 + \mathcal{A}_1.$$

$$\mathcal{A}_1 := \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & \Phi \\ 0 & 0 & 0 \end{pmatrix},$$

$$\mathcal{A} = \mathcal{A}_0 + \mathcal{A}_1.$$

Theorem

The operator $(\mathcal{A}, D(\mathcal{A}))$ generates a strongly continuous semigroup.

Proof.

Apply Miyadera-Voigt perturbation theorem. □

The perturbed non-linear stochastic problem

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = (c_j u_j')'(t, x) \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d^\alpha(t), \\ \dot{d}^\alpha(t) = -\sum_{j=1}^m \phi_{j\alpha} u_j'(t, v_\alpha) + b_\alpha d^\alpha(t) + \int_{-r}^0 d^\alpha(t + \theta) \mu(d\theta) \\ u_j(0, x) = u_j^0(x), \\ d^\alpha(0) = d_\alpha^0, \\ d^\alpha(\theta) = \eta_\alpha^0(\theta). \end{array} \right.$$

The perturbed non-linear stochastic problem

$$\left\{ \begin{array}{l} \dot{u}_j(t, x) = (c_j u_j')'(t, x) + f_j(t, x, u_j(t, x)) \\ u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d^\alpha(t), \\ \dot{d}^\alpha(t) = -\sum_{j=1}^m \phi_{j\alpha} u_j'(t, v_\alpha) + b_\alpha d^\alpha(t) + \int_{-r}^0 d^\alpha(t + \theta) \mu(d\theta) \\ u_j(0, x) = u_j^0(x), \\ d^\alpha(0) = d_\alpha^0, \\ d^\alpha(\theta) = \eta_\alpha^0(\theta). \end{array} \right.$$

The perturbed non-linear stochastic problem

$$\left\{ \begin{array}{l}
 \dot{u}_j(t, x) = (c_j u_j')'(t, x) + f_j(t, x, u_j(t, x)) + \\
 \hspace{15em} + g_j(t, x, u_j(t, x)) \dot{W}_j^1(t, x), \\
 u_j(t, v_\alpha) = u_l(t, v_\alpha) =: d^\alpha(t), \\
 \dot{d}^\alpha(t) = -\sum_{j=1}^m \phi_{j\alpha} u_j'(t, v_\alpha) + b_\alpha d^\alpha(t) + \int_{-r}^0 d^\alpha(t+\theta) \mu(d\theta) \\
 \hspace{15em} + \tilde{g}_\alpha(t, d^\alpha(t), d_t^\alpha) \dot{W}_\alpha^2(t, v_\alpha), \\
 u_j(0, x) = u_j^0(x), \\
 d^\alpha(0) = d_\alpha^0, \\
 d^\alpha(\theta) = \eta_\alpha^0(\theta).
 \end{array} \right.$$

Assumption

$$|g_j(t, x, y_1)| \leq C_j, \quad |g_j(t, x, y_1) - g_j(t, x, y_2)| \leq K_j |y_1 - y_2|;$$

$$|\tilde{g}_\alpha(t, x, \eta)| \leq C_\alpha, \quad |\tilde{g}_\alpha(t, x, \eta) - \tilde{g}_\alpha(t, y, \zeta)| \leq K_\alpha (|x - y|_n + |\eta - \zeta|_{z^2}).$$

$$|f_j(t, x, y_1)| \leq C_j, \quad |f_j(t, x, y_1) - f_j(t, x, y_2)| \leq K_j |y_1 - y_2|.$$

Assumption

$$|g_j(t, x, y_1)| \leq C_j, \quad |g_j(t, x, y_1) - g_j(t, x, y_2)| \leq K_j |y_1 - y_2|;$$

$$|\tilde{g}_\alpha(t, x, \eta)| \leq C_\alpha, \quad |\tilde{g}_\alpha(t, x, \eta) - \tilde{g}_\alpha(t, y, \zeta)| \leq K_\alpha (|x - y|_n + |\eta - \zeta|_{z^2}).$$

$$|f_j(t, x, y_1)| \leq C_j, \quad |f_j(t, x, y_1) - f_j(t, x, y_2)| \leq K_j |y_1 - y_2|.$$

Remark

$f_j(t, x, y)$ can be assumed also to be non-Lipschitz of polynomial growth.

The abstract equation

$$\begin{cases} d\mathbf{X}(t) = [\mathcal{A}\mathbf{X}(t) + F(t, \mathbf{X})] dt + G(t, \mathbf{X}(t))dW(t), & t \geq 0, \\ \mathbf{X}(0) = \mathbf{X}_0 \in \mathcal{E}^2, \end{cases}$$

Theorem

There exists a unique mild solution in the sense that

$$\mathbf{X}(t) = \mathcal{T}(t)\mathbf{X}_0 + \int_0^t \mathcal{T}(t-s)F(s, \mathbf{X}(s))ds + \int_0^t \mathcal{T}(t-s)G(s, \mathbf{X}(s))dW(s).$$

Proof.



Theorem

There exists a unique mild solution in the sense that

$$\mathbf{X}(t) = \mathcal{T}(t)\mathbf{X}_0 + \int_0^t \mathcal{T}(t-s)F(s, \mathbf{X}(s))ds + \int_0^t \mathcal{T}(t-s)G(s, \mathbf{X}(s))dW(s).$$

Proof.

Main difficulty: treat the stochastic convolution

$$\int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$



Theorem

There exists a unique mild solution in the sense that

$$\mathbf{X}(t) = \mathcal{T}(t)\mathbf{X}_0 + \int_0^t \mathcal{T}(t-s)F(s, \mathbf{X}(s))ds + \int_0^t \mathcal{T}(t-s)G(s, \mathbf{X}(s))dW(s).$$

Proof.

Main difficulty: treat the stochastic convolution

$$\int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$

Standard assumption $G(s, \mathbf{u}(s)) \in \mathcal{L}_2(\mathcal{X}^2)$



Theorem

There exists a unique mild solution in the sense that

$$\mathbf{X}(t) = \mathcal{T}(t)\mathbf{X}_0 + \int_0^t \mathcal{T}(t-s)F(s, \mathbf{X}(s))ds + \int_0^t \mathcal{T}(t-s)G(s, \mathbf{X}(s))dW(s).$$

Proof.

Main difficulty to treat the stochastic convolution

$$\int_0^t \mathcal{T}(t-s)G(s, \mathbf{u}(s))dW(s).$$

We only require $G(s, \mathbf{u}(s)) \in \mathcal{L}(\mathcal{X}^2)$



proof continued...

The matrix operator \mathcal{A} contains $A_\theta := \frac{\partial}{\partial \theta}$

\mathcal{A} does not generate an analytic C_0 -semigroup

proof continued...

The matrix operator \mathcal{A} contains $A_\theta := \frac{\partial}{\partial \theta}$

\mathcal{A} does not generate an analytic C_0 -semigroup

Proposition

$\mathcal{T}(t)G(s, \mathbf{X}) \in \mathcal{L}_2(\mathcal{X}^2; \mathcal{E}^2)$ such that

$$|\mathcal{T}(t)G(s, \mathbf{X})|_{HS} \leq Mt^{-\frac{1}{4}}(1 + |\mathbf{X}|_{\mathcal{E}^2})$$

Proof.

Technical computations exploiting the explicit form for $\mathcal{T}(t)$. □

Main motivations

Notation

Non-local Kirchhoff condition

The perturbed non-linear stochastic problem

Time-Delayed Kirchhoff condition

The perturbed non-linear stochastic problem

Application to optimal control

Financial applications

Application to optimal control

$$\begin{cases} d\mathbf{X}^z(t) = [\mathbf{A}\mathbf{X}^z(t) + F(t, \mathbf{X}^z) + G(t, \mathbf{X}^z(t))R(t, \mathbf{X}^z(t), z(t))] dt + \\ \quad \quad \quad + G(t, \mathbf{X}^z(t))dW(t), \\ \mathbf{X}^z(t_0) = \mathbf{X}_0 \in \mathcal{E}^2, \end{cases}$$

$$J(t_0, \mathbf{X}_0, z) = \mathbb{E} \int_{t_0}^T l(t, \mathbf{X}^z(t), z(t)) dt + \mathbb{E}\varphi(\mathbf{X}^z(T)) \rightarrow \min .$$

Admissible Control System (acs)

$$\left(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P}, (W(t))_{t \geq 0}, z\right)$$

- ▶ $\left(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P}\right)$ is a complete probability space, where the filtration $(\mathcal{F}_t)_{t \geq 0}$ satisfies the usual assumptions;
- ▶ $(W(t))_{t \geq 0}$ is a \mathcal{F}_t -adapted Wiener process taking values in \mathcal{E}^2 ;
- ▶ z is a process taking values in the space Z , predictable with respect to the filtration $(\mathcal{F}_t)_{t \geq 0}$, and such that $z(t) \in \mathcal{Z}$ \mathbb{P} -a.s., for almost any $t \in [t_0, T]$, being \mathcal{Z} a suitable domain of Z .

Assumption

$$\begin{aligned} |R(t, \mathbf{X}, z) - R(t, \mathbf{Y}, z)|_{\mathcal{E}^2} &\leq C_R(1 + |\mathbf{X}|_{\mathcal{E}^2} + |\mathbf{Y}|_{\mathcal{E}^2})^m |\mathbf{X} - \mathbf{Y}|_{\mathcal{E}^2}, \\ |R(t, \mathbf{X}, z)|_{\mathcal{E}^2} &\leq C_R; \end{aligned}$$

$$\begin{aligned} |l(t, \mathbf{X}, z) - l(t, \mathbf{Y}, z)| &\leq C_l(1 + |\mathbf{X}|_{\mathcal{E}^2} + |\mathbf{Y}|_{\mathcal{E}^2})^m |\mathbf{X} - \mathbf{Y}|_{\mathcal{E}^2}, \\ |l(t, \mathbf{0}, z)|_{\mathcal{E}^2} &\geq -C, \\ \inf_{z \in \mathcal{Z}} l(t, \mathbf{0}, z) &\leq C_l; \end{aligned}$$

$$|\varphi(\mathbf{X}) - \varphi(\mathbf{Y})| \leq C_\varphi(1 + |\mathbf{X}|_{\mathcal{E}^2} + |\mathbf{Y}|_{\mathcal{E}^2})^m |\mathbf{X} - \mathbf{Y}|_{\mathcal{E}^2}.$$

Girsanov theorem

$$W^\zeta(t) := W(t) - \int_{t_0 \wedge t}^{t \wedge T} R(s, \mathbf{X}(s), \zeta) ds,$$

Girsanov theorem

$$W^\zeta(t) := W(t) - \int_{t_0 \wedge t}^{t \wedge T} R(s, \mathbf{X}(s), \zeta) ds,$$

$$\begin{cases} d\mathbf{X}^z(t) = [A\mathbf{X}^z(t) + F(t, \mathbf{X}^z) + G(t, \mathbf{X}^z(t))R(t, \mathbf{X}^z(t), z(t))] dt + \\ \quad + G(t, \mathbf{X}^z(t))dW(t), \\ \mathbf{X}^z(t_0) = \mathbf{X}_0 \in \mathcal{E}^2, \end{cases}$$

Girsanov theorem

$$W^\zeta(t) := W(t) - \int_{t_0 \wedge t}^{t \wedge T} R(s, \mathbf{X}(s), \zeta) ds,$$

$$\begin{cases} d\mathbf{X}^z(t) = [A\mathbf{X}^z(t) + F(t, \mathbf{X}^z)] dt + G(t, \mathbf{X}^z(t)) dW^\zeta(t), \\ \mathbf{X}^z(t_0) = \mathbf{X}_0 \in \mathcal{E}^2, \end{cases}$$

The HJB equation

$$\psi(t, \mathbf{X}, \mathbf{Y}) := - \inf_{z \in \mathcal{Z}} \{I(t, \mathbf{X}, z) + \mathbf{Y}R(t, \mathbf{X}, z)\},$$

$$\Gamma(t, \mathbf{X}, \mathbf{Y}) := \{z \in \mathcal{Z} : \psi(t, \mathbf{X}, \mathbf{Y}) + I(t, \mathbf{X}, z) + \mathbf{Y}R(t, \mathbf{X}, z) = 0\},$$

$$\begin{cases} \frac{\partial w(t, \mathbf{X})}{\partial t} + \mathcal{L}_t w(t, \mathbf{X}) = \psi(t, \mathbf{X}, \nabla^G w(t, \mathbf{X})), \\ w(T, \mathbf{X}) = \varphi(\mathbf{X}), \end{cases}$$

∇^G being the **generalized directional gradient**.

Theorem

Let w be a mild solution to the HJB equation, and chose ρ to be an element of the generalized directional gradient $\nabla^G w$. Then, for all ACS, we have that $J(t_0, \mathbf{X}_0, z) \geq w(t_0, \mathbf{X}_0)$, and the equality holds if and only if the following feedback law is verified by z and \mathbf{u}^z

$$z(t) = \Gamma(t, \mathbf{X}^z(t), G(t, \rho(t, \mathbf{X}^z(t)))) , \quad \mathbb{P} - \text{a.s. for a.a. } t \in [t_0, T].$$

Moreover, if there exists a measurable function $\gamma : [0, T] \times \mathcal{E}^2 \times \mathcal{E}^2 \rightarrow \mathcal{Z}$ with

$$\gamma(t, \mathbf{X}, \mathbf{Y}) \in \Gamma(t, \mathbf{X}, \mathbf{Y}), \quad t \in [0, T], \mathbf{X}, \mathbf{Y} \in \mathcal{X}^2,$$

then there also exists, at least one ACS such that

$$\bar{z}(t) \gamma(t, \mathbf{X}^{\bar{z}}(t), \rho(t, \mathbf{X}^{\bar{z}}(t))), \quad \mathbb{P} - \text{a.s. for a.a. } t \in [t_0, T].$$

Eventually, we have that $\mathbf{X}^{\bar{z}}$ is a mild solution.

Main motivations

Notation

Non-local Kirchhoff condition

The perturbed non-linear stochastic problem

Time-Delayed Kirchhoff condition

The perturbed non-linear stochastic problem

Application to optimal control

Financial applications

System of interconnected banks

Works in progress with L. Di Persio (UniVr), L. Prezioso (UniVr-UniTn), A. Bressan (Penn State University) and Y. Jiang (Penn State University).

System of interconnected banks

Works in progress with L. Di Persio (UniVr), L. Prezioso (UniVr-UniTn), A. Bressan (Penn State University) and Y. Jiang (Penn State University).

- ▶ Multiple defaults of banks;
- ▶ Optimal control with terminal probability constraints;
- ▶ Stackelberg equilibrium;
- ▶ Stochastic impulse control.

System interconnected banks: the setting

- ▶ **value of the i -th bank** associated to the vertex v_i , $i = 1, \dots, n$;
- ▶ **liabilities matrix** $\mathcal{L}(t) = (L_{i,j}(t))_{n \times n}$
- ▶ $u_i(t)$ the **payment made** at time $t \in [0, T]$ by v_i ;
- ▶ $\bar{u}_i(t) = \sum_{j=1}^n L_{i,j}(t)$ the **total nominal obligation** of the node i towards all other nodes;
- ▶ **relative liabilities matrix** $\Pi(t) = (\pi_{i,j}(t))$ defined as

$$\pi_{i,j}(t) = \begin{cases} \frac{L_{i,j}(t)}{\bar{u}_i(t)} & \bar{u}_i(t) > 0, \\ 0 & \text{otherwise} . \end{cases}$$

- ▶ the **cash inflow** of the node i is given by $\sum_{j=1}^n (\Pi_{i,j}(t))^T u_j(t)$.

System interconnected banks: the setting

total value of node v_i at time $t \in [0, T]$

$$\bar{V}^i(t) = \sum_{j=1}^n (\Pi_{i,j}(t))^T u_j(t) + X^i(t) - u_i(t).$$

System interconnected banks: the setting

- ▶ **liabilities** evolve according to

$$\frac{d}{dt}L_{i,j}(t) = \mu_{ij}L_{i,j}(t),$$

- ▶ **exogenous asset** $X^i(t)$ evolves according to

$$dX^i(t) = X^i(t) (\mu^i dt + \sigma^i dW^i(t)), \quad i = 1, \dots, n.$$

- ▶ **continuous (deterministic) default boundaries** for bank i

$$X^i(t) \leq v^i(t) := \begin{cases} R^i \left(\bar{u}_i(t) - \sum_{j=1}^n (\Pi_{i,j}(t))^T \bar{u}_j(t) \right) & t < T, \\ \bar{u}_i(t) - \sum_{j=1}^n (\Pi_{i,j}(t))^T \bar{u}_j(t) & t = T, \end{cases}$$

- ▶ R^i , $i = 1, \dots, n$, representing the **recovery rate** of the bank i .

System interconnected banks: the optimal control problem

- ▶ **financial supervisor**, (*lender of last resort*, (LOLR)), aims at saving the network from default;
- ▶ LOLR minimizes the quadratic cost whilst maximizing the distance of each bank from the respective default boundary

$$J(x, \alpha) := \mathbb{E} \left[\int_0^{\hat{\tau}} \left(-\mathbf{L}(\mathbf{X}(t)) + \frac{1}{2} \|\alpha(t)\|^2 \right) dt - \mathbf{G}(\mathbf{X}(\hat{\tau}^n)) \right],$$

- ▶ $\hat{\tau}$ **random terminal time of default**;
- ▶ **controlled process**

$$dX^i(t) = X^i(t) (\mu^i dt + \sigma^i dW^i(t)) + \alpha^i(t) dt, \quad i = 1, \dots, n.$$

System interconnected banks: the optimal control problem

- ▶ after first default we have a new system $i = 1, \dots, n$

$$dX_1^i(t) = X_1^i(t) (\mu_1^i dt + \sigma_1^i dW^i(t)) + \alpha_1^i(t) dt, \quad i = 1, \dots, n-1.$$

- ▶ LOLR minimizes the quadratic cost whilst maximizing the distance of each bank from the respective default boundary

$$J_1(x, \alpha) := \mathbb{E} \left[\int_{\hat{\tau}}^{\hat{\tau}^1} \left(-\mathbf{L}_1(\mathbf{X}_1(t)) + \frac{1}{2} \|\alpha_1(t)\|^2 \right) dt - \mathbf{G}_1(\mathbf{X}_1(\hat{\tau}^1)) \right],$$

- ▶ $\hat{\tau}^1$ random terminal time of default;

System interconnected banks: the optimal control problem

- ▶ after first default we have a new system $i = 1, \dots, n$

$$dX_1^i(t) = X_1^i(t) (\mu_1^i dt + \sigma_1^i dW^i(t)) + \alpha_1^i(t) dt, \quad i = 1, \dots, n-1.$$

- ▶ LOLR minimizes the quadratic cost whilst maximizing the distance of each bank from the respective default boundary

$$J_1(x, \alpha) := \mathbb{E} \left[\int_{\hat{\tau}}^{\hat{\tau}^1} \left(-\mathbf{L}_1(\mathbf{X}_1(t)) + \frac{1}{2} \|\alpha_1(t)\|^2 \right) dt - \mathbf{G}_1(\mathbf{X}_1(\hat{\tau}^1)) \right],$$

- ▶ $\hat{\tau}^1$ **random terminal time of default**;
- ▶ and so on until no nodes are left in the system;

System interconnected banks: the optimal control problem

- ▶ multiple optimal control problems with random terminal time;
- ▶ stochastic maximum principle for global multiple stochastic optimal control problem;

The maximum principle

Theorem

[Maximum Principle]

$$\partial_a H(t, \bar{\mathbf{X}}(t), \bar{\alpha}(t), \bar{Y}(t), \bar{Z}(t)) (\bar{\alpha}(t) - \tilde{\alpha}) \leq 0,$$

where each $(Y^{\pi^k}(t), Z^{\pi^k}(t))$ solves the following BSDE's

$$\begin{cases} -dY^{\pi^{n-1}}(t) &= \partial_x H^{\pi^{n-1}}(t, \mathbf{X}^{\pi^{n-1}}(t), \alpha^{\pi^{n-1}}(t), Y^{\pi^{n-1}}(t), Z^{\pi^{n-1}}(t))dt - Z^{\pi^{n-1}}dW(t), \\ Y^{\pi^{n-1}}(\hat{\tau}^n) &= \partial_x \mathbf{G}^{\pi^{n-1}}(\hat{\tau}^n, \mathbf{X}^{\pi^{n-1}}(\hat{\tau}^n)), \end{cases}$$

$$\begin{cases} -dY^{\pi^k}(t) &= \partial_x H^{\pi^k}(t, \mathbf{X}^{\pi^k}(t), \alpha^{\pi^k}(t), Y^{\pi^k}(t), Z^{\pi^k}(t))dt - Z^{\pi^k}dW(t), \\ Y^{\pi^k}(\hat{\tau}^{k+1}) &= \partial_x \mathbf{G}^{\pi^k}(\hat{\tau}^{k+1}, \mathbf{X}^{\pi^k}(\hat{\tau}^{k+1})) + \bar{Y}^{k+1}(\hat{\tau}^{k+1}), \end{cases}$$

$$\begin{cases} -dY^0(t) &= \partial_x H^0(t, \mathbf{X}^0(t), \alpha^0(t), Y^0(t), Z^0(t))dt - Z^0dW(t), \\ Y^0(\hat{\tau}) &= \partial_x \mathbf{G}^0(\tau_1, \mathbf{X}^0(\tau_1)) + \bar{Y}^1(\tau_1), \end{cases}$$

The optimal control with constrained probability of success

- ▶ LOLR minimizes amount of money lent

$$J(x, \alpha) = \frac{1}{2} \int_0^T \|\alpha(s)\|^2 ds;$$

under **fixed probability of default**

$$\mathbb{P}(X^i(T) \geq v^i(T)) \geq q^i, \quad i = 1, \dots, n,$$

- ▶ **controlled process**

$$dX^i(t) = X^i(t) (\mu^i dt + \sigma^i dW^i(t)) + \alpha^i(t) dt, \quad i = 1, \dots, n.$$

The optimal control with constrained probability of success

- ▶ two regions for the optimal solution:

The optimal control with constrained probability of success

- ▶ two regions for the optimal solution:
- ▶ **Region I**: the probability constraints is satisfied;
- ▶ optimal solution $\alpha(t) \equiv 0$;

The optimal control with constrained probability of success

- ▶ two regions for the optimal solution:
- ▶ **Region I**: the probability constraints is satisfied;
- ▶ optimal solution $\alpha(t) \equiv 0$;
- ▶ **Region II**: the probability constraints is **not** satisfied;
- ▶ we guess $\alpha^i(t) = \psi(t)X^i(t)$
- ▶ optimal solution

$$\psi^i = \frac{\ln v^i(T) - \ln x_0}{t_1} - \left(\sqrt{2} \operatorname{Erf}^{-1}(1 - 2q^i) \right) \sigma^i \frac{1}{\sqrt{T}} + \frac{(\sigma)^2}{2} - \mu^i.$$

Thank you for your attention!