

Optimal control of trading algorithms: a general impulse control approach

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- Output of trading algorithm and gain/cost function

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Viscosity characterization

- Domain of definition

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- Viscosity characterization

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- ▶ “Obtained price”: $S_\tau + \eta(v; \tau, \tau + \delta)$ with

$$\eta(v; \tau, \tau + \delta) = \alpha \cdot \underbrace{\psi_{BA}(\tau, \tau + \delta)}_{\text{Bid-Ask spread}} + \kappa \cdot \sigma(\tau, \tau + \delta) \underbrace{\left(\frac{v}{V(\tau, \tau + \delta)} \right)^\gamma}_{\text{asked volume ratio}}.$$

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- ▶ Remark: η introduced to take into account quantitatively the aggregated effect on price.

Classical approaches

- ▶ Original framework: a priori discretization of the trading phases [Almgren and Chriss, 2000], taking into account real time analytics came from continuous time models [Almgren, 2009].
- ▶ Modified framework: inclusion of new effect
 - ▶ statistical effects [Lehalle, 2008],
 - ▶ specific properties of the price diffusion process (mean reverting) [Lehalle, 2009],
 - ▶ information at an orderbook level [Hewlett, 2007],
 - ▶ Bayesian estimation of the market trend [Almgren and Lorenz, 2008].

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- ▶ Offer the capability to model the market underlying moves via time-continuous models.
- ▶ Algorithmic trading process is the one of switching between those states:
 - ▶ the **passive regime**: no slice in market, price formation process will continue to take place without interaction with the controlled order,
 - ▶ the **active regime**: parametrized slice in market, duration bounded from below by a constant $\underline{\delta}$, characteristics of a slice are chosen just before its launch, cannot be modified until it ends.

Advantages

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- ▶ Also to control *meta trading algorithms*: optimal launch of *sequence of traditional algorithms* (the first to proposed this possibility).
- ▶ Continuous-time allows the use of traditional models and tools from quantitative finance.

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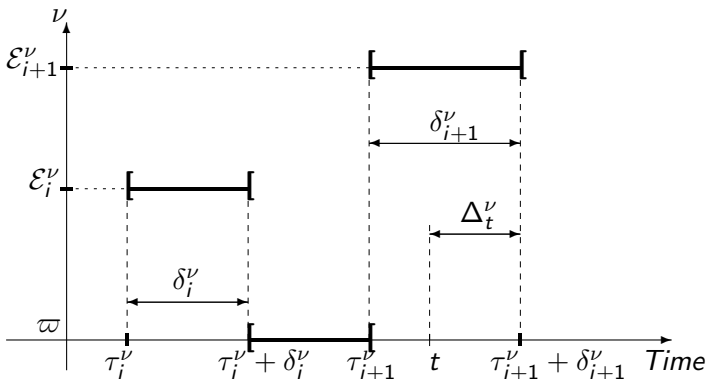
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- ▶ $(\delta_i, \mathcal{E}_i)$ is \mathcal{F}_{τ_i} -measurable, $i \geq 1$,
- ▶ $\nu : t \in [\tau_i, \tau_i + \delta_i) \mapsto \nu_t$: value of the parameter at t , $\nu_t = \varpi \in \mathbb{R}^d \setminus E$ for $t \in A((\tau_i, \delta_i)_{i \geq 1})$, defined as

$$A((\tau_i, \delta_i)_{i \geq 1}) := \mathbb{R}_+ \setminus \left(\bigcup_{i \geq 1} [\tau_i, \tau_i + \delta_i) \right).$$

Control policy



- ▶ $\nu_t = \varpi \mathbf{1}_{t \in A((\tau_i, \delta_i)_{i \geq 1})} + \sum_{i \geq 1} \mathbf{1}_{t \in [\tau_i, \tau_i + \delta_i)} \mathcal{E}_i$, $t \in [0, T]$,
- ▶ $\Delta_t^\nu := \sum_{i \geq 1} [\tau_i^\nu + \delta_i^\nu - t]^+ \mathbf{1}_{t \geq \tau_i^\nu}$, $t \in [0, T]$,
- ▶ $\bar{E} := E \cup \{\varpi\}$.

Dynamics - Objective functional

- ▶ $(t, x) \in [0, T] \times \mathbb{R}^d$, $X_{t,x}^\nu$ strong solution of

$$X_{t,x}^\nu(s) = x + \mathbf{1}_{s \geq t} \left(\int_t^s b(X_{t,x}^\nu(r), \nu_r) dr + \int_t^s a(X_{t,x}^\nu(r), \nu_r) dW_r \right. \\ \left. + \sum_{i \geq 1} \beta(X_{t,x}^\nu(\tau_i^\nu -), \mathcal{E}_i^\nu, \delta_i^\nu) \mathbf{1}_{t < \tau_i^\nu \leq s} \right).$$

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- ▶ over the admissible set

$$\mathcal{S}_{t,\delta,e} := \left\{ \nu \in \mathcal{S} : \nu_s = e \text{ for } s \in [t, t + \delta) \text{ and } \Delta_{t+\delta}^\nu = 0 \right\},$$

$(\delta, e) \in \mathbb{R}_+ \times \bar{E}$: initial state (remaining latency, parameters).

Value function

- ▶ $J(t, x; \nu) := \mathbb{E} [\Pi_{t,x}(\nu)]$ is well defined for all $\nu \in \mathcal{S}$ and admits at most polynomial growth.
- ▶ Technical reason related to the DPP, consider only admissible trading strategies $\nu \in \mathcal{S}_{t,\delta,e}$ such that ν is independent on \mathcal{F}_t , denote by $\mathcal{S}_{t,\delta,e}^a$ (see [Bouchard and Touzi, 2009]).
- ▶ Value function

$$V(t, x, \delta, e) := \sup_{\nu \in \mathcal{S}_{t,\delta,e}^a} J(t, x; \nu).$$

Percent of Volume (PoV) Algorithm

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$$\min_{\nu} \mathbb{E} \left[\underbrace{\ell \left(0 + \int_0^T \tilde{S}_t q(\nu_t) V_t dt \right)}_{\text{running cost}} + \underbrace{(S_T + c(Q_T^\nu, S_T, V_T)) (Q_T^\nu)^+}_{\text{final cost}} \right]$$

for ℓ convex, polynomial growth, $\tilde{S}_t = S_t + \eta(\nu_t, S_t, V_t)$.

Domain of definition of V

- ▶ Natural domain

$$D := \{(t, x, \delta, e) \in [0, T] \times \mathbb{R}^d \times ((0, \infty) \times E) \cup \{(0, \varpi)\}\} \\ : t + \delta \in [\underline{\delta}, T) \text{ or } e = \varpi \},$$

- ▶ which can be decomposed in two main regions:

- ▶ *active region* : $\delta > 0$ and $e \neq \varpi$

$$D_{E, >0} := \{(t, x, \delta, e) \in [0, T] \times \mathbb{R}^d \times (0, \infty) \times E : t + \delta \in [\underline{\delta}, T)\} .$$

- ▶ *passive region*: $e = \varpi$, and therefore $\delta = 0$

$$D_{\varpi} := [0, T] \times \mathbb{R}^d \times \{0, \varpi\} .$$

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- ▶ and can be completed by boundary regions

- ▶ Boundary of active region $\delta \rightarrow 0$ and $t + \delta \rightarrow T$:

$$D_{E,0} := [\underline{\delta}, T) \times \mathbb{R}^d \times \{0\} \times E,$$

$$D_{E,T} := \{(t, x, \delta, e) \in [0, T] \times \mathbb{R}^d \times (0, \infty) \times E : \underline{\delta} \leq t + \delta = T\}.$$

- ▶ Time boundary: $D_T := \{T\} \times \mathbb{R}^d \times \mathbb{R}_+ \times \bar{E}$.

- ▶ Closure of domain $\bar{D} :=$

$$\{(t, x, \delta, e) \in [0, T] \times \mathbb{R}^d \times \mathbb{R}_+ \times \bar{E} : t + \delta \in [\underline{\delta}, T) \text{ or } e = \varpi\}.$$

Special value of V

- ▶ For $\delta = T - t$ and $e \in E$ (i.e., keep e until maturity):

$$V(t, x, T - t, e) = \mathcal{V}(t, x, e) := \mathbb{E} \left[g(\mathcal{X}_{t,x}^e(T)) + f(\mathcal{X}_{t,x}^e(T), e) \right] ,$$
$$\mathcal{X}_{t,x}^e(s) = x + \int_t^s b(\mathcal{X}_{t,x}^e(r), e) dr + \int_t^s a(\mathcal{X}_{t,x}^e(r), e) dW_r .$$

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- ▶ Standard arguments imply that \mathcal{V} continuous, and for each $e \in E$, it is a viscosity solution of

$$-\mathcal{L}^e \varphi(t, x) = 0 \text{ on } [0, T) \times \mathbb{R}^d, \quad \varphi(T, x) = g(x) + f(x, e) \text{ on } \mathbb{R}^d,$$

where the Dynkin operator $\mathcal{L}^e \varphi$ defined for $e \in \bar{E}$, and a smooth function φ .

Passive region

- ▶ Rely on dynamic programming principle: for any $[t, T]$ -valued stopping time ϑ :

$$V(t, x, \delta, e) = \sup_{\nu \in \mathcal{S}_{t, \delta, e}^a} \mathbb{E} \left[V(\vartheta, X_{t, x}^\nu(\vartheta), \Delta_{\vartheta}^\nu, \nu_\vartheta) + \sum_{i \in \mathbb{I}_{t, \vartheta}^\nu} f(X_{t, x}^\nu(\tau_i^\nu + \delta_i^\nu), \mathcal{E}_i^\nu) \right].$$

- ▶ For $(t, x, \delta, e) \in D_\varpi$, possible to immediately launch algorithm with new set of parameters $(\delta', e') \in [\underline{\delta}, T - t] \times E$. Taking $\vartheta = t$: $V(t, x, 0, \varpi) \geq \mathcal{M}[V](t, x)$,

$$\mathcal{M}[V](t, x) := \sup_{(\delta', e') \in [\underline{\delta}, T - t] \times E} V(t, x + \beta(x, e', \delta'), \delta', e'),$$

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- ▶ Also able to wait before passing a new order, i.e. choose $\nu = \varpi$ on some time interval $[t, t + \delta')$ with $\delta' > 0$, by arbitrariness of $\vartheta < t + \delta'$:

$$-\mathcal{L}^\varpi V(t, x, 0, \varpi) \geq 0.$$

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- ▶ Dynamic programming principle:

$$\min \{ -\mathcal{L}^\varpi V(t, x, 0, \varpi) ; V(t, x, 0, \varpi) - \mathcal{M}[V](t, x) \} = 0.$$

Active region

- Rely on dynamic programming principle: for any $[t, T]$ -valued stopping time ϑ :

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- For $(t, x, \delta, e) \in D_{E, > 0}$, cannot change the parameter before the end of the initial latency period $\delta > 0$. Choosing ϑ arbitrarily small:

$$\left(-\mathcal{L}^e + \frac{\partial}{\partial \delta} \right) V(t, x, \delta, e) = 0.$$

Boundary conditions

- ▶ Active region:

$$V(t, x, \delta, e) = V(t, x, 0, \varpi) + f(x, e), \quad \text{if } (t, x, \delta, e) \in D_{E,0},$$

$$V(t, x, \delta, e) = \mathcal{V}(t, x, e), \quad \text{if } (t, x, \delta, e) \in D_{E,T}.$$

- ▶ Terminal condition:

$$V(t, x, \delta, e) = g(x) + f(x, e), \quad \text{if } (t, x, \delta, e) \in D_T.$$

Viscosity characterization

Define

$$\mathcal{H}\varphi := \begin{cases} (-\mathcal{L}^e + \frac{\partial}{\partial \delta}) \varphi(\cdot, \delta, e) & \text{on } D_{E, >0}, \\ \varphi(\cdot, \delta, e) - \varphi(\cdot, 0, \varpi) - f(x, e) & \text{on } D_{E, 0}, \\ \varphi(\cdot, \delta, e) - \mathcal{V}(\cdot, e) & \text{on } D_{E, T}, \\ \min \{ -\mathcal{L}^\varpi \varphi(\cdot, \delta, e); \varphi(\cdot, \delta, e) - \mathcal{M}[\varphi](\cdot) \} & \text{on } D_\varpi, \\ \varphi(\cdot, \delta, e) - g(\cdot) - f(\cdot, e) & \text{on } D_T. \end{cases}$$

Also define for $(t, x, \delta, e) \in \bar{D}$

$$V^*(t, x, \delta, e) := \limsup_{(t', x', \delta', e') \in D \rightarrow (t, x, \delta, e)} V(t', x', \delta', e')$$

$$V_*(t, x, \delta, e) := \liminf_{(t', x', \delta', e') \in D \rightarrow (t, x, \delta, e)} V(t', x', \delta', e').$$

Viscosity characterization (cont.)

Theorem

The function V_ (resp. V^*) is a viscosity supersolution (resp. subsolution) of $\mathcal{H}\varphi = 0$ on \bar{D} .*

Proof and comparison theorem omitted.

What remain to do?

- ▶ Numerical resolution by finite difference method
- ▶ Convergence verified similarly in [Barles and Souganidis, 1991].

Percent of Volume Algorithm - Theoretical case

Parameters:

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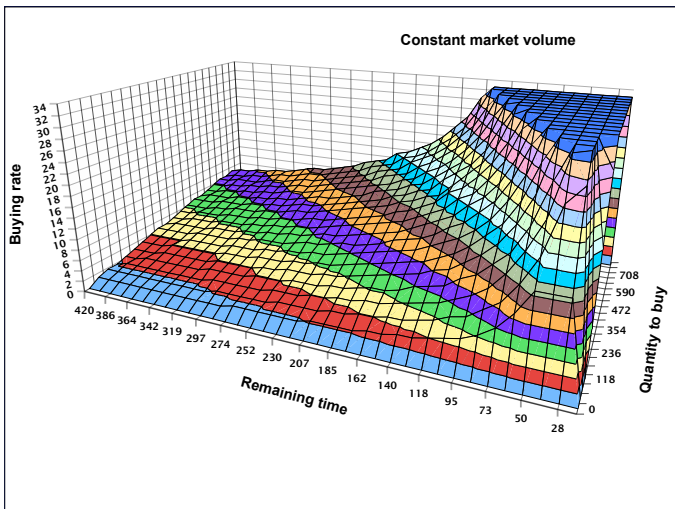
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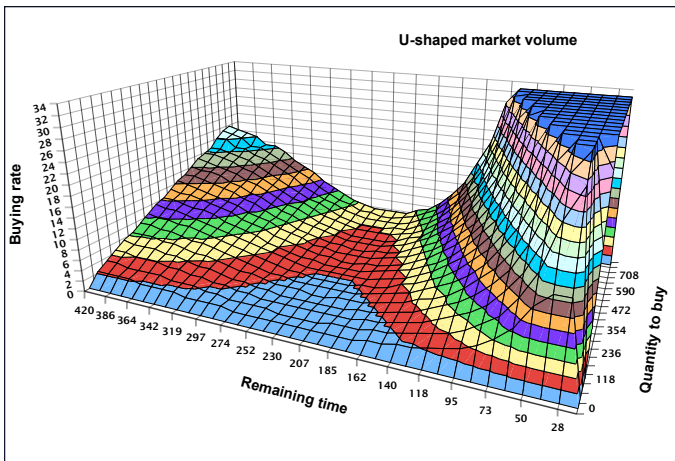
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- ▶ ℓ is the identity, simplifies the numerical resolution since linear in y -variable.

PoV algorithm - Case flat market volume $V_t \equiv 100$



PoV algorithm - Case U-shaped volume

$$V_t = 100(1.1 - \sin(\pi t/T))$$



Percent of Volume Algorithm - Real case

Volume and volatility estimated from real data (France Telecom Jan. 2008 to Dec. 2008), normalized such that average daily volume = 2000.

$S_0 = 10$, $Q_0 = 50$, maximal rate $E_{max} = 0.1$.

Functions: $\eta(e, s, v) = 0.2e^{1.1}$, $c(q, s, v) = 0.3q^+$, $\ell(y) = (y^+)^2$.

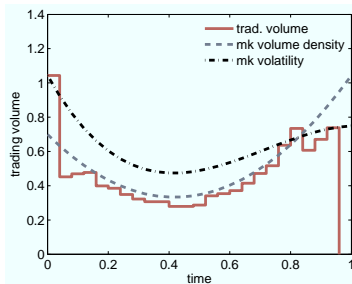


Figure: Volume - Volatility - Average trading curves

Some simulated trajectories

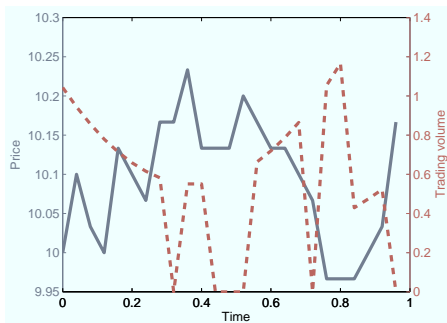


Figure: Simulated price and volume - 1

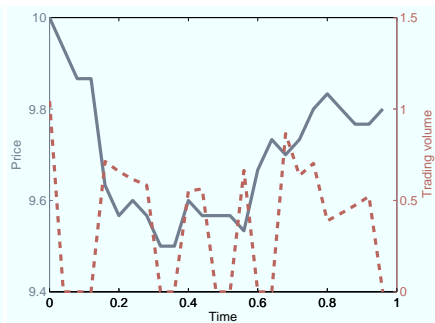


Figure: Simulated price and volume - 2

Thank you for your attention



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