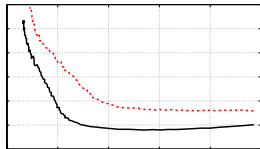
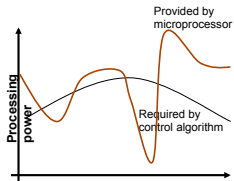


# An Intuitive Algorithm for Control with Limited Communication and Processing Resources

Daniel E. Quevedo

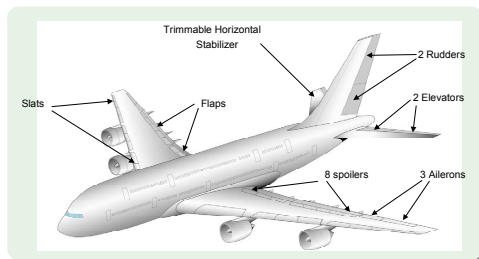
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March 2016



## Motivating Example:

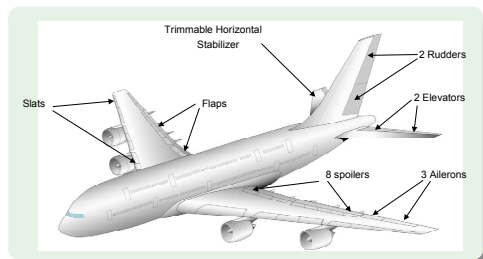
# Communication and Processing in an A380 Aircraft



- The Avionics Full Duplex Switched Ethernet **Network** serves as a backbone to low level networks, e.g., based on CAN.
- Fly-by-wire requires **500 km of cables** and many **interconnects**. This adds to weight, cost and possible fire hazards.
- Fly-by-**wireless** is being considered. Due to dropouts and delays, communication links are **not transparent** and need to be taken into account in the design.

Motivating Example:

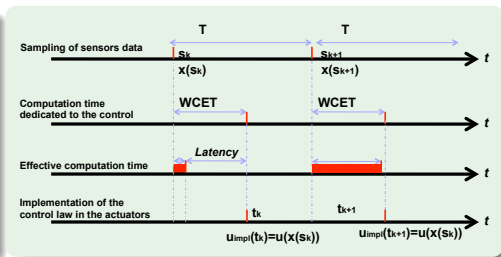
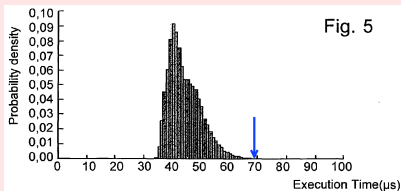
## Communication and **Processing** in an A380 Aircraft



- Eight control computers (and a back-up module) need to **divide their attention** to various loops, including
  - ▶ attitude control,
  - ▶ direction of flight,
  - ▶ engine controls.
- Processing power available for, and required by, each loop is time-varying.

# Traditional Control Design: hard real-time

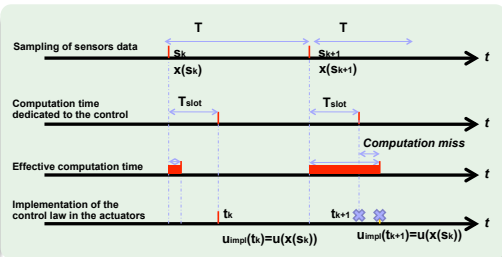
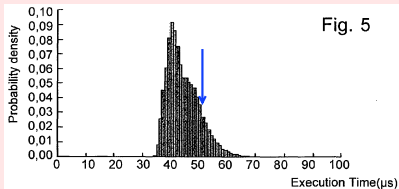
## Execution time distribution



- By using a deadline larger than the worst-case execution time (WCET) a **deterministic** control loop is obtained.
- As processing architectures become **more complex**, execution time distributions tend to have longer tails. Thus:
  - ▶ The WCET becomes more **difficult to determine**.
  - ▶ Computing and communication resources are **idle** more often: Inherent conservatism leads to oversized and heavy components.

# Control with short deadlines (2013 Airbus patent)

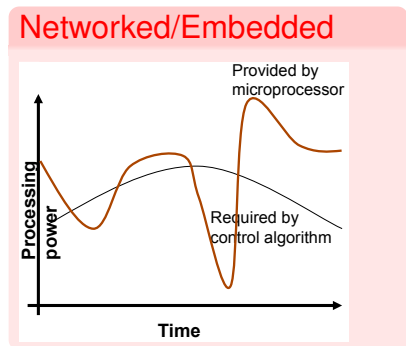
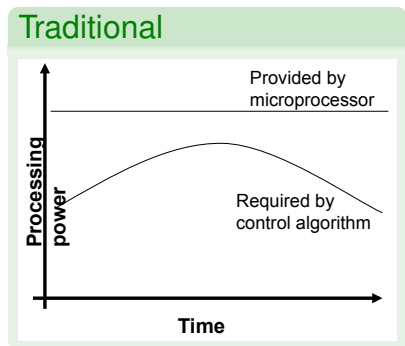
## Execution time distribution



- Shorter deadlines lead to a **stochastic** loop which uses processor and communication resources **more efficiently**.
- At times, processing resources are **insufficient** for evaluating the control policy.
- Once a **maximum number** of consecutive deadline misses is reached, an auxiliary processor is called upon.

More general situation:

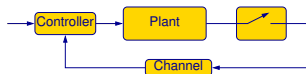
## Processing Power Mismatch in Networked and Embedded Systems



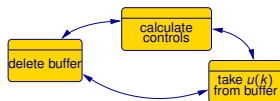
- The traditional assumption about the processor **always being able to execute the control algorithm** during the available computation slot may break down.

# This talk

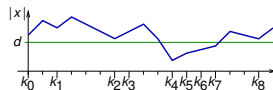
- 1 presents a modeling framework for closed-loop control, when **processing and communication resources are limited**,



- 2 describes an **intuitive algorithm** to synthesise such loops,



- 3 illustrates how **stability** can be analysed using random-time state-dependent drift conditions.



# Some previous works of Interest

## Stochastic Networked Control

- Hespanha, Dahleh, Sinopoli, Teel, Heemels, etc

## Event-triggered Estimation and Control

- Transmit and compute only when an event occurs:  
Åström, Tabuada, Lemmon, Blind, etc.

## Control with limited Processing Resources

- Computation-performance tradeoffs for MPC: McGovern, Cervin
- Allow for deadline misses: Seuret
- “Anytime Control” (control is refined on-line, calculations can be terminated at any time): Bhattacharya, Greco, Bicchi



# Outline

## 1 Event-triggered Control with Dropouts

- System Model
- Baseline Algorithm
- Numerical Example

## 2 Anytime Control Algorithm

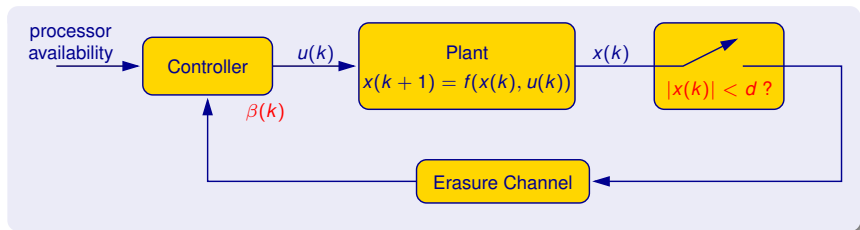
- Method Description
- Numerical Example - revisited

## 3 Stability Analysis

- Assumptions
- The Baseline Algorithm
- The Anytime Algorithm
- Comparison of Bounds

## 4 Conclusions

# System Model



- The quantity  $d$  is a design parameter which trades **communication channel utilization** for **control performance**.
- Transmission between sensor and controller node is through a **delay-free link with dropouts**:

$$\beta(k) = \begin{cases} 0 & \text{if } x(k) \text{ is received with errors (a dropout occurs),} \\ 1 & \text{if } x(k) \text{ is received error-free,} \\ 2 & \text{if the sensor did not transmit at time } k \text{ (i.e., } |x(k)| < d \text{).} \end{cases}$$

- We are interested in a situation, where a “good” state-feedback controller  $\kappa: \mathbb{R}^n \rightarrow \mathbb{R}^p$  has been **pre-designed**.
- Processing resources for control may, at times, be **insufficient** to evaluate  $\kappa$  within the pre-allocated time-slot of length  $\tau$ .
- A **direct implementation of the control policy  $\kappa$** , yields the

## Baseline Algorithm

$$u(k) = \begin{cases} \kappa(x(k)), & \text{if } \beta(k) = 1 \text{ and } \kappa(x(k)) \text{ was evaluated} \\ & \text{between times } kT \text{ and } kT + \tau, \\ \mathbf{0}_p, & \text{otherwise,} \end{cases}$$

where  $u(k)$  with  $k \in \mathbb{N}_0$  denotes the plant input which is applied during the interval  $[kT + \tau, (k + 1)T + \tau)$ .

# Numerical Example

## Plant model and controller

- Plant model with i.i.d. **disturbance** distributed as  $\mathcal{N}(0, 1)$ :

$$x(k+1) = -x(k) + 0.1 \sin(x(k)) + u(k) + w(k), \quad x(0) = 20.$$

- Control policy is taken as:

$$\kappa(x) = x - 0.1 \sin(x) + \rho|x|, \quad \rho = 0.9.$$

## Resources

$$\Pr\{\beta(k) = 1 \mid |x(k)| \geq d\} = 0.5$$

$$\Pr\{\text{processor is available} \mid \beta(k) = 1\} = 0.8$$

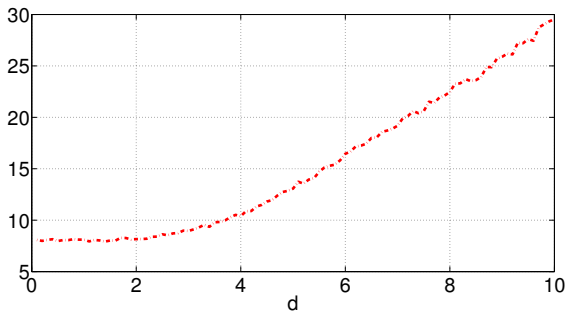
The closed loop is characterised by:

$$x(k+1) = \begin{cases} \rho|x(k)| + w(k), & \text{if processor is available} \\ & \text{and } \beta(k) = 1, \\ -x(k) + 0.1 \sin(x(k)) + w(k), & \text{otherwise.} \end{cases}$$

## Empirical Cost

$$\frac{1}{500} \left( \sum_{k=201}^{700} x^2(k) \right),$$

averaged over 1000 realisations.

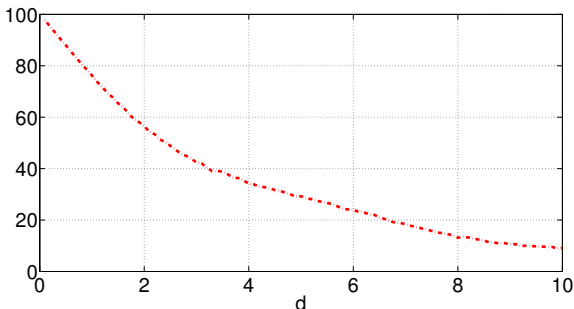


Larger thresholds give a worse control performance!

## Channel Utilisation (%)

$$\frac{\text{Total number of time steps at which } \beta(k) \neq 2}{\text{Total number of time steps}},$$

averaged over 1000 realisations.



Larger thresholds lead to less communication uses!

Whilst the **baseline algorithm** is simple, it is by no means clear that it cannot be outperformed by more elaborate control formulations.

- We will next present an intuitive control algorithm.
- The purpose is to make efficient use of the communication and processing resources available.
- The algorithm calculates **sequences of tentative future inputs**.
- These are stored in a local **buffer**.
- Buffered values may be used when, at some future time steps, the **processor availability** precludes any control calculations, or a **dropout** occurs ( $\beta(k) = 0$ ).

# Outline

## 1 Event-triggered Control with Dropouts

- System Model
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## 2 Anytime Control Algorithm

- **Method Description**
- Numerical Example - revisited

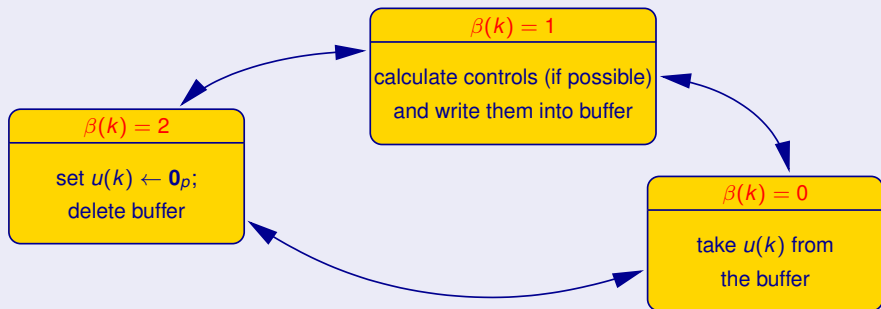
## 3 Stability Analysis

- Assumptions
- The Baseline Algorithm
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## 4 Conclusions



# Event-triggered Anytime Control Algorithm



- If  $\beta(k) = 1$ , then  $x(k)$  is used to calculate  $N(k) \in \{0, 1, \dots, \Lambda\}$  tentative control values **using**  $\kappa$ :

$$u_0(k) = \kappa(x(k))$$

$$u_1(k) = \kappa(f(x(k), u_0(k))), \quad \text{etc.}$$

- This sequence is stored in a **local buffer** of size  $\Lambda$ . Its contents may be used when the **processor is unavailable** or when  $\beta(k + \ell) = 0$ .

## Comments

- The algorithm does not require prior knowledge of processor availability. Therefore, the control task can be **preempted**.
- The buffer state  $b(k)$  provides the current plant input,  $u(k) = b_1(k)$ .
- If  $N(k) > 1$ , then  $b(k)$  also contains **suggested future inputs**.
- If the buffer **runs out of tentative plant inputs**, then  $u(k) = \mathbf{0}_p$ .

We introduce the

**effective buffer length**

$$\lambda(k) = \begin{cases} N(k) & \text{if } N(k) \geq 1, \\ \max\{0, \lambda(k-1) - 1\} & \text{if } N(k) = 0 \text{ and } \beta(k) \in \{0, 1\}, \\ 0 & \text{if } \beta(k) = 2. \end{cases}$$

## Example

Suppose that  $\Lambda = 4$  and that  $\{N(0), N(1), N(2), N(3)\} = \{4, 0, 1, 2\}$ .

The Anytime algorithm provides

$$\{b(0), b(1), b(2), b(3)\} = \left\{ \begin{bmatrix} u_0(0) \\ u_1(0) \\ u_2(0) \\ u_3(0) \end{bmatrix}, \begin{bmatrix} u_1(0) \\ u_2(0) \\ u_3(0) \\ \mathbf{0}_p \end{bmatrix}, \begin{bmatrix} u_0(2) \\ \mathbf{0}_p \\ \mathbf{0}_p \\ \mathbf{0}_p \end{bmatrix}, \begin{bmatrix} u_0(3) \\ u_1(3) \\ \mathbf{0}_p \\ \mathbf{0}_p \end{bmatrix} \right\}$$

$$\{\lambda(0), \lambda(1), \lambda(2), \lambda(3)\} = \{4, 3, 1, 2\}, \quad \text{and plant inputs}$$

$$\{u(0), \dots, u(3)\} = \{\kappa(x(0)), \kappa(f(x(0), \kappa(x(0))))\}, \kappa(x(2)), \kappa(x(3))\}.$$

If the baseline-algorithm is used, then

$$\{u(0), u(1), u(2), u(3)\} = \{\kappa(x(0)), \mathbf{0}_p, \kappa(x(2)), \kappa(x(3))\}.$$

# Outline

## 1 Event-triggered Control with Dropouts

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- Numerical Example

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- Method Description
- **Numerical Example - revisited**

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- Assumptions
- The Baseline Algorithm
- The Anytime Algorithm
- Comparison of Bounds

## 4 Conclusions

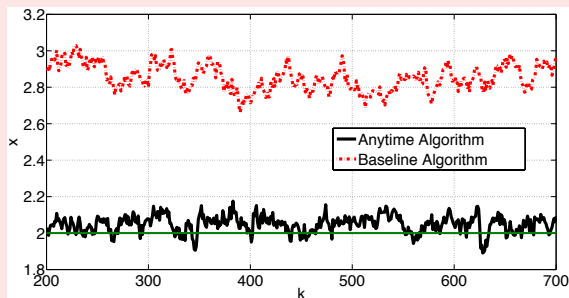
# Numerical Example

## Resources

- Suppose that  $\Lambda = 4$  and that

$$\Pr\{\beta(k) = 1 \mid |x(k)| \geq d\} = 0.5$$

$$\Pr\{N(k) = j \mid \beta(k) = 1\} = 0.2, \quad j \in \{0, 1, 2, 3, 4\}$$

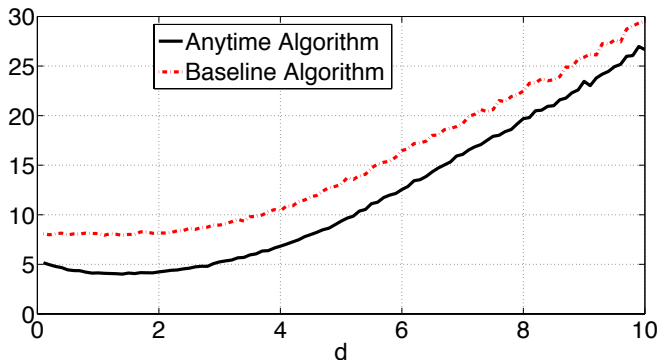


- State trajectory with  $d = 2$ .
- The anytime control algorithm **outperforms** the baseline controller.

## Empirical Cost

$$\frac{1}{500} \left( \sum_{k=201}^{700} x^2(k) \right),$$

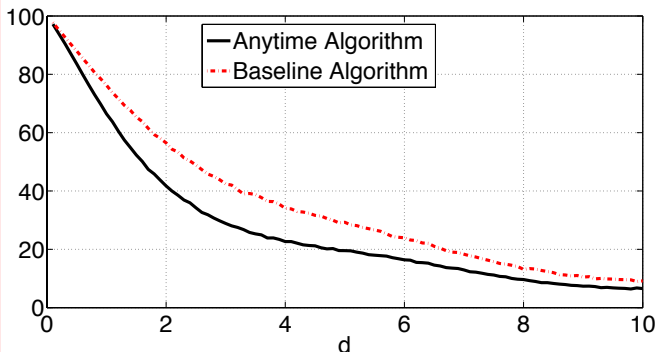
averaged over 1000 realisations.



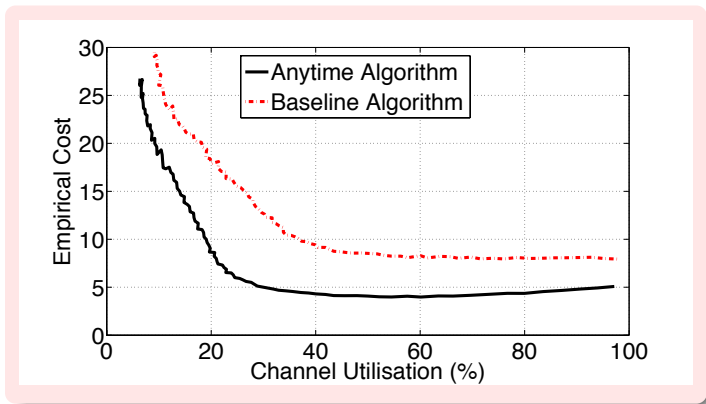
## Channel Utilisation (%)

$$\frac{\text{Total number of time steps at which } \beta(k) \neq 2}{\text{Total number of time steps}},$$

averaged over 1000 realisations.



# Empirical Cost versus Channel Utilisation



## Performance Gains

For a given transmission rate, the proposed anytime control algorithm reduces the empirical cost by approximately 40-50%.



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# Standing Assumptions

## Globally Stabilising Nominal Controller

There exist functions  $V: \mathbb{R}^n \rightarrow \mathbb{R}_{\geq 0}$ ,  $\varphi_1, \varphi_2 \in \mathcal{K}_\infty$ ,<sup>a</sup> a constant  $\rho \in [0, 1)$ , and a **control policy**  $\kappa: \mathbb{R}^n \rightarrow \mathbb{R}^p$ , such that

$$\begin{aligned}\varphi_1(|x|) &\leq V(x) \leq \varphi_2(|x|), \\ V(f(x, \kappa(x))) &\leq \rho V(x), \quad \forall x \in \mathbb{R}^n.\end{aligned}$$

---

<sup>a</sup>A function  $\varphi: \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$  is of *class- $\mathcal{K}_\infty$*  ( $\varphi \in \mathcal{K}_\infty$ ), if it is continuous, zero at zero, strictly increasing, and unbounded.

## Open-loop bound

With  $V$  as above, there exists  $\alpha \in \mathbb{R}_{\geq 0}$  such that<sup>a</sup>

$$V(f(x, \mathbf{0}_p)) \leq \alpha V(x), \quad \forall x \in \mathbb{R}^n.$$

---

<sup>a</sup>For the numerical example described before, we have  $\alpha = 1.1$ .

## Processor availability is i.i.d.

The process  $\{N\}_{\mathbb{N}_0}$  has conditional probability distribution

$$\Pr\{N(k) = j \mid \beta(k) = 1\} = p_j, \quad j \in \{0, 1, 2, \dots, \Lambda\},$$

where  $p_j \in [0, 1)$  are given.

For other realizations of  $\beta(k)$ , no plant inputs are calculated:

$$\Pr\{N(k) = 0 \mid \beta(k) \in \{0, 2\}\} = 1.$$

## Packet dropouts are i.i.d.

The transmissions are Bernoulli with packet transmission success probability

$$\Pr\{\beta(k) = 1 \mid |x(k)| \geq d\} = q.$$

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- **The Baseline Algorithm**
- The Anytime Algorithm
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# The Baseline Algorithm

- The closed loop is characterised by:

$$x(k+1) = \begin{cases} f(x(k), \kappa(x(k))), & \text{if } N(k) \geq 1, \\ f(x(k), \mathbf{0}_\rho), & \text{if } N(k) = 0. \end{cases}$$

- We denote via  $p_0$  the probability that the controller is unable to calculate any control input, despite  $x(k)$  being available.

## Stochastic Stability with the Baseline Algorithm

Suppose that  $\mathbf{E}\{\varphi_2(|x(0)|)\} < \infty$  and that

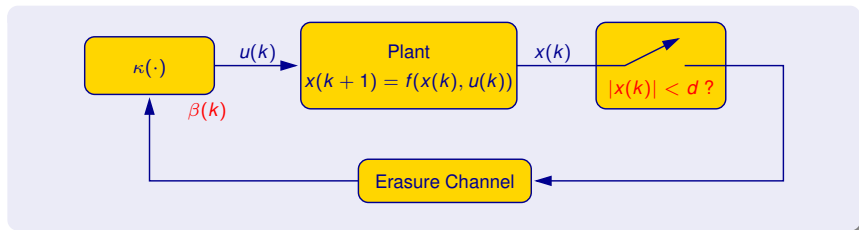
$$\Gamma \triangleq (1 - q)\alpha + q(p_0\alpha + (1 - p_0)\rho) < 1.$$

Then there exist finite  $\gamma$  and  $\mu$  such that

$$\mathbf{E}\{\varphi_1(|x(k)|)\} \leq \gamma\Gamma^k + \mu, \quad \forall k \in \mathbb{N}_0.$$

If  $d = 0$ , then  $\mu = 0$ .

# Special case: event-triggering with an erasure channel



- If the processor is always available ( $p_0 = 0$ ), then the sufficient condition for stochastic stability reduces to:

$$\Gamma \triangleq (1 - q)\alpha + q\rho < 1,$$

where:

- ▶  $q$  is the transmission success probability,
- ▶  $\alpha$  is the open-loop bound on the plant dynamics, and
- ▶  $\rho$  is the closed-loop contraction factor ensured by the control law  $\kappa$ .

## Sketch of proof

- The process  $\{x(k)\}$ ,  $k \in \mathbb{N}_0$  is **Markovian**.
- Using the assumptions and writing  $x$  for  $x(0)$ , we have:

$$\begin{aligned} \mathbf{E}\{V(x(1)) \mid x\} &= \sum_{j=0}^2 \mathbf{E}\{V(x(1)) \mid x, \beta(0) = j\} \Pr\{\beta(0) = j \mid x\} \\ &< \Gamma V(x) + (\alpha - \Gamma)\varphi_2(d), \quad \forall x. \end{aligned}$$

- Thus, using the Markov property, we obtain

$$\mathbf{E}\{\varphi_1(|x(k)|) \mid x\} \leq \Gamma^k V(x) + \frac{(\alpha - \Gamma)\varphi_2(d)}{1 - \Gamma} < \infty, \quad \forall k \in \mathbb{N}_0.$$

- Taking expectation with respect to the distribution of the initial state  $x(0)$  establishes the result.

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## 1 Event-triggered Control with Dropouts

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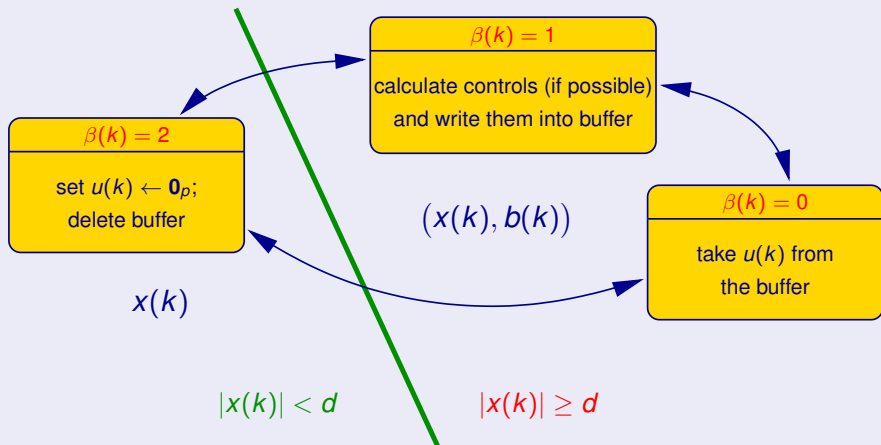
## 3 Stability Analysis

- Assumptions
- The Baseline Algorithm
- **The Anytime Algorithm**
- Comparison of Bounds

## 4 Conclusions



# Preliminaries



- Due to buffering,  $\{x(k)\}$ ,  $k \in \mathbb{N}_0$  is **not a Markov process**.
- This complicates the analysis significantly.

## Preliminaries

- To study stability of the event-based anytime algorithm, we will develop a **state-dependent random-time drift condition** of the form:

$$\mathbf{E}\{V(x(k_{i+1})) \mid x(k_i) = \chi\} \leq D + \Omega V(\chi), \quad \Omega < 1,$$

where  $\{k_0, k_1, k_2, \dots\}$  are **special** random time instants.

- If  $\{x(k_i) : i \in \mathbb{N}_0\}$  is Markovian, then the above would ensure exponential boundedness **at the instants  $k_i$** :

$$\mathbf{E}\{V(x(k_i)) \mid x(k_0) = \chi\} \leq \Omega^i V(\chi) + \frac{D}{1 - \Omega}, \quad \forall i \in \mathbb{N}_0.$$

- Depending on
  - system behaviour in-between instants  $k_i$
  - the distribution of  $\{k_{i+1} - k_i\}$

boundedness **at all instants  $k \in \mathbb{N}_0$**  may follow.

# The Randomly Sampled Process

- We begin our analysis, by denoting the random time steps where **the buffer is empty** via

$$\mathcal{K} = \{k_i\}, \quad i \in \mathbb{N}_0,$$

where

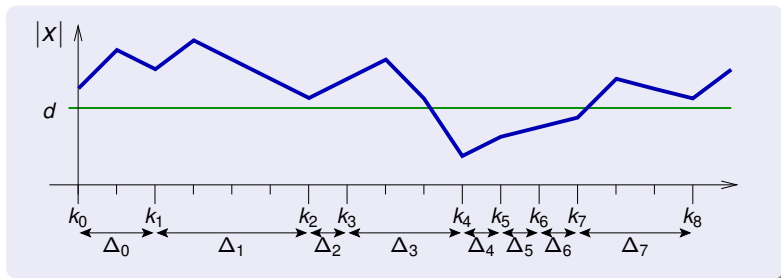
$$k_{i+1} = \inf \{k \in \mathbb{N} : k > k_i, \lambda(k) = 0\}, \quad k_0 = 0.$$

- We also describe the amount of time steps between consecutive elements of  $\mathcal{K}$  via 
$$\Delta_i \triangleq k_{i+1} - k_i, \quad i \in \mathbb{N}_0$$
- The following property of the **randomly sampled process**  $x$  is key:

## Lemma

The plant state sequence **at the time steps**  $k_i \in \mathcal{K}$ , namely  $\{x(k_i) : k_i \in \mathcal{K}\}$ , is Markovian.

# System Behaviour

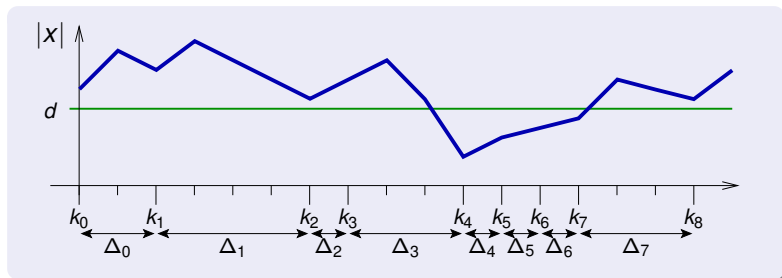


- In the present disturbance-free case, the plant inputs are simply given by

$$u(k_i) = \mathbf{0}_p, \quad \forall k_i \in \mathcal{K}$$

$$u(k_i + \ell) = \kappa(x(k_i + \ell)), \quad \forall \ell \in \{1, \dots, \Delta_i - 1\}.$$

# Evolution of $V(x(k_i))$

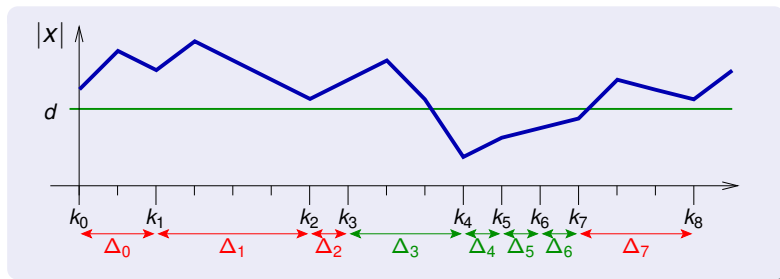


- It is then easy to see that

$$\mathbf{E}\{V(x(k_{i+1})) \mid x(k_i) = \chi, \Delta_i = \delta\} \leq \alpha \rho^{\delta-1} V(\chi), \quad \forall \chi \in \mathbb{R}^n.$$

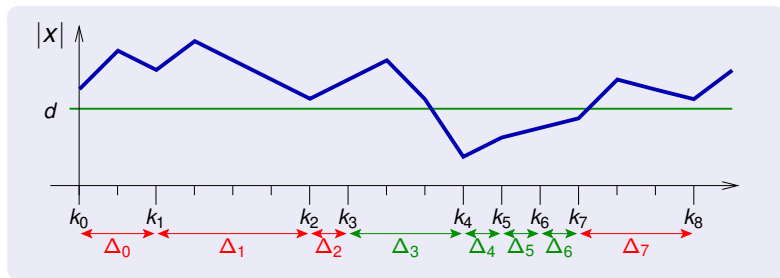
- Unfortunately, due to the **event-triggering** mechanism, the distribution of  $\{\Delta_i\}_{i \in \mathbb{N}_0}$  depends on  $x(k_i)$  and is **difficult** to characterise.
- Hence establishing a suitable drift condition is not so easy!

# Conditioning Events



- It turns out to be convenient to distinguish between the two cases:
  - 1 the buffer is emptied due to **lack of resources** ( $\beta(k_{i+1}) \in \{0, 1\}$ ), and
  - 2 it is emptied triggered by **the plant state being in the desired region**.
- Only the first case influences stability conditions.

# Finding an Upper-bound on the Drift



- Accordingly, one can condition on  $\beta(k_{i+1})$  and use the law of total expectation to show that

$$\mathbf{E}\{V(x(k_{i+1})) \mid x(k_i)\} \leq \varphi_2(d) + \mathbf{E}\{V(x(k_{i+1})) \mid x(k_i), \beta(k_{i+1}) \neq 2\}.$$

- Now, we can condition on  $\Delta_j$  to
  - establish exponential boundedness **at the instants**  $k_i \in \mathcal{K}$ , and
  - upper-bound  $\mathbf{E}\{\sum_{k=k_i}^{k_{i+1}-1} V(x(k)) \mid x(k_i), \beta(k_{i+1}) \neq 2\}$ .
- This leads to...

# Main Result

## Stochastic Stability with the proposed Algorithm

Suppose that  $\mathbf{E}\{\varphi_2(|x(0)|)\} < \infty$  and that

$$\Omega \triangleq \sum_{\delta \in \mathbb{N}} \alpha \rho^{\delta-1} \mathbf{Pr}\{\Delta_i = \delta \mid \beta(k_{i+1}) \neq 2\} < 1.$$

Then there exist finite  $\gamma, \mu$  such that

$$\max_{k \in \{k_i, k_i+1, \dots, k_{i+1}-1\}} \mathbf{E}\{\varphi_1(|x(k)|)\} \leq \gamma \Omega^i + \mu, \quad \forall i \in \mathbb{N}.$$

If  $d = 0$ , then  $\mu = 0$ .

- The **conditional distribution**

$$\mathbf{Pr}\{\Delta_i = \delta \mid \beta(k_{i+1}) \neq 2\} = \mathbf{Pr}\{\Delta_i = \delta \mid |x(k_{i+1})| \geq d\}.$$

depends only on  $p_j$  and  $q$  and can be easily characterised using finite Markov Chain methods (“first return times to  $\lambda = 0$ ”).



## Comments

- Our result establishes a condition on
  - ▶ plant,
  - ▶ control law,
  - ▶ channel, and
  - ▶ processor availability

which ensures **stochastic stability** of the event-based anytime control loop.

- The analysis can be extended to situations where processor and communication resources are not i.i.d., but **correlated**.
- Under continuity assumptions, related stability conditions can be derived for plant models **with disturbances**.

# Outline

## 1 Event-triggered Control with Dropouts

- System Model
- Baseline Algorithm
- Numerical Example

## 2 Anytime Control Algorithm

- Method Description
- Numerical Example - revisited

## 3 Stability Analysis

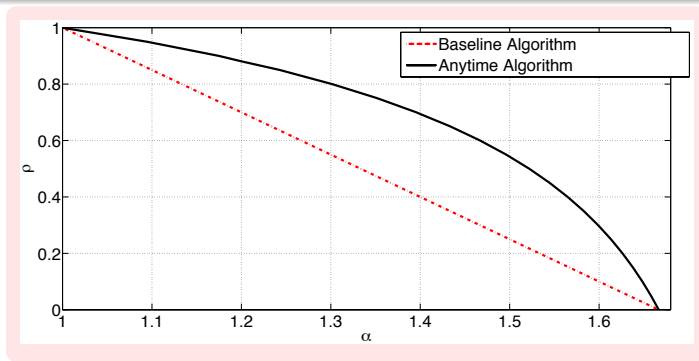
- Assumptions
- The Baseline Algorithm
- The Anytime Algorithm
- **Comparison of Bounds**

## 4 Conclusions

## Resources

- Suppose that the buffer size is set to  $\Lambda = 4$  and that
 
$$\Pr\{\beta(k) = 1 \mid |x(k)| \geq d\} = 0.5$$

$$\Pr\{N(k) = j \mid \beta(k) = 1\} = 0.2, \quad j \in \{0, 1, 2, 3, 4\}$$



The **stability regions** in the  $\alpha$ - $\rho$  plane established for the anytime control algorithm are larger than those for the baseline controller.

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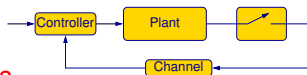
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## 4 Conclusions

# Conclusions

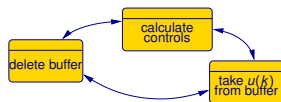
- We have presented a framework for the study of control when **processor availability** and communication resources are **random**.

- ▶ The sensor node is **event-triggered** and transmits data using a communication link prone to **dropouts**.

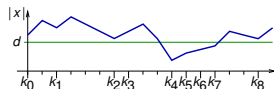


- ▶ The control algorithm is executed with a processor that can provide only time-varying and a priori unknown resources.

- To better utilise the processor, the plant inputs are calculated by an algorithm that provides **sequences**.



- For general non-linear systems, we used **stochastic Lyapunov methods** to obtain sufficient conditions for stability.



## Future Work

Many research problems remain open, e.g.,

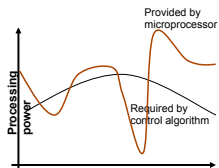
- characterising closed loop **performance**,
- studying event-based transmission strategies **with memory**, and
- developing **processor scheduling and cooperation** strategies.

## Further Reading

- 1 D. E. Quevedo, V. Gupta, W.-J. Ma and S. Yüksel, “Stochastic Stability of Event-Triggered Anytime Control,” *IEEE Trans. Automat. Contr.*, December 2014
- 2 D. E. Quevedo, W.-J. Ma and V. Gupta, “Anytime Control using Input Sequences with Markovian Processor Availability,” *IEEE Trans. Automat. Contr.*, February 2015
- 3 B. Demirel, V. Gupta, D. E. Quevedo and M. Johansson, “On the trade-off between control performance and communication cost in event-triggered control,” *IEEE Trans. Autom. Contr.*, under review.

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Thank You!