

# Model Predictive Control for the Acquisition Queue and Related Queueing Networks

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QTNA 2010, Beijing,  
July 24, 2010.

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\*Supported by the Netherlands Organization for Scientific Research (NWO-VIDI grant 639.072.072).

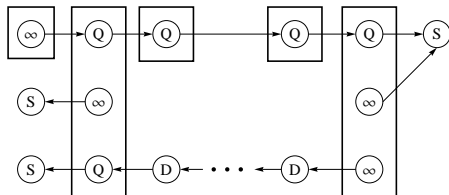
# Overview and Main Story: Control of Queueing Networks

- Queueing Networks:
  - Jobs
  - Servers
  - Queues
  - Routes
  - Scheduling Policy
- Desired:
  - High throughput, low WIP, steady output
  - Sensible computable control
  - Methodological and mathematical structure of the control
- In this talk:

A control methodology based on MPC

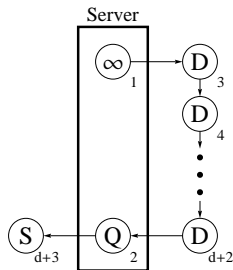
# Our Queueing Network Models

- Discrete time  $n = 0, 1, \dots$
- $K$  job classes,  $L$  servers
- Types of classes:
  - $\infty$  – Source
  - $Q$  – Queue
  - $D$  – Delay
  - $S$  – Sink
- Deterministic routes
- Randomness due to "batch" arrivals" ( $\infty$  classes),  $\tilde{u}_k, m_k$
- Processing capacity: jobs per server per time unit,  $c_i, i = 1, \dots, L$
- Control Policy – How do servers allocate capacity among  $Q$  and  $\infty$  ?



## A Structured Example: The Acquisition Queue

D. Denteneer, J. van Leeuwen, and I. Adan. The acquisition queue. *Queueing Systems*, 56(3):229-240, 2007.



# A Controlled Markov Chain

- $P = \{p_{kk'}\}$  – routing matrix,  $C$  – constituency matrix
- i.i.d jobs generated at sources,  $\tilde{u}^{*U}$  – generic r.v. of  $U$ -fold sum
- $\{X(n)\}$  is a controlled Markov chain, with control  $U(n) = f(X(n))$

$$X_k(n+1) = \begin{cases} X_k(n) + \sum_{k' \in \mathcal{K}_D} X_{k'}(n)p_{k'k} + \sum_{k' \in \mathcal{K}_{\{Q,\infty\}}} \tilde{u}_{k'}^{*U_{k'}(n)} p_{k'k} - U_k(n), & k \in \mathcal{K}_Q \text{ (queue)} \\ \sum_{k' \in \mathcal{K}_D} X_{k'}(n)p_{k'k} + \sum_{k' \in \mathcal{K}_{\{Q,\infty\}}} \tilde{u}_{k'}^{*U_{k'}(n)} p_{k'k}, & k \in \mathcal{K}_D \text{ (delay)} \\ X_k(n) + \sum_{k' \in \mathcal{K}_D} X_{k'}(n)p_{k'k} + \sum_{k' \in \mathcal{K}_{\{Q,\infty\}}} \tilde{u}_{k'}^{*U_{k'}(n)} p_{k'k}, & k \in \mathcal{K}_S \text{ (sink)} \end{cases}$$

## Matrix form

$$\begin{bmatrix} X_Q(n+1) \\ X_D(n+1) \\ X_S(n+1) \end{bmatrix} = \begin{bmatrix} I & P'_{DQ} & 0 \\ 0 & P'_{DD} & 0 \\ 0 & P'_{DS} & I \end{bmatrix} \begin{bmatrix} X_Q(n) \\ X_D(n) \\ X_S(n) \end{bmatrix} + \begin{bmatrix} P'_{\infty Q} M_{\infty} & P'_{QQ} - I \\ P'_{\infty D} M_{\infty} & P'_{QD} \\ P'_{\infty S} M_{\infty} & P'_{QS} \end{bmatrix} \begin{bmatrix} U_{\infty}(n) \\ U_Q(n) \end{bmatrix} + \begin{bmatrix} P'_{\infty Q} \\ P'_{\infty D} \\ P'_{\infty S} \end{bmatrix} \tilde{u}(U_{\infty}(n))$$

Elements of  $\tilde{u}(\cdot)$  are  $\tilde{u}_k^{*U_k(n)} - U_k(n)m_k$

s.t.

$$\begin{bmatrix} 0 & 0 & 0 & -I & 0 \\ 0 & 0 & 0 & 0 & -I \\ -I & 0 & 0 & 0 & I \\ 0 & 0 & 0 & C_{\infty} & C_Q \end{bmatrix} \begin{bmatrix} X_Q(n) \\ X_D(n) \\ X_S(n) \\ U_{\infty}(n) \\ U_Q(n) \end{bmatrix} \leq \begin{bmatrix} 0 \\ 0 \\ 0 \\ c \end{bmatrix}$$

## Control as a Linear System

$$X(n+1) = AX(n) + BU(n) + \text{zero mean noise}$$

s.t.

$$F \begin{bmatrix} X(n) \\ U(n) \end{bmatrix} \leq g$$

## Our Control Methodology

- Ignore noise
- Assume state and control  $(X(\cdot), U(\cdot))$  are continuous in value
- Find a **reference trajectory**
- Apply "standard" control-theoretic methods for **tracking** the reference trajectory
- Use **Model Predictive Control** (MPC) using a Quadratic Programming (QP) formulation

## Illustrative Example: Acquisition Queue with $d = 3$

$$\begin{bmatrix} D_1(n+1) \\ D_2(n+1) \\ D_3(n+1) \\ Q(n+1) \\ S(n+1) \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} D_1(n) \\ D_2(n) \\ D_3(n) \\ Q(n) \\ S(n) \end{bmatrix} + \begin{bmatrix} m & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} U_\infty(n) \\ U_Q(n) \end{bmatrix}$$

### Maximal Throughput

$$\delta = \lim_{n \rightarrow \infty} \frac{1}{n} S(n) = m \frac{c}{1+m},$$

### A Reference Trajectory

$$D_1^r(n) = D_2^r(n) = D_3^r(n) = Q^r(n) = U_\infty^r(n) = U_Q^r(n) = \delta, \quad S^r(n) = \delta n$$

Error Dynamics:  $X^e(n) = X(n) - X^r(n)$ ,  $U^e(n) = U(n) - U^r(n)$

Also satisfy  $X^e(n+1) = A X^e(n) + B U^e(n)$

Our controller tries to regulate  $X^e(n)$  on 0

# The MPC Approach

## Action of Controller at Time $n$

- Look at  $X^e(n)$
- Plan an optimal schedule for a **time horizon** of  $N$  time units:
  - Optimize the variables  $U^e(n), \dots, U^e(n + N - 1)$
  - These yield predictions of  $X^e(n + 1), \dots, X^e(n + N)$
  - Practical objective (QP):

$$\sum_{i=n}^{n+N-1} \hat{X}^e(i+1)' Q \hat{X}^e(i+1) + U^e(i)' R U^e(i)$$

- After optimizing – **use first step**:
  - $U(n) = U^e(n) + U^r(n)$
  - Round off  $U(n)$  and insure feasibility
- Repeat in next time step

Parameters: Time horizon,  $N$ . Positive definite cost matrixes,  $Q$ ,  $R$



## Precise Formulation of the QP (for illustration)

$$\begin{aligned} & \min_{\underline{U}^e} \quad \underline{U}^{e'} (\underline{B}' \underline{Q} \underline{B} + \underline{R}) \underline{U}^e + 2X_0^{e'} \underline{A}' \underline{Q} \underline{B} \underline{U}^e \\ \text{s.t.} \quad & \begin{bmatrix} \underline{C} \\ \underline{S}_{UQ}^+ \\ \underline{S}_{UQ}^- \\ \underline{S}_{XQ}^+ \\ \underline{S}_{XQ}^- \\ -I \end{bmatrix} \underline{U}^e \leq \begin{bmatrix} \underline{c} \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ \underline{S}_{XQ}^+ \\ \underline{S}_{XQ}^- \\ 0 \end{bmatrix} \underline{X}^r + \begin{bmatrix} -\underline{C} \\ -\underline{S}_{UQ}^+ \\ -\underline{S}_{UQ}^- \\ I \end{bmatrix} \underline{U}^r + \begin{bmatrix} 0 \\ \underline{S}_{XQ} \\ \underline{S}_{XQ} \underline{A} \\ 0 \end{bmatrix} X_0^e \end{aligned}$$

$\underline{Q}$ ,  $\underline{R}$  are block diagonal matrixes of  $Q$  and  $R$ . The  $S$  matrixes "select" elements. The following matrixes are used for prediction:

$$\underline{A} = \begin{bmatrix} A \\ A^2 \\ \vdots \\ A^N \end{bmatrix}, \quad \underline{B} = \begin{bmatrix} B & 0 & \dots & 0 \\ AB & B & & \vdots \\ \vdots & & \ddots & \\ A^{N-1}B & \dots & & B \end{bmatrix}$$

Observe: If  $\underline{U}^r$  is constant as well as  $\underline{X}^r$  on the  $Q$ -classes then control law is a function of  $X_0^e$  only

## Numerical Illustration

# Acquisition Queue Threshold vs. MPC

Example:  $c = 10$ ,  $d = 10$ ,  $m = 3$

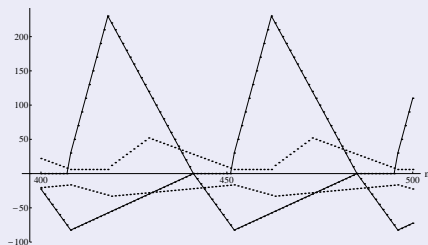
## A Simple Threshold Control Law (Van Leeuwen et. al. 2007)

$$U_{\infty}(n) = \alpha + (c - Q(n))^+, \quad U_Q(n) = c - U_{\infty}(n)$$

$\alpha < c/(1 + m)$  (for stability)

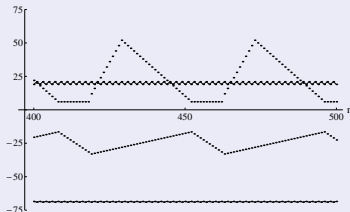
Example:  $d = 10$ ,  $m = 3$ , no noise

Assume no noise, optimize  $\alpha$ :  $\alpha = 2$  is best

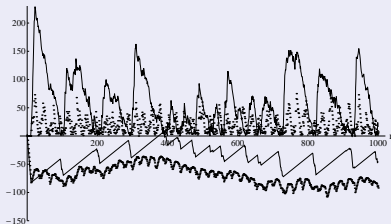


# MPC Appears Better than Threshold

Compare  $\alpha = 2$  with MPC ( $Q = 1, R = 1, N = 30$ )



Add noise (Geometrically distributed acquisitions)



# A More Complex Network

## Use Linear Program (LP) to Find a Reference Trajectory

$$\begin{aligned} & \max \quad \sum_{i=1}^4 w_i r_i \\ \text{s.t.} \quad & \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 1/m_3 & 1 \\ 1 & 1/m_2 & 0 & 1/m_4 \end{bmatrix} \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ r_4 \end{bmatrix} \leq \begin{bmatrix} c_1 m_1 \wedge c_3 \wedge c_4 \\ c_2 \\ c_5 \end{bmatrix}, \\ & r_i \geq 0, \quad i = 1, 2, 3, 4. \end{aligned}$$

$$\rho \in [0, 1]$$

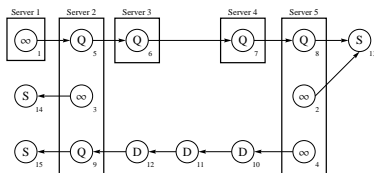
$$\text{(route 1)} \quad U_1^r(n) = \rho r_1^* / m_1, \quad X_5^r(n) = X_6^r(n) = X_7^r(n) = X_8^r(n) = U_5^r(n) = U_6^r(n) = U_7^r(n) = U_8^r(n) = \rho r_1^*,$$

$$\text{(route 2)} \quad U_2^r(n) = \rho r_2^* / m_2,$$

$$\text{(route 3)} \quad U_3^r(n) = \rho r_3^* / m_3,$$

$$\text{(route 4)} \quad U_4^r(n) = \rho r_4^* / m_4, \quad X_{10}^r(n) = X_{11}^r(n) = X_{12}^r(n) = X_9^r(n) = U_9^r(n) = \rho r_4^*,$$

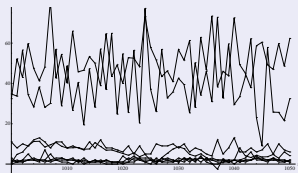
$$\text{(sinks)} \quad X_{13}^r(n) = \rho(r_1^* + r_2^*)n, \quad X_{14}^r(n) = \rho r_3^* n, \quad X_{15}^r(n) = \rho r_4^* n.$$



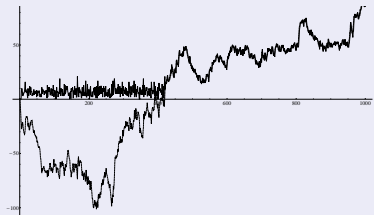
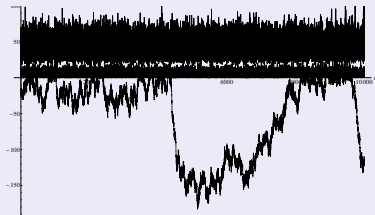
# A More Complex Network (cont.)

Parameters set such that  $r_i^* > 0, i = 1, 2, 3, 4, Q = I, R = I, \rho = 1$

$N = 5$ , Stable



$N = 4$ , Stable in  $Q$ 's (not in output).  $N = 3$  Unstable



# Stability?

## Continuous Deterministic Case

- Add **end point constraint**:  $X^e(N) = 0$
- Main Theoretical Result: If feasible solution exists then resulting system is asymptotically stable
- Alternative: Take  $N = \infty$

## Discrete Stochastic Case

- No general result
- Some hope of proving positive recurrence for "toy examples" by analyzing the solution of the QP when  $X_0^e$  is far from the origin
- Practical alternative: Use end point constraint. When QP is not feasible, don't work on  $\infty$  classes

# Conclusion

- Main idea: View queueing network as controlled linear system with noise – apply MPC – appears to "work well"
- General theory: (1) Stability properties (2) Bounds on performance... "hard to obtain"
- At least... Hope for explicit stochastic analysis of some toy examples
- Immediate extensions (in progress): (1) Observers (2) inverse optimality of other controllers - e.g. dead beat
- Interesting to experiment: Incorporating the effect of noise in the reference value for the queue levels



Questions?