## From classical to quantum quadratic cost control Luigi Accardi

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# Contents

1. Classical Linear Control	3
1.1. Deterministic Control	3
1.2. Stochastic Control	4
2. Quantum Evolutions and Langevin Equations	5
2.1. First Order White Noise	6
2.2. Square of White Noise	7
3. Quantum Control	10
3.1. First order white noise	10
3.2. Square of white noise	11
4. Appendix: <i>Mathematica</i> algorithms	12
References	13

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Abstract. Controlling the size of the solution of a (deterministic, stochastic or quantum stochastic) differential equation, by minimizing an appropriate cost functional, is very important in classical and quantum engineering. Of particular importance is the case of linear differential equations and quadratic cost functionals, since in that case the control processes can be explicitly calculated. In this paper we review some basic aspects of the classical theory and we present our results in the quantum case, obtained over the past few years.

#### 1. Classical Linear Control

1.1. **Deterministic Control.** In the classical deterministic case we consider a system whose evolution over a finite time interval is modelled by the solution  $x = \{x_t : t \in [0, T]\} \in C([0, T], \mathbb{R}^n)\}$  of an ordinary differential equation of the form [38]

(1.1) 
$$dx_t = (A x_t + u_t) dt$$

(1.2) 
$$x_0 = x, \ t \in [0, T]$$

where  $A \in \mathcal{B}(\mathbb{R}^n)$ , the space of bounded linear operators on  $\mathbb{R}^n$ , and  $u \in L_{\infty}([0,T],\mathbb{R}^n)$  or  $L_2([0,T],\mathbb{R}^n)$ . Although we consider here the finite-dimensional case, the concepts and the results can be extended from  $\mathbb{R}^n$  to any Hilbert space  $\mathcal{H}$ .

We assume that we can interfere with the performance of the model by choosing the "control process"  $u = \{u_t : t \in [0,T]\}$  so as to minimize a certain "performance (or cost) functional" J(u). There is a wide variety of such functionals designed for specific models. However, the most computationally accessible one is the "quadratic" performance functional of the form

(1.3) 
$$J(u) = \int_0^T \left( \langle x_t, Q x_t \rangle + \langle u_t, u_t \rangle \right) dt + \langle x_T, \Pi x_T \rangle$$

where  $\langle \cdot, \cdot \rangle$  denotes the usual inner product in the Euclidean space  $\mathbb{R}^n$ ,  $\Pi \in \mathcal{B}(\mathbb{R}^n)$ ,  $Q \in \mathcal{B}(\mathbb{R}^n)$ ,  $\Pi \geq 0$ ,  $Q \geq 0$ . If the size of  $x = \{x_t : t \in [0, T]\}$  is small, the performance functional (1.3) can serve as an approximation to many other functionals which are more adapted to the specific problem considered but also more computationally complex. Before one looks for the optimal control process, the system to be controlled must be "observable", "controllable", and "stabilizable". The definition of these concepts is as follows [35, 36, 38]:

**Observability**: Since the state  $x_t$  of the system may only be accessible through an observation process  $y_t = P x_t$ , where  $P \in \mathcal{B}(\mathbb{R}^n)$ , we must be able to recreate  $x_t$  (or equivalently

 $x_0$ ) from  $y_t$ . If P = 1 we speak of a "completely observable" system. Otherwise the system is only "partially observable".

**Controllability**: Given an initial state  $x_0$ , we should be able to choose the control process  $u = \{u_t : t \in [0, T]\}$  so that the system will be steered in a finite time  $t_1 \in [0, T]$  to a desired state  $x_1$ .

**Stabilizability**: In order to consider large terminal times T, we need the system to exhibit good long-run behavior i.e to eventually settle down to some steady-state behavior. From the mathematical point of view, this amounts to the asymptotic stability of the initial state of  $x = \{x_t : t \in [0, T]\}$  or, equivalently, to the existence of a "feedback" control  $u_t = K x_t$ , where  $K \in \mathcal{B}(\mathbb{R}^n)$ , for which the system (1.1)-(1.2) is asymptotically stable.

The performance functional (1.3) is particularly useful in the case when a system must operate at or near a particular state, chosen here to be the origin. We can think of the first term of (1.3) as a penalty for being too far away from the origin on (0, T), the second as a penalty for using too much control and the third as a penalty for being too far away from the target at the final time T. The main result in the completely observable, classical case is the following:

**Theorem 1.** The performance functional (??) associated with the system (??)-(??) is minimized by the feedback control process

(1.4) 
$$u_t = -\Pi_t x_t$$

where  $\{\Pi_t : t \in [0,T]\}$  is the solution of the Riccati differential equation

(1.5) 
$$\frac{d}{dt}\Pi_t + A^* \Pi_t + \Pi_t A + Q - \Pi_t^2 = 0$$

(1.6) 
$$\Pi_T = \Pi$$

If we restrict to  $u_t = -K x_t$ , i.e to feedback controls with a time-independent coefficient, then equations (??)-(??) are replaced by the "algebraic" Riccati equation

(1.7) 
$$A^* \Pi + \Pi A + Q - \Pi^2 = 0$$

1.2. Stochastic Control. In this case we consider systems whose time evolution is affected by noise. We assume that the noise can be accurately described by Brownian motion. Specifically, we consider systems whose time-evolution is described by the solution  $x = \{x_t : t \in [0, T]\}$  of a stochastic differential equation of the form

(1.8) 
$$dx_t = (A x_t + u_t) dt + C dB_t$$

(1.9) 
$$x_0 = x, \ t \in [0,T]$$

where A and u are as in (??)-(??) with the added assumtion that u is a stochastic process,  $C \in \mathcal{B}(\mathbb{R}^n)$ , and  $B = \{B_t : t \ge 0\}$  is a vector (in this case *n*-dimensional) Brownian motion. The performance functional (??) takes the form

(1.10) 
$$J(u) = E(\int_0^T (\langle x_t, Q x_t \rangle + \langle u_t, u_t \rangle) dt + \langle x_T, \Pi x_T \rangle)$$

where E denotes mathematical expectation.

For completely observable systems, Theorem 1 remains true in the stochastic case. For partially observable systems, i.e when  $x = \{x_t : t \in [0,T]\}$  is available only through an observation process  $y = \{y_t : t \in [0,T]\}$  satisfying

$$(1.11) dy_t = H x_t dt + dW_t$$

where  $H \in \mathcal{B}(\mathbb{R}^n)$ , and  $W = \{W_t : t \in [0, T]\}$  is a vector (in this case *n*-dimensional) Brownian motion independent of  $B = \{B_t : t \in [0, T]\}$ , the main result is as follows:

**Theorem 2.** The performance functional (??) associated with the system (??)-(??) and (??) is minimized by the feedback control process

(1.12) 
$$u_t = -\Pi_t \hat{x_t}$$

where  $\{\Pi_t : t \in [0,T]\}$  is the solution of the Riccati equation

(1.13) 
$$\frac{d}{dt}\Pi_t + A^* \Pi_t + \Pi_t A + Q - \Pi_t^2 = 0$$

(1.14) 
$$\Pi_T = \Pi$$

and  $\hat{x} = {\hat{x}_t : t \in [0, T]}$  is the minimum mean-square estimate of  $x = {x_t : t \in [0, T]}$ given  ${y_s : s \le t}$ , obtained through the Bucy-Kalman filter [36, 38, 39].

The field of classical deterministic and stochastic control is very well developed. For proofs, details and more information we refer to [34, 35, 36, 38, 39].

## 2. QUANTUM EVOLUTIONS AND LANGEVIN EQUATIONS

In the Schrödinger picture of quantum mechanics, the state of a quantum system is described (in Dirac's notation) by a time dependent ket vector  $|\psi_t\rangle$  evolving in accordance to Schrödinger's equation

(2.1) 
$$i\hbar \frac{d}{dt} |\psi_t\rangle = H_t |\psi_t\rangle$$

where  $H_t$  is the Hamiltonian of the system. Quantum mechanical observables are represented by time independent self adjoint operators  $X_0$  acting on the state space. In the Heisenberg picture, the state of the system is represented by a time independent state vector  $|\psi_0\rangle$  and it is the observables  $X_t$  that vary with time. The connection between the two pictures is provided by the unitary "time evolution operators"  $U_t$  that satisfy

(2.2) 
$$X_t = j_t(X_0) = U_t^* X_0 U_t$$

and

(2.3) 
$$|\psi_t\rangle = U_t |\psi_0\rangle$$

In the conservative (i.e time independent Hamiltonian) case

$$(2.4) U_t = e^{-\frac{i}{\hbar}tH}$$

The differential equation satisfied by the  $U_t$ 's is called an "evolution" equation, while the one satisfied by the  $X_t$ 's is called a Langevin equation. In general, the Hamiltonian operator is a sum of "creation", "annihilation" and "number" operators and the above mentioned equations contain noise terms defined in terms of such operators. In what follows we will consider systems and noises represented as operators acting on a Hilbert space  $\mathcal{H}$  and Boson Fock space  $\Gamma(L^2(\mathbb{R}_+,\mathcal{K}))$  respectively. The Boson Fock space  $\Gamma = \Gamma(L^2(\mathbb{R}_+,\mathcal{K}))$  can be defined as the Hilbert space completion of the linear span of the "exponential vectors"  $\psi(f)$ under the inner product

(2.5) 
$$<\psi(f),\psi(g)>=e^{< f,g>}$$

where  $f, g \in L^2(\mathbb{R}_+, \mathcal{K})$ . The set  $\mathcal{K}$  will be  $\mathbb{C}$  or  $l_2(\mathbb{N})$  depending on what kind of noise we consider. Noise will be defined as time dependent operators on the Fock space  $\Gamma(L^2(\mathbb{R}_+, \mathcal{K}))$  with differentials defined in terms of the Hida white noise functionals  $a_t^{\dagger}$  and  $a_t$ .

For  $f \in L^2(\mathbb{R}_+, \mathcal{K})$  and an adjointable linear operator F on  $L^2(\mathbb{R}_+, \mathcal{K})$ , the "annihilation", "creation" and "conservation" operators A(f),  $A^{\dagger}(f)$  and  $\Lambda(F)$  respectively, are defined on the exponential vectors of  $\Gamma$  by

(2.6) 
$$A(f)\psi(g) = \langle f, g \rangle \psi(g)$$

(2.7) 
$$A^{\dagger}(f)\psi(g) = \frac{\partial}{\partial\epsilon}|_{\epsilon=0}\psi(g+\epsilon f)$$

(2.8) 
$$\Lambda(F)\psi(g) = \frac{\partial}{\partial\epsilon}|_{\epsilon=0}\psi(e^{\epsilon F}g)$$

where F must be such that the exponential  $e^{\epsilon F}$  is defined. The Itô multiplication table associated with  $A(\cdot)$ ,  $A^{\dagger}(\cdot)$  and  $\Lambda(\cdot)$  is

•	$dA_t^{\dagger}(f_1)$	$d\Lambda_t(F_1)$	$dA_t(f_1)$	dt
$dA_t^{\dagger}(f_2)$	0	0	0	0
$d\Lambda_t(F_2)$	$dA_t^{\dagger}(F_2f_1)$	$d\Lambda_t(F_2F_1)$	0	0
$dA_t(f_2)$	$\langle f_2, f_1 \rangle dt$	$dA_t(F_1^*f_2)$	0	0
dt	0	0	0	0.

2.1. First Order White Noise. The first order (Hudson-Parthasarathy) quantum stochastic differentials  $dA_t$ ,  $dA_t^{\dagger}$ , and  $d\Lambda_t$  are defined by

6

(2.9) 
$$dA_t = A(\chi_{[t,t+dt]})$$

(2.10) 
$$dA_t^{\dagger} = A^{\dagger}(\chi_{[t,t+dt]})$$

(2.11) 
$$d\Lambda_t = \Lambda(\chi_{[t,t+dt]})$$

In terms of white noise, the basic noise differentials are

(2.12) 
$$dA_t = a_t dt, \, dA_t^{\dagger} = a_t^{\dagger} dt, \, d\Lambda_t = a_t^{\dagger} a_t dt.$$

Quantum evolutions in the tensor product  $\mathcal{H} \otimes \Gamma(L^2(\mathbb{R}_+, \mathcal{K}))$  have the form

(2.13) 
$$dU_t = -((iH + \frac{1}{2}L^*L) dt + L^*W dA_t - L dA_t^{\dagger} + (1 - W) d\Lambda_t) U_t$$

$$(2.14) t \in [0,T], U_0 = 1$$

where H, L, W are in  $\mathcal{B}(\mathcal{H})$ , with U unitary and H self-adjoint. The corresponding Langevin equation is

(2.15) 
$$dj_t(X) = j_t(i[H, X] - \frac{1}{2}(L^*LX + XL^*L - 2L^*XL)) dt + j_t([L^*, X] W) dA_t + j_t(W^* [X, L]) dA_t^{\dagger} + j_t(W^* X W - X) d\Lambda_t (2.16) j_0(X) = X, t \in [0, T]$$

2.2. Square of White Noise. The square of white noise (SWN) commutation relations are a functional extension of the  $sl(2;\mathbb{R})$  commutation relations

(2.17) 
$$[B^-, B^+] = M, [M, B^+] = 2B^+, [M, B^-] = -2B^-$$

where

$$(2.18) (B^-)^* = B^+, \ M^* = M$$

Following "renormalization", the SWN noise differentials are initially defined by

(2.19) 
$$dB_t^- = a_t^2 dt, \, dB_t^+ = a_t^{\dagger^2} dt, \, dM_t = a_t^{\dagger} a_t dt$$

A representation of the  $sl(2;\mathbb{R})$  Lie algebra on  $l_2(\mathbb{N})$  is defined by

(2.20) 
$$\rho^+(B^{+n}M^kB^{-l}) e_m = \theta_{n,k,l,m} e_{n+m-l}.$$

where  $e_m$ ,  $m = 0, 1, 2, \cdots$  is any orthonormal basis of  $l_2(\mathbb{N})$ ,

(2.21) 
$$\theta_{n,k,l,m} := H(n+m-l)\sqrt{\frac{m-l+n+1}{m+1}} 2^k (m-l+1)_n (m+1)^{(l)} (m-l+1)^k,$$

H(x) is the Heaviside function (H(x) = 0 for x < 0; H(x) = 1 for  $x \ge 0$ ),

$$0^0 = 1, \ (B^+)^n = (B^-)^n = N^n = 0, \ \text{for } n < 0,$$

and "factorial powers" are defined by

$$x^{(n)} = x(x-1)\cdots(x-n+1)$$
  
(x)<sub>n</sub> = x(x+1)\cdots(x+n-1)  
(x)<sub>0</sub> = x<sup>(0)</sup> = 1

Using this representation we obtain

(2.22) 
$$dM_t = d\Lambda_t(\rho^+(M)) + dt$$

(2.23) 
$$dB_t^+ = d\Lambda_t(\rho^+(B^+)) + dA_t^\dagger(e_0)$$

(2.24) 
$$dB_t^- = d\Lambda_t(\rho^+(B^-)) + dA_t(e_0)$$

To obtain a closed Itô multiplication table we use as basic SWN differentials

(2.25) 
$$d\Lambda_{n,k,l}(t) = d\Lambda_t(\rho^+(B^{+n}M^kB^{-l}))$$

$$(2.26) dA_m(t) = dA_t(e_m)$$

(2.27) 
$$dA_m^{\dagger}(t) = dA_t^{\dagger}(e_m)$$

where  $n,k,l,m\in\{0,1,\ldots\},$  with Itô multiplication table

(2.28) 
$$d\Lambda_{\alpha,\beta,\gamma}(t) \, d\Lambda_{a,b,c}(t) = \sum_{\alpha,\gamma,a,b} c^{\lambda,\rho,\sigma,\omega,\epsilon}_{\beta,\gamma,a,b} \, d\Lambda_{a+\alpha-\gamma+\lambda,\omega+\sigma+\epsilon,\lambda+c}(t)$$

(2.29) 
$$d\Lambda_{\alpha,\beta,\gamma}(t) \, dA_n^{\dagger}(t) = \theta_{\alpha,\beta,\gamma,n} \, dA_{\alpha+n-\gamma}^{\dagger}(t)$$

(2.30) 
$$dA_m(t) d\Lambda_{a,b,c}(t) = \theta_{c,b,a,m} dA_{c+m-a}(t)$$

(2.31) 
$$dA_m(t) dA_n^{\dagger}(t) = \delta_{m,n} dt$$

where

(2.32) 
$$c^{\lambda,\rho,\sigma,\omega,\epsilon}_{\beta,\gamma,a,b} = \binom{\gamma}{\lambda} \binom{\gamma-\lambda}{\rho} \binom{\beta}{\omega} \binom{b}{\epsilon} 2^{\beta+b-\omega-\epsilon} S_{\gamma-\lambda-\rho,\sigma} a^{(\gamma-\lambda)} (a+\lambda-1)^{(\rho)} (a-\gamma+\lambda)^{\beta-\omega} \lambda^{b-\epsilon}$$

 $S_{\gamma-\lambda-\rho,\sigma}$  are the Stirling numbers of the first kind and  $\sum$  in (2.28) denotes the finite sum

$$\sum_{\lambda=0}^{\gamma} \sum_{\rho=0}^{\gamma-\lambda} \sum_{\sigma=0}^{\gamma-\lambda-\rho} \sum_{\omega=0}^{\beta} \sum_{\epsilon=0}^{b}$$

All other products of differentials are equal to zero.

Quantum evolutions are of the form

(2.33)  

$$dU_{t} = \left(\left(-\frac{1}{2}\left(D_{-}^{*}|D_{-}^{*}\right) + iH\right)dt + d\mathcal{A}_{t}(D_{-})\right) + d\mathcal{A}_{t}^{\dagger}\left(-r(W)D_{-}^{*}\right) + d\mathcal{L}_{t}(W-I)\right)U_{t}$$
(2.34)  

$$U_{0} = 1$$

(2.34)

while Langevin equations are of the form

(2.35)  

$$dj_{t}(X) = j_{t}(i [X, H] - \frac{1}{2} \{ (D_{-}^{*} | D_{-}^{*}) X \} + (r(W)D_{-}^{*} | X r(W)D_{-}^{*}) ) dt + j_{t}(d\mathcal{A}_{t}^{\dagger}(D_{-}^{*} X - r(W^{*} X \circ W)D_{-}^{*})) + j_{t}(d\mathcal{A}_{t}(X D_{-}l(W^{*} \circ X W)D_{-})) + j_{t}(d\mathcal{L}_{t}(W^{*} X \circ W - X)) + j_{t}(d\mathcal{L}_{t}(W^{*} X \circ W - X)) \\ j_{0}(X) = X, t \in [0, T].$$

where H is a bounded self-adjoint system operator, W is a  $\circ$ -product (see (2.44) for the definition of the o-product) unitary operator and  $D_{-} = \sum_{m} D_{-,m} \otimes e_{m}$ , where the  $D_{m}$ 's are bounded system operators.

In equations (2.33)-(2.34) and (2.35)-(2.36) we have used

(i) evolution coefficients:

$$(2.37) D_+ = \sum_n D_{+,n} \otimes e_n$$

$$(2.38) D_{-} = \sum_{m} D_{-,m} \otimes e_m$$

(2.39) 
$$D_1 = \sum_{\alpha,\beta,\gamma} D_{1,\alpha,\beta,\gamma} \otimes \rho^+ (B^{+\alpha} M^{\beta} B^{-\gamma})$$

(2.40) 
$$E_1 = \sum_{a,b,c} E_{1,a,b,c} \otimes \rho^+ (B^{+a} M^b B^{-c})$$

where the left hand sides of the tensor products corespond to bounded system operators

(ii) module operators  $\mathcal{A}$ ,  $\mathcal{A}^{\dagger}$  and  $\mathcal{L}$  generically defined by:

(2.41) 
$$\mathcal{A}(a \otimes \xi) = a \otimes A(\xi)$$

(2.42) 
$$\mathcal{A}^{\dagger}(a \otimes \xi) = a \otimes A^{\dagger}(\xi)$$

(2.43) 
$$\mathcal{L}(a \otimes T) = a \otimes \Lambda(T)$$

and

(iii) basic operations:

$$(2.44) \quad D_1 \circ E_1 = \sum_{\alpha,\beta,\gamma,a,b,c} \sum c^{\lambda,\rho,\sigma,\omega,\epsilon}_{\beta,\gamma,a,b} D_{1,\alpha,\beta,\gamma} E_{1,a,b,c} \otimes \rho^+ (B^{+a+\alpha-\gamma+\lambda} M^{\omega+\sigma+\epsilon} B^{-\lambda+c})$$

$$(2.45) \qquad (D^* | D_+) = \sum D p p D + p \otimes 1$$

$$(2.46) r(D_1)D_1 = \sum_{n=1}^{\infty} D_1 \cdot a_n \theta_1 \cdot a_n \cdots + D_n \cdots + a_n \theta_n$$

(2.46) 
$$r(D_1)D_+ = \sum_{n,\alpha,\beta,\gamma} D_{1,\alpha,\beta,\gamma}\theta_{\alpha,\beta,\gamma,n-\alpha+\gamma}D_{+,n-\alpha+\gamma}\otimes e_n$$

(2.47) 
$$l(E_1)D_- = \sum_{n,\alpha,\beta,\gamma} D_{,n+\alpha-\gamma}\theta_{\gamma,\beta,\alpha,n+\alpha-\gamma}E_{1,\alpha,\beta,\gamma} \otimes e_n$$

where  $\sum$  is as in (??). The SWN Ito table can be concisely written as

(2.48) 
$$d\mathcal{A}_t(D_-) \, d\mathcal{A}_t^{\dagger}(D_+) = (D_-^*|D_+) \, dt$$

(2.49) 
$$d\mathcal{L}_t(D_1) \, d\mathcal{L}_t(E_1) = d\mathcal{L}_t(D_1 \circ E_1)$$

(2.50) 
$$d\mathcal{L}_t(D_1) \, d\mathcal{A}_t^{\dagger}(D_+) = d\mathcal{A}_t^{\dagger}(r(D_1)D_+)$$

(2.51) 
$$d\mathcal{A}_t(D_-) d\mathcal{L}_t(E_1) = d\mathcal{A}_t(l(E_1)D_-)$$

For details we refer to [2]-[10], [12], [15]-[24], [26]-[28], [33], [37], [39].

## 3. Quantum Control

3.1. First order white noise. We consider Langevin equations of the form (??)-(??) associated with evolution equations of the form (??)-(??). Generalizing from the clasical case, we consider quadratic cost functionals of the form

(3.1) 
$$J_{\xi,T}(L,W) = \int_0^T \left[ \|j_t(X)\xi\|^2 + \frac{1}{4} \|j_t(L^*L)\xi\|^2 \right] dt + \frac{1}{2} \|j_T(L)\xi\|^2$$

where T is an arbitrary terminal time,  $\xi = u \otimes \psi(f) \in \mathcal{H} \otimes \Gamma(L^2(\mathbb{R}_+, \mathcal{K}))$  is arbitrary, and the system operators L, W are viewed as controls, chosen to minimize  $J_{\xi,T}(L,W)$ . This cost functional is obtained from the cost functional

(3.2) 
$$Q_{\xi,T}(u) = \int_0^T \left[ \langle U_t \xi, X^2 U_t \xi \rangle + \langle u_t \xi, u_t \xi \rangle \right] dt - \langle u_T \xi, U_T \xi \rangle$$

associated with (??)-(??) as in the classical case, by restricting to feedback controls  $u_t =$  $-\frac{1}{2}L^*LU_t$ . The main result is as follows:

**Theorem 3.** Let X be a system space observable such that the pair (i H, X) is stabilizable  $(i.e \exists K \in \mathcal{B}(\mathcal{H}) \text{ such that } iH + KX \text{ is the generator of an asymptotically stable semigroup}$  $\mathcal{F}_t$  i.e  $\exists M > 0$  and  $\omega < 0$  such that  $||\mathcal{F}_t|| \leq M e^{\omega t}$ . The quadratic performance functional  $J_{\xi,T}(L,W)$  is minimized by

(3.3) 
$$L = \sqrt{2} \Pi^{1/2} W_1 \text{ (polar decomposition of L)}$$

and

$$(3.4) W = W_2$$

10

where  $\Pi$  is the positive self-adjoint solution of the algebraic Riccati equation

(3.5) 
$$i[H,\Pi] + \Pi^2 + X^2 = 0$$

and  $W_1, W_2$  are bounded unitary system operators commuting with  $\Pi$ . Moreover

(3.6) 
$$\min_{L,W} J_{\xi,T}(L,W) = \langle \xi, \Pi \xi \rangle$$

independent of T.

Some early work on the quadratic cost control of quantum processes was done by V.P. Belavkin [24] who considered evolutions with scalar coefficients, and classical noise without jumps i.e W was 1, and the coefficients of  $dA_t$  and  $dA_t^{\dagger}$  were equal, thus amounting to stochastic differential equations driven by classical Brownian motion  $A_t + A_t^{\dagger}$ .

3.2. Square of white noise. In this case, corresponding to (??)-(??) and (??)-(??), we consider the cost functional

$$(3.7) J_{\xi,T}(D_{-},W) = \int_0^T \left[ \|j_t(X)\xi\|^2 + \frac{1}{4} \|j_t((D_{-}^*|D_{-}^*))\xi\|^2 \right] dt + \frac{1}{2} < \xi, j_T((D_{-}^*|D_{-}^*))\xi > 0$$

where  $D_{-}$ , W are the controls, to be chosen so as to minimize  $J_{\xi,T}(D_{-}, W)$ . The main result has as follows:

**Theorem 4.** Let X be a bounded self-adjoint system operator such that the pair (i H, X) is stabilizable. The performance functional  $J_{\xi,T}(D_-, W)$  is minimized by choosing

$$(3.8) D_{-} = \sum_{n} D_{-,n} \otimes e_{n}$$

and

(3.9) 
$$W = \sum_{\alpha,\beta,\gamma} W_{\alpha,\beta,\gamma} \otimes \rho^+ (B^{+\alpha} M^{\beta} B^{-\gamma})$$

such that

(3.10) 
$$\frac{1}{2} \left( D_{-}^{*} | D_{-}^{*} \right) = \left( \frac{1}{2} \sum_{n} D_{-,n} D_{-,n}^{*} \right) \otimes 1 = \Pi_{-}$$

and

(3.11) 
$$[D_{-,n}, D_{-,m}] = [D_{-,n}, D^*_{-,m}] = 0$$

(3.12) 
$$[D_{-,n}, W_{\alpha,\beta,\gamma}] = [D_{-,n}, W^*_{\alpha,\beta,\gamma}] = 0$$

for all  $n, m, \alpha, \beta, \gamma$ , where  $\Pi$  is the positive self-adjoint solution of the algebraic Riccati equation

(3.13) 
$$i[H,\Pi] + \Pi^2 + X^2 = 0$$

Moreover

(3.14) 
$$\min_{D_{-},W} J_{\xi,T}(D_{-},W) = <\xi, \Pi \xi >$$

independent of T.

For proofs and details on the material presented in this section we refer to [1, 3, 11, 13, 14, 25, 29, 30, 31, 32].

## 4. Appendix: Mathematica algorithms

The calculation of the product of two stochastic differentials, in the case of the square of white noise, can be made easy with the use of symbolic programming. Following is a *Mathematica* algorithm for computing (??)-(??). The algorithm also computes the product of the Hudson-Parthasarathy differentials (??)-(??) as a special case (rf. [7]).

**Algorithm 1.** This algorithm computes the, in general, noncommutative products of the generalized SWN stochastic differentials  $d\Lambda_{n,k,l}(t)$ ,  $dA_m(t)$  and  $dA_m^{\dagger}(t)$ , where n, k, l, m = 0, 1, ..., and "time" dt. Each sentence corresponds to a new input. Inputs are separated by space.

$$\begin{split} p[x_{-},y_{-}] &= \mathbf{If} \; [x == y == 0, 1, x^{\wedge} y] \\ u[x_{-},n_{-}] &= \mathbf{Product}[x - i + 1, \{i, 1, n\}] \\ v[x_{-},n_{-}] &= \mathbf{Product}[x + i - 1, \{i, 1, n\}] \\ \theta[n_{-},k_{-},l_{-},m_{-}] &= \mathbf{If} \; [n + m - 1 < 0, 0, Sqrt[(m - l + n + 1)/(m + 1)]2^{\wedge} k \; v[m - l + 1, n] \; u[m + 1, l] \; p[m - l + 1, k]] \\ c[\beta_{-},\gamma_{-},a_{-},b_{-},\lambda_{-},\rho_{-},\sigma_{-},\omega_{-},\epsilon_{-}] &= \\ \mathbf{Binomial}[\gamma,\lambda] \; \mathbf{Binomial}[\gamma - \lambda,\rho] \; \mathbf{Binomial}[\beta,\omega] \; \mathbf{Binomial}[b,\epsilon] \; 2^{\wedge}(\beta + b - \omega - \epsilon) \\ stirling \mathbf{S1}[\gamma - \lambda - \rho,\sigma] \; u[a,\gamma - \lambda] \; u[a + \lambda - 1,\rho] \; p[a - \gamma + \lambda,\beta - \omega] \; p[\lambda, b - \epsilon] \\ \mathbf{NCM}[d\Lambda[\alpha_{-},\beta_{-},\gamma_{-}], d\Lambda[a_{-},b_{-},s_{-}]] &= \; \mathbf{Sum}[c[\beta,\gamma,a,b,\lambda,\rho,\sigma,\omega,\epsilon] \; d\Lambda[a + \alpha - \gamma + \lambda,\omega + \sigma + \epsilon,\lambda + s], \{\lambda,0,\gamma\}, \{\rho,0,\gamma - \lambda\}, \{\sigma,0,\gamma - \lambda - \rho\}, \{\omega,0,\beta\}, \{\epsilon,0,b\}] \\ \mathbf{NCM}[d\Lambda[a_{-},b_{-},c_{-}]] \; = \; \theta[a,b,c,m] dA^{\dagger}[a + m - c] \\ \mathbf{NCM}[d\Lambda[m_{-}], d\Lambda[a_{-},b_{-},c_{-}]] &= \; \theta[c,b,a,m] dA[c + m - a] \\ \mathbf{NCM}[dA[m_{-}], dA^{\dagger}[n_{-}]] &= \; \mathbf{KroneckerDelta}[m,n] dt \\ \mathbf{NCM}[dA^{\dagger}[m_{-}], dA^{\dagger}[n_{-}]] &= \; 0 \\ \\ \mathbf{NCM}[dA^{\dagger}[m_{-}], dA^{\dagger}[n_{-}]] &= \; 0 \\ \end{aligned}$$

12

$$\begin{split} \mathbf{NCM}[dA^{\dagger}[m_{-}], d\Lambda[\alpha_{-}, \beta_{-}, \gamma_{-}]] &= 0\\ \mathbf{NCM}[d\Lambda[\alpha_{-}, \beta_{-}, \gamma_{-}], dA[m_{-}]] &= 0\\ \mathbf{NCM}[d\Lambda[\alpha_{-}, \beta_{-}, \gamma_{-}], dt] &= 0\\ \mathbf{NCM}[dt, d\Lambda[\alpha_{-}, \beta_{-}, \gamma_{-}]] &= 0\\ \mathbf{NCM}[dA[m_{-}], dt] &= 0\\ \mathbf{NCM}[dt, dA[m_{-}]] &= 0\\ \mathbf{NCM}[dt, dA[m_{-}]] &= 0\\ \mathbf{NCM}[dt, dA^{\dagger}[m_{-}], dt] &= 0\\ \mathbf{NCM}[dt, dA^{\dagger}[m_{-}]] &= 0\\ \mathbf{NCM}[dt, dA^{\dagger}[m_{-}]] &= 0 \end{split}$$

For example, using the above algorithm to compute  $d\Lambda_{4,1,2}(t) d\Lambda_{1,2,1}(t)$  we obtain

 $\begin{aligned} \text{NCM}[d\Lambda[4,1,2], d\Lambda[1,2,1]] &= 8d\Lambda[4,1,2] + 16d\Lambda[4,2,2] + 10d\Lambda[4,3,2] + 2d\Lambda[4,4,2] + \\ 32d\Lambda[5,0,3] + 32d\Lambda[5,1,3] + 10d\Lambda[5,2,3] + d\Lambda[5,3,3] \end{aligned}$ 

while for  $d\Lambda_{4,2,1}(t) dA_2^{\dagger}(t)$  we obtain

 $\text{NCM}[d\Lambda[4, 2, 1], dA^{\dagger}[2]] = 48\sqrt{5} dA^{\dagger}[5]$ 

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