

# *LET'S CONTROL EVERYTHING!*

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*LET'S CONTROL*

**EVERYTHING**

*LET'S*

**CONTROL**

*EVERYTHING*

*LET **US** CONTROL EVERYTHING*



# CENTRAL THEMES OF THIS TALK...

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- **CONTROL** is pervasive
- **CONTROL** is not just for systems  $\dot{x}(t) = f(x, u, t)$   
(if you are a hammer, everything looks like a nail...)
- **CONTROL** doesn't have to always be "sophisticated"
- **Principles** of **CONTROL THEORY** (**FEEDBACK**, **DYNAMICS**, etc) matter more than specific methodologies
- "When our classifications start breaking down, we know we are learning something exciting..."



# OUTLINE

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*A somewhat personal account of how the “control mindset” can lead to solutions of intriguing, unconventional problems, which in turn stimulate new theoretical developments*

- *1980's*



- Manufacturing systems, kanban control  
➔ the roots of Discrete Event Systems

- *1990's*



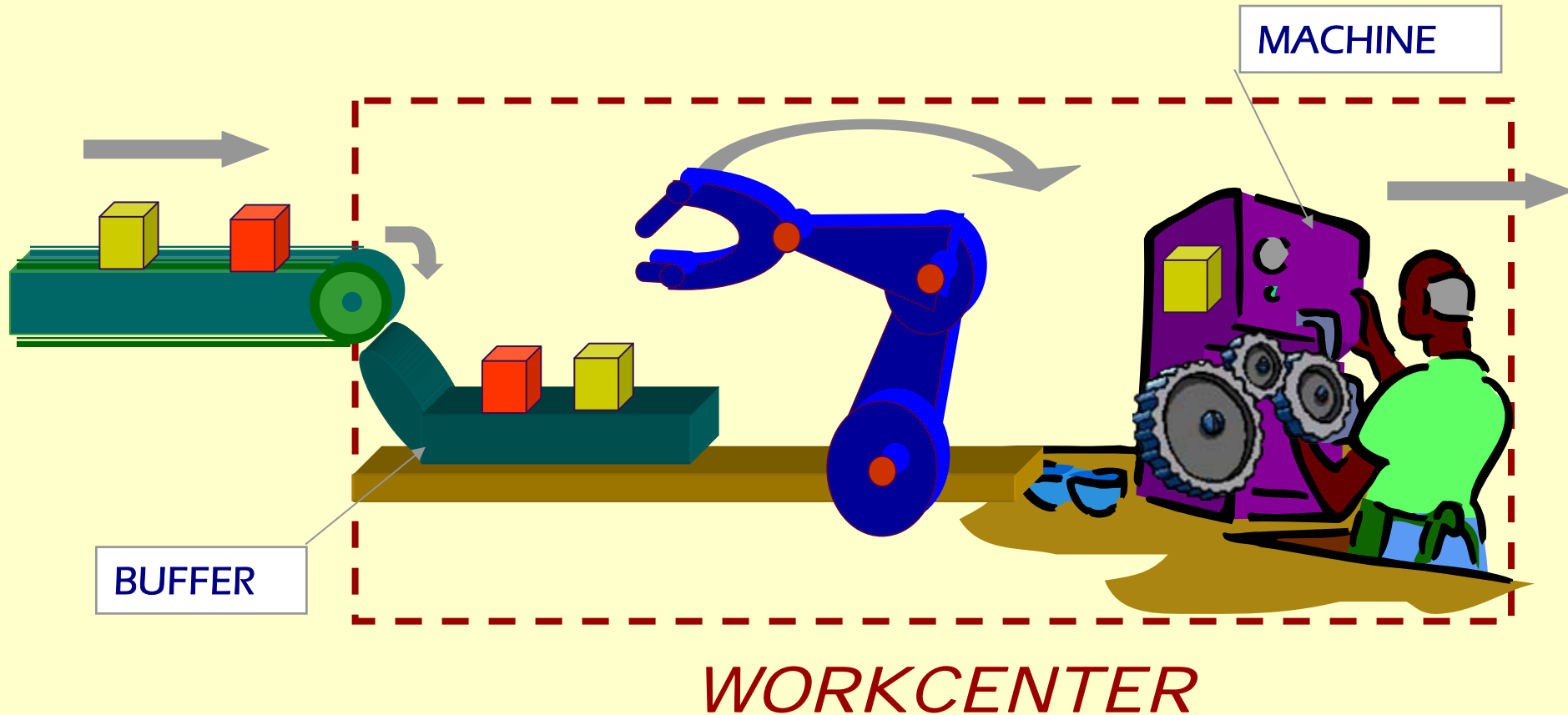
- Learning from sample paths of complex systems  
➔ controlling elevators, Australian mines, air traffic, communication networks, command-control systems

- *FUTURE*

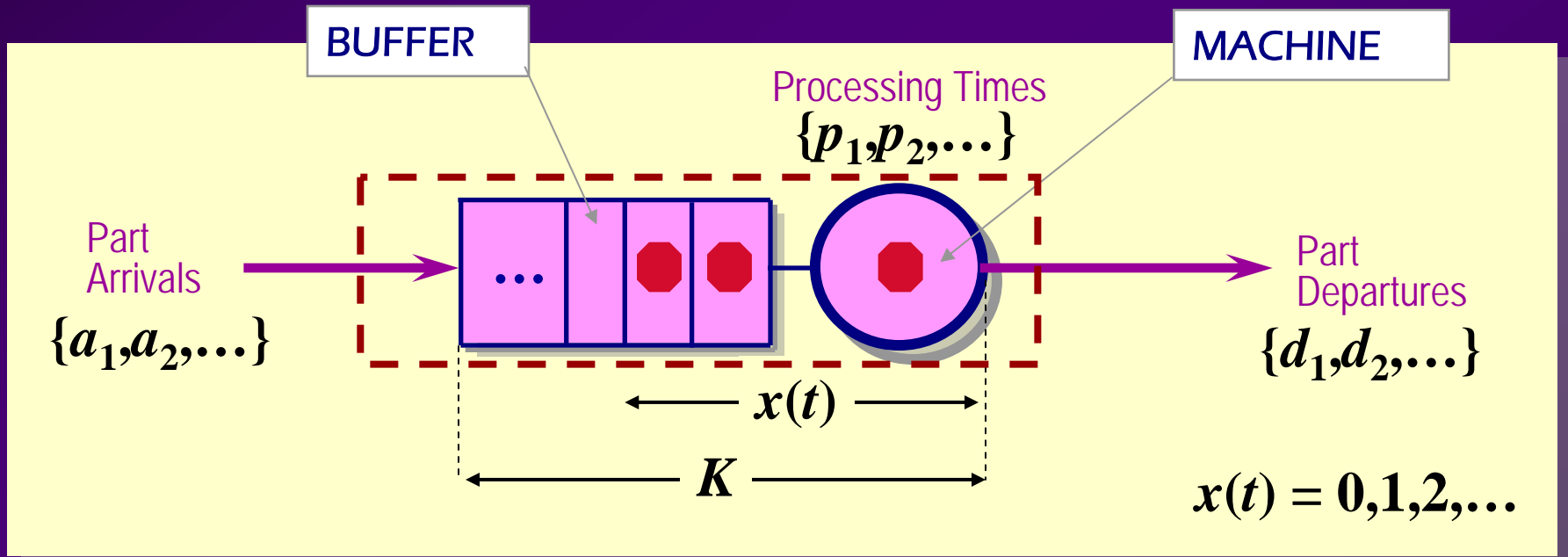
- Hybrid systems, complexity, computation...



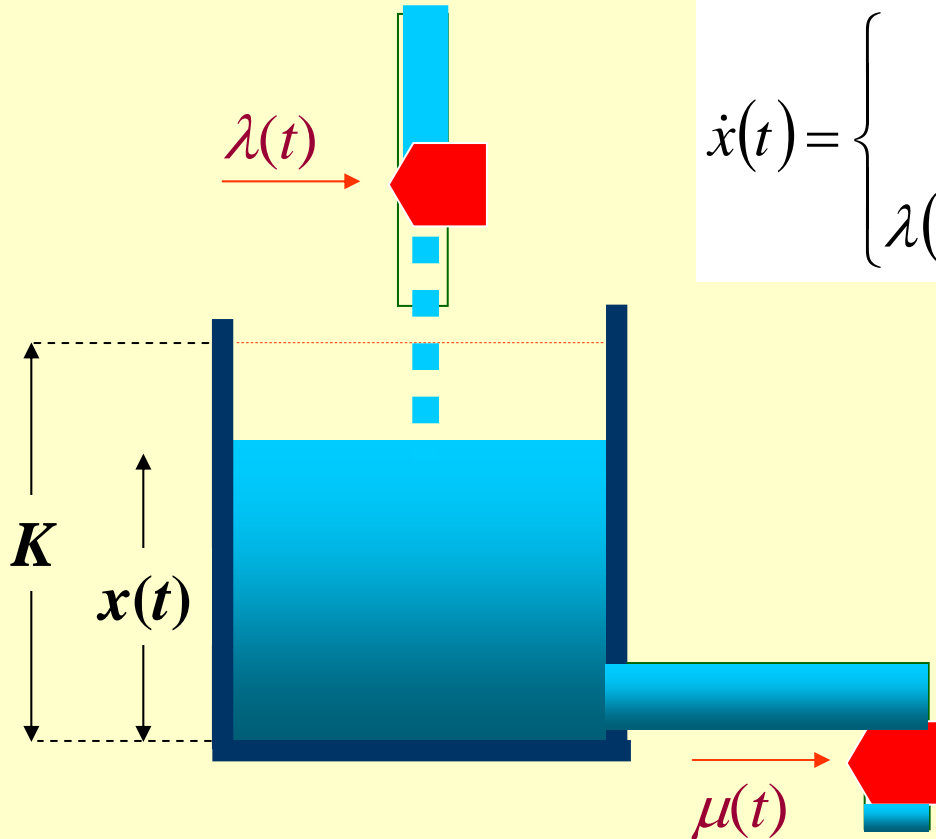
# CONTROL IN MANUFACTURING SYSTEMS



A model for a manufacturing workcenter capturing part-by-part behavior:



## A continuous flow model for a manufacturing workcenter:

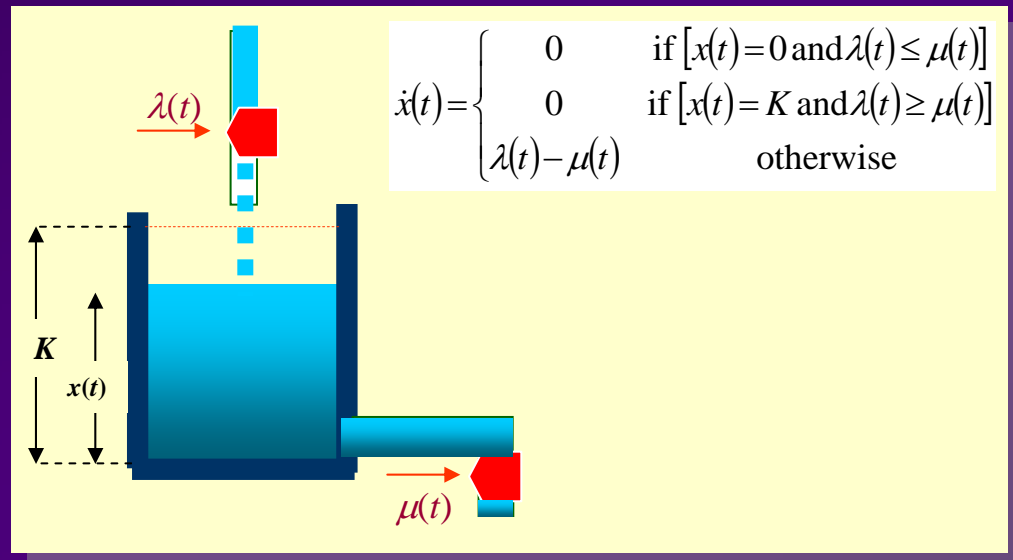


$$\dot{x}(t) = \begin{cases} 0 & \text{if } [x(t) = 0 \text{ and } \lambda(t) \leq \mu(t)] \\ 0 & \text{if } [x(t) = K \text{ and } \lambda(t) \geq \mu(t)] \\ \lambda(t) - \mu(t) & \text{otherwise} \end{cases}$$

$$\dot{x}(t) = f(x, u, t) \text{ ???}$$

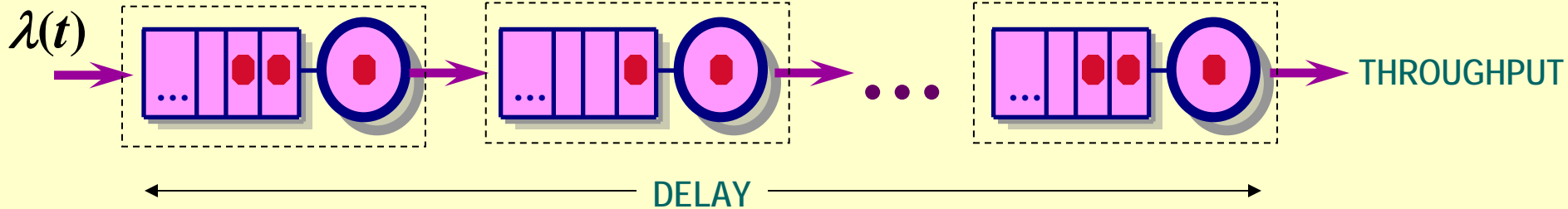
Limitations of the continuous flow model:

- Can only analyze *averages*
- Cannot deal with part-by-part control issues such as:
  - Is  $n$ th part guaranteed to be served within  $T$  time units?
  - If a part is within  $T$  time units from its due-date, serve it next
  - Prioritize **RED** parts over **YELLOW** parts





Manufacturing system with  $N$  sequential operations:



INCREASE  $\lambda(t)$

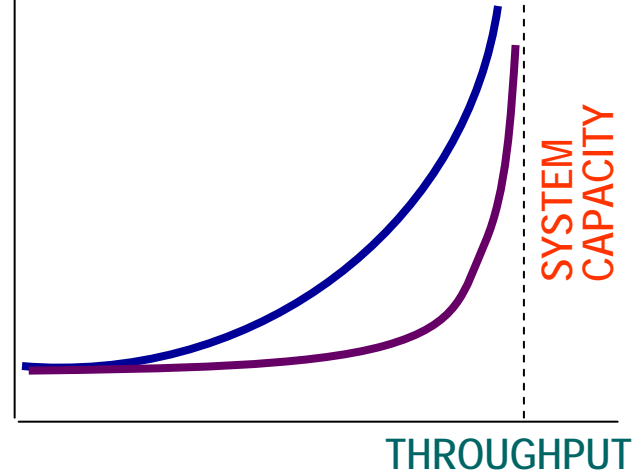
THROUGHPUT  
increases  
(GOOD)



average DELAY  
increases  
(BAD)

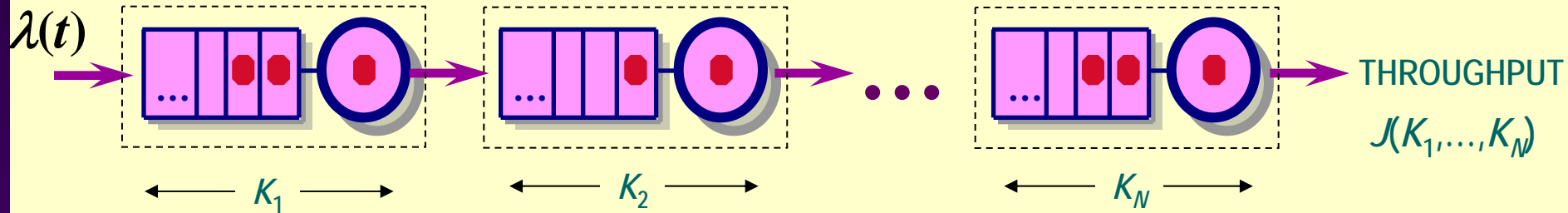


AV. DELAY



# TWO PROBLEMS

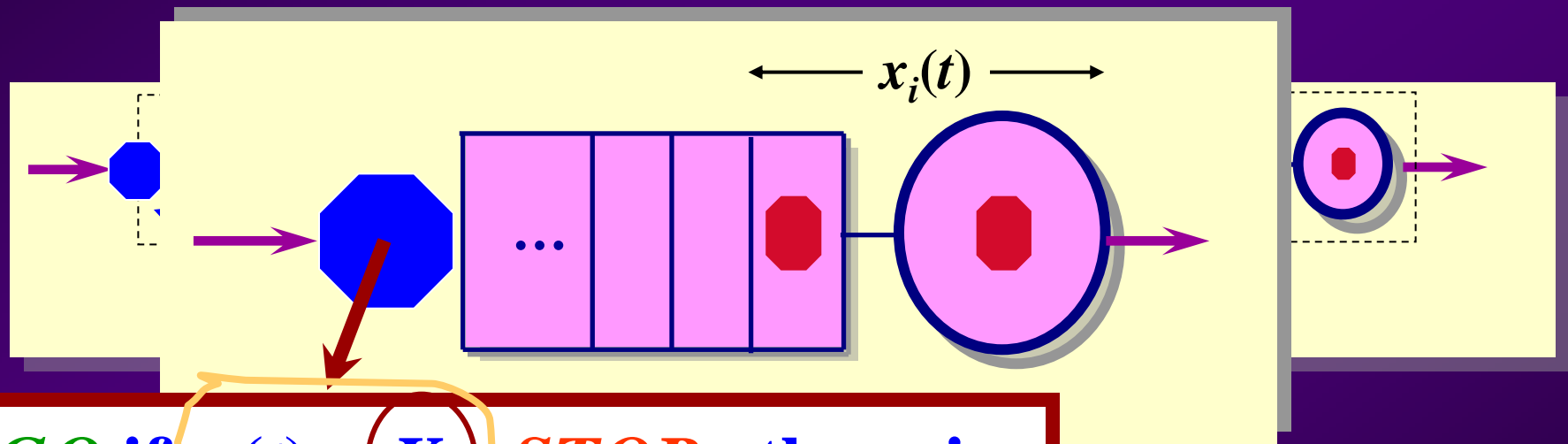
## 1. BUFFER ALLOCATION (FIAT, circa 1979)



$$\max_{K_1, \dots, K_N} J(K_1, \dots, K_N) \quad \text{s.t.} \quad \sum_{i=1}^N K_i = C$$

PARAMETRIC OPTIMIZATION

## 2. FLOW CONTROL



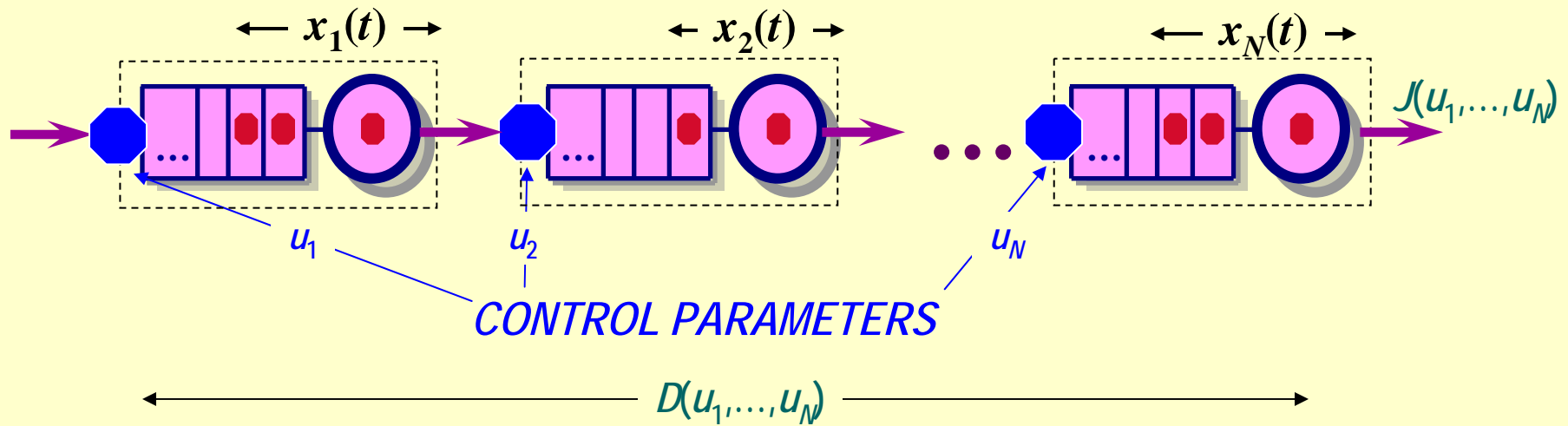
**GO** if  $x_i(t) < K_i$ , **STOP** otherwise

FEEDBACK

No. of *KANBAN (tickets)*  
allocated to stage  $i$

# TWO PROBLEMS

CONTINUED



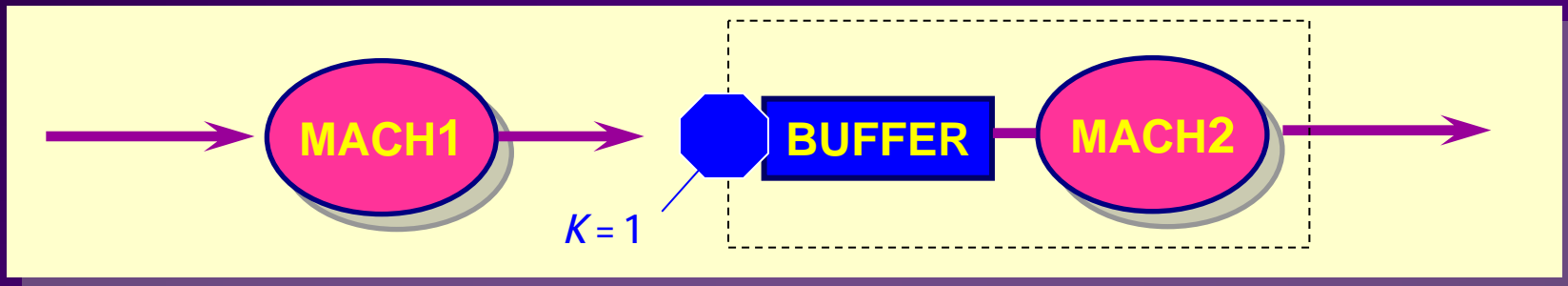
$$\max_{u_1, \dots, u_N} J(u_1, \dots, u_N) \text{ s.t. } \begin{cases} D(u_1, \dots, u_N) \leq C \\ \text{system dynamics} \end{cases}$$

DYNAMIC OPTIMIZATION



# SUPERVISORY CONTROL PROBLEM

*Supervise the proper execution of simple kanban-based control*



1. **MACH1** can only start when **BUFFER** is empty.
2. **MACH2** can only start when **BUFFER** is full.
3. **MACH1** cannot start when **MACH2** is down.
4. If both **MACH1** and **MACH2** are down, then **MACH2** is repaired first

# THE STUDY OF THESE PROBLEMS HAS LED TO...

---

- New modeling frameworks paralleling  $\dot{x}(t) = f(x, u, t)$

- Supervisory Control theory: *enable/disable controllable events*

*Ramadge, Wonham, Krogh, Lin, Rudie, Lafortune, etc.*

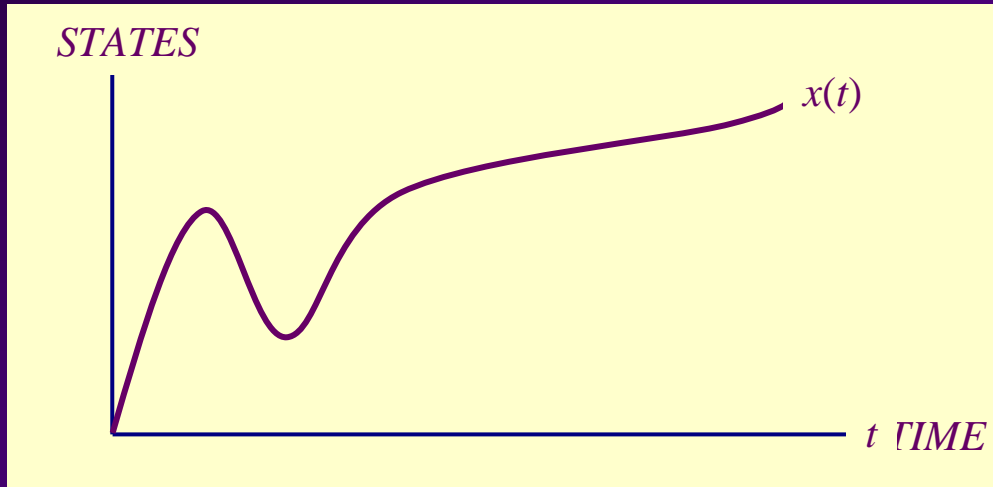
- Perturbation Analysis theory: *learning from state trajectories*

*Ho, Cassandras, Cao, Glasserman, Gong, etc.*



# TIME-DRIVEN vs EVENT-DRIVEN SYSTEMS

TIME-DRIVEN  
SYSTEM



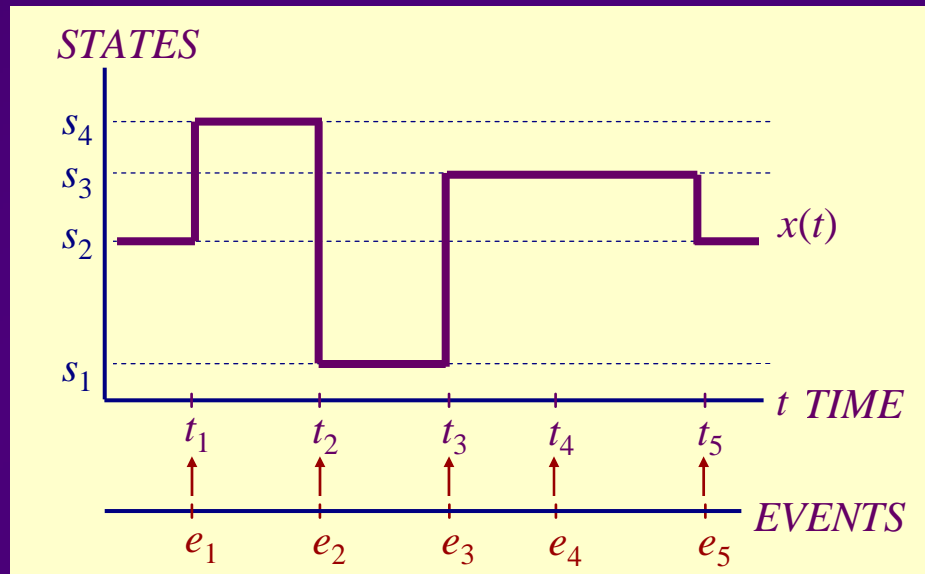
STATE SPACE:

$$X = \mathfrak{R}$$

DYNAMICS:

$$\dot{x} = f(x, t)$$

EVENT-DRIVEN  
SYSTEM



STATE SPACE:

$$X = \{s_1, s_2, s_3, s_4\}$$

DYNAMICS:

$$x' = f(x, t)$$



# MODELING FOUNDATIONS

**AUTOMATON:**  $(E, X, \Gamma, f, x_0)$

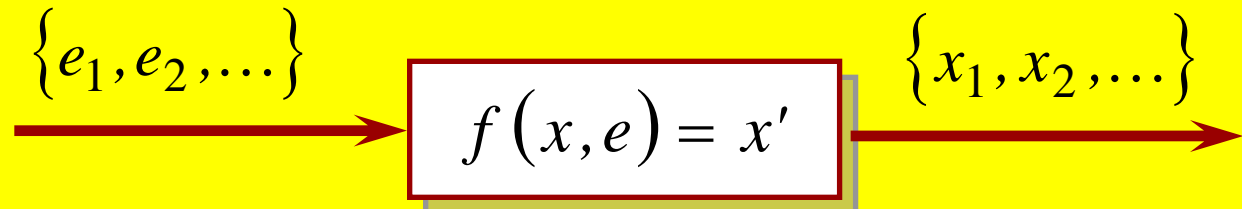
$E$ : Event Set

$X$ : State Space

$\Gamma(x)$ : Set of *feasible* or *enabled* events at state  $x$

$f$ : State Transition Function  $f: X \times E \rightarrow X$   
(undefined for events  $e \notin \Gamma(x)$ )

$x_0$ : Initial State,  $x_0 \in X$



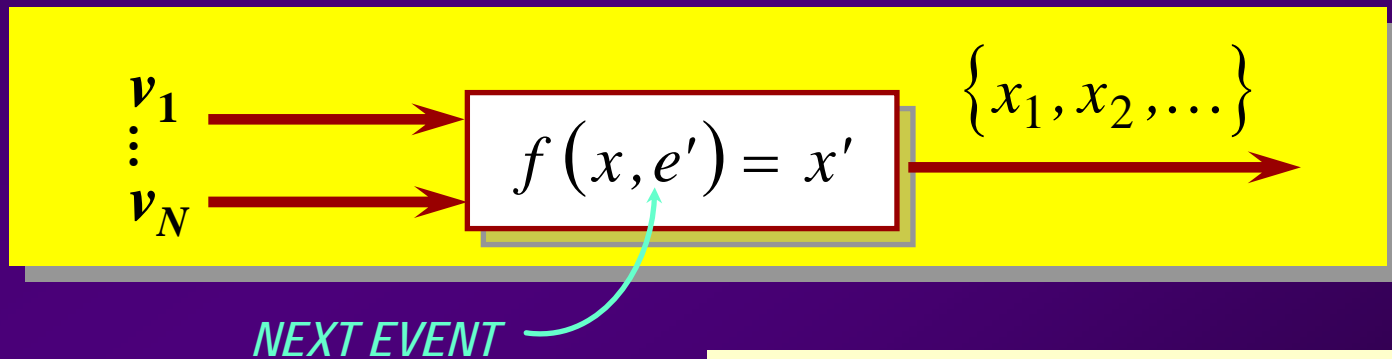


# TIMED AUTOMATON

Add a **Clock Structure  $V$**  to the automaton:  $(E, X, \Gamma, f, x_0, V)$   
where:

$$V = \{v_i : i \in E\}$$

and  $v_i$  is a **Clock or Lifetime sequence**:  $v_i = \{v_{i1}, v_{i2}, \dots\}$   
one for each event  $i$



Need an *internal mechanism* to determine  
*NEXT EVENT*  $e'$  and hence  
*NEXT STATE*  $x' = f(x, e')$



# HOW THE TIMED AUTOMATON WORKS...

## ➤ CURRENT STATE

$x \in X$  with feasible event set  $\Gamma(x)$

## ➤ CURRENT EVENT

$e$  that caused transition into  $x$

## ➤ CURRENT EVENT TIME

$t$  associated with  $e$



Associate a

***CLOCK VALUE/RESIDUAL LIFETIME***  $y_i$   
with each feasible event  $i \in \Gamma(x)$



# HOW THE TIMED AUTOMATON WORKS... *CONTINUED*

- **NEXT/TRIGGERING EVENT  $e'$  :**

$$e' = \arg \min_{i \in \Gamma(x)} \{y_i\}$$

- **NEXT EVENT TIME  $t'$  :**

$$t' = t + y^*$$

$$\text{where: } y^* = \min_{i \in \Gamma(x)} \{y_i\}$$

- **NEXT STATE  $x'$  :**

$$x' = f(x, e')$$



# HOW THE TIMED AUTOMATON WORKS... *CONTINUED*



Determine new **CLOCK VALUES**  $y'_i$   
for every event  $i \in \Gamma(x)$

$$y'_i = \begin{cases} y_i - y^* & i \in \Gamma(x'), i \in \Gamma(x), i \neq e' \\ v_{ij} & i \in \Gamma(x') - \{\Gamma(x) - e'\} \\ 0 & \text{otherwise} \end{cases}$$

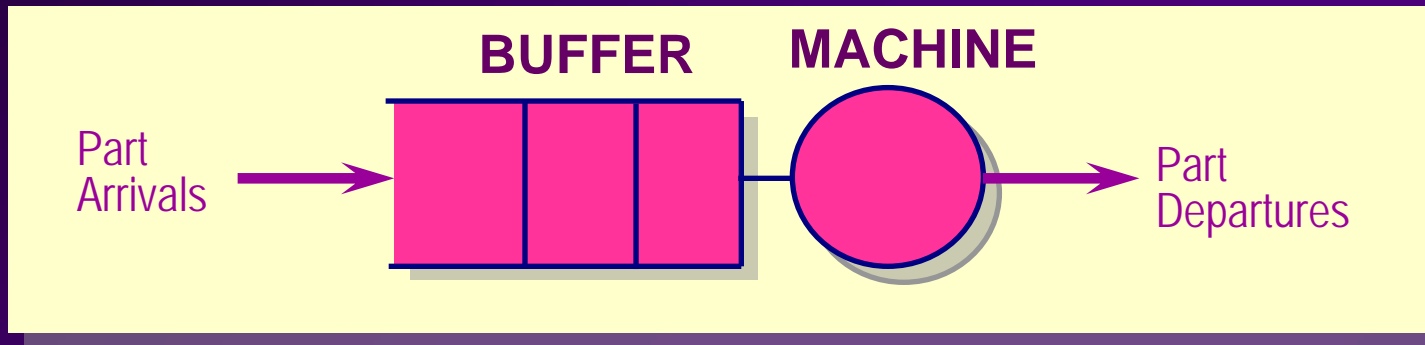
where:  $v_{ij}$  = new lifetime for event  $i$

EVENT CLOCKS  
ARE STATE VARIABLES

$$\begin{array}{l} v_1 \\ \vdots \\ v_N \end{array} \begin{array}{l} \longrightarrow \\ \longrightarrow \end{array} \begin{array}{l} x' = f(x, e'), \quad e' = \arg \min_{i \in \Gamma(x)} \{y_i\} \\ y' = \mathbf{g}(y, x, V) \end{array} \longrightarrow \{x_1, x_2, \dots\}$$



# TIMED AUTOMATON - AN EXAMPLE



$$E = \{a, d\}$$

$$X = \{0, 1, 2, \dots\}$$

$$\Gamma(x) = \{a, d\}, \text{ for all } x > 0$$

$$\Gamma(0) = \{a\}$$

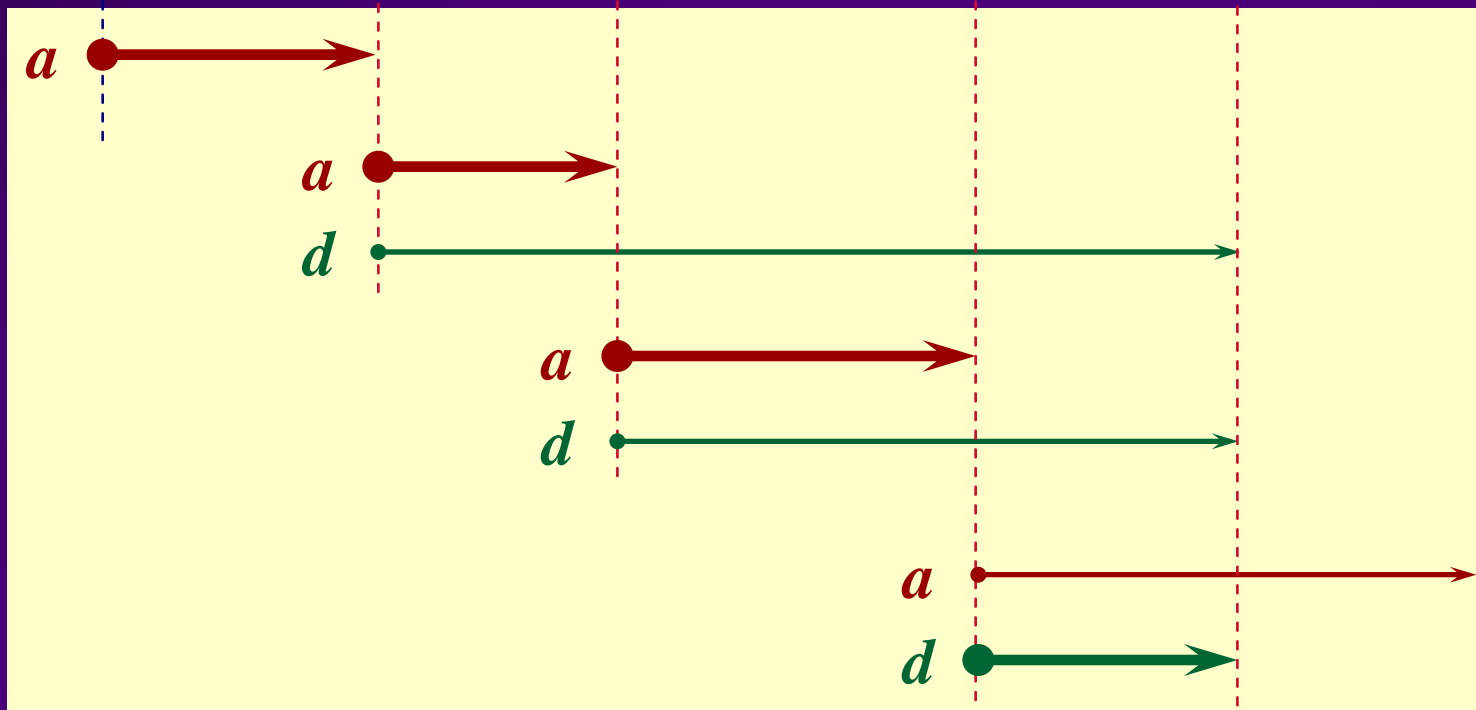
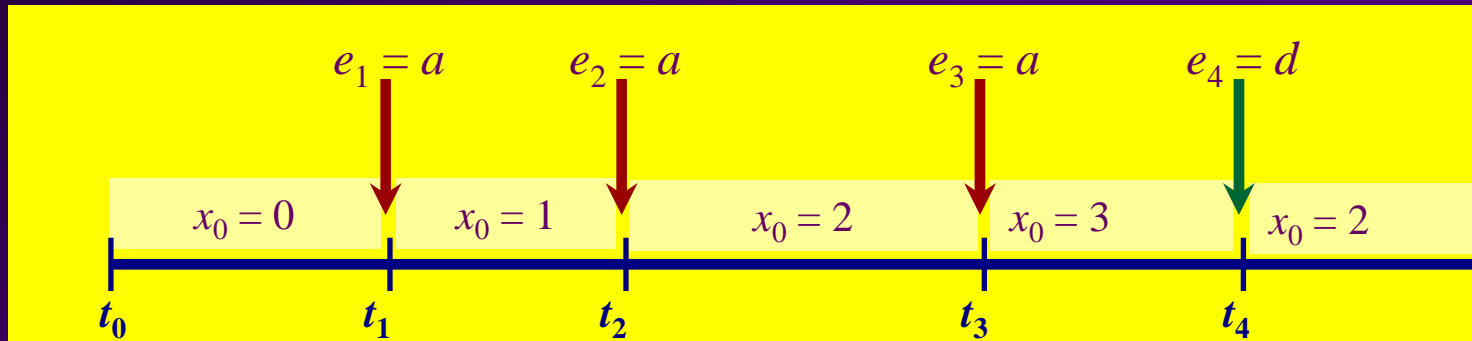
$$f(x, e') = \begin{cases} x + 1 & e' = a \\ x - 1 & e' = d, x > 0 \end{cases}$$

$$\text{Given input : } \mathbf{v}_a = \{v_{a1}, v_{a2}, \dots\}, \mathbf{v}_d = \{v_{d1}, v_{d2}, \dots\}$$

# TIMED AUTOMATON

## - A TYPICAL SAMPLE PATH

CONTINUED



# STOCHASTIC TIMED AUTOMATON

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- Same idea with the Clock Structure consisting of *Stochastic Processes*
- Associate with each event  $i$  a *Lifetime Distribution* based on which  $\nu_i$  is generated

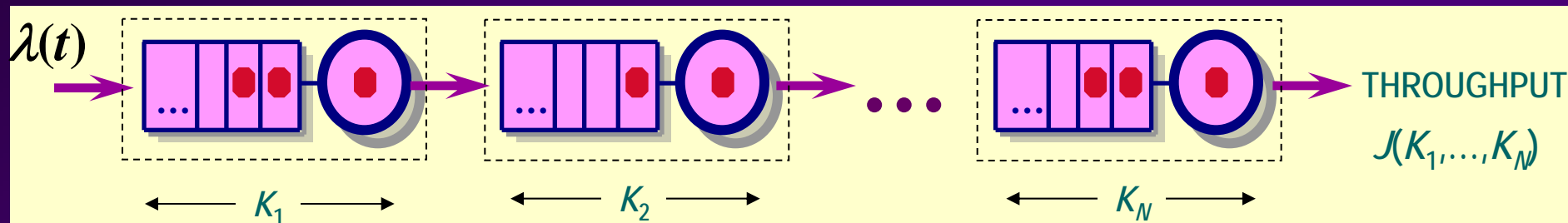


## Generalized Semi-Markov Process (GSMP)

In a simulator,  $\nu_i$  is generated through a pseudorandom number generator



# BACK TO THE *BUFFER ALLOCATION* PROBLEM



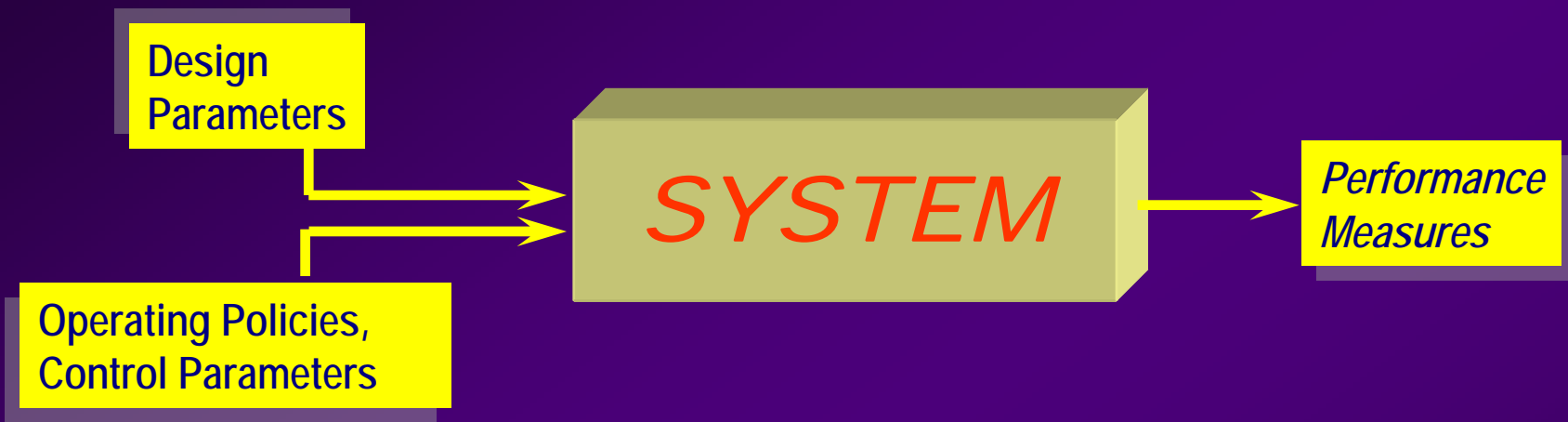
$$\max_{K_1, \dots, K_N} J(K_1, \dots, K_N) \text{ s.t. } \sum_{i=1}^N K_i = C$$

PARAMETRIC OPTIMIZATION





# LEARNING BY TRIAL AND ERROR

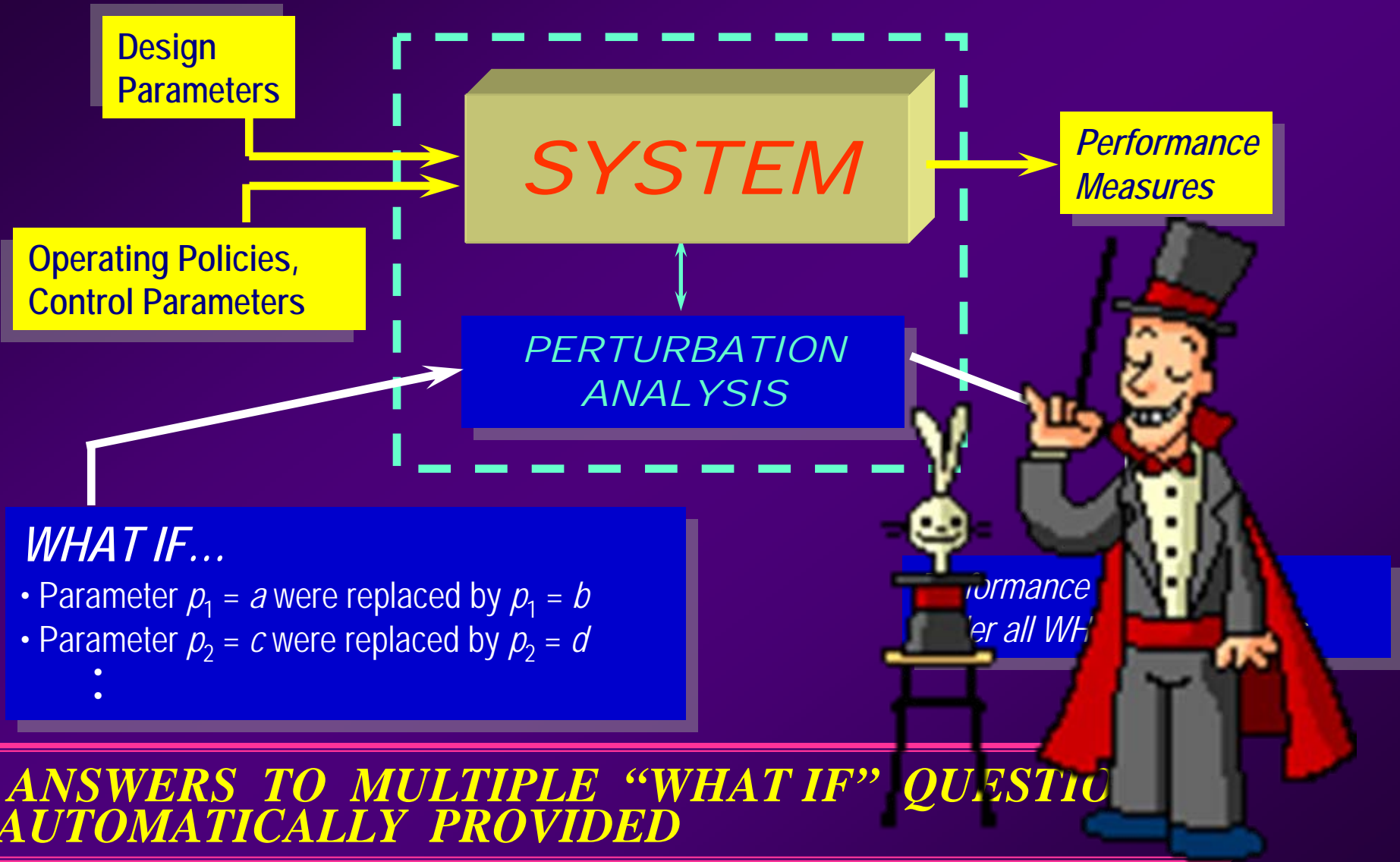


## CONVENTIONAL TRIAL-AND-ERROR ANALYSIS (e.g., simulation)

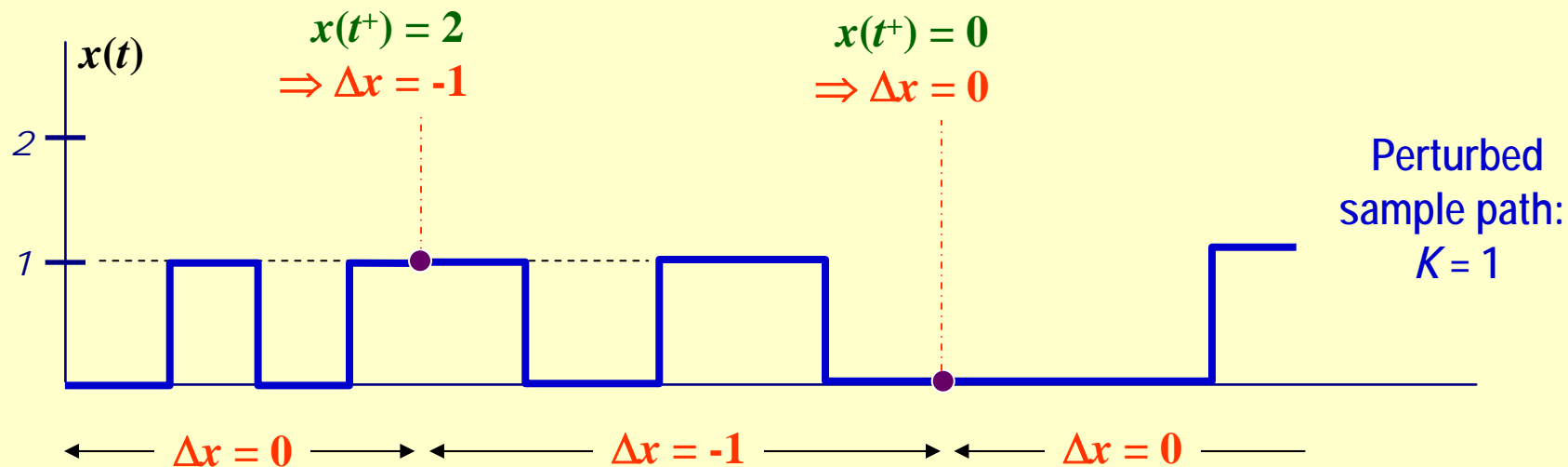
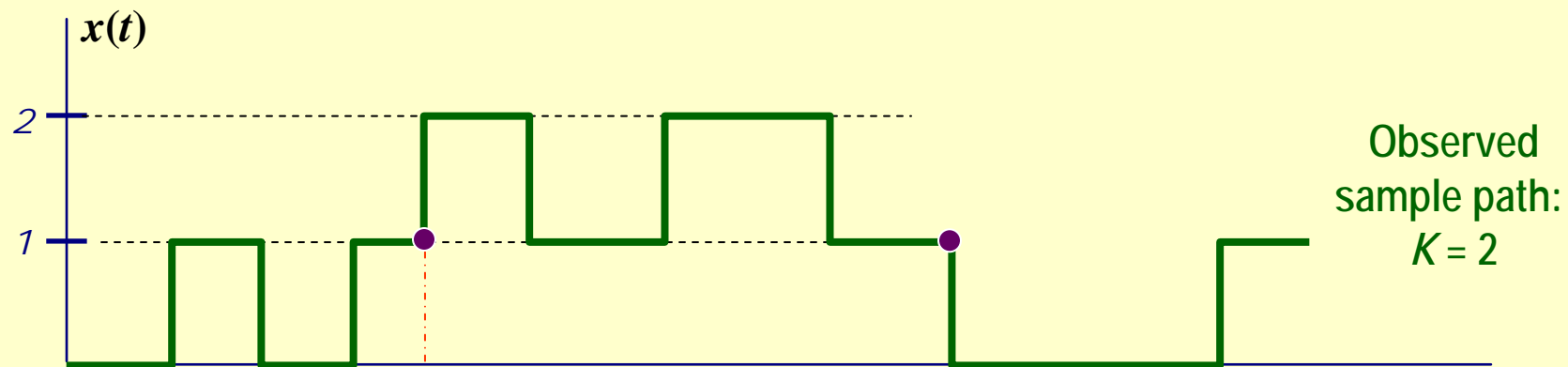
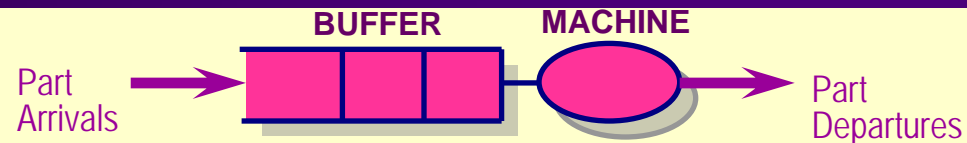
- *Repeatedly change parameters/operating policies*
- *Test different conditions*
- *Answer multiple WHAT IF questions*



# LEARNING THROUGH *PERTURBATION ANALYSIS*



# PERTURBATION ANALYSIS





*PERTURBATION DYNAMICS OBTAINED  
FROM OBSERVED NOMINAL SAMPLE PATH ONLY!*

$$\Delta x(t+\delta; \theta, \Delta\theta) = f[\Delta x(t; \theta, \Delta\theta), x(t; \theta); \theta, \Delta\theta]$$

Why does this work?

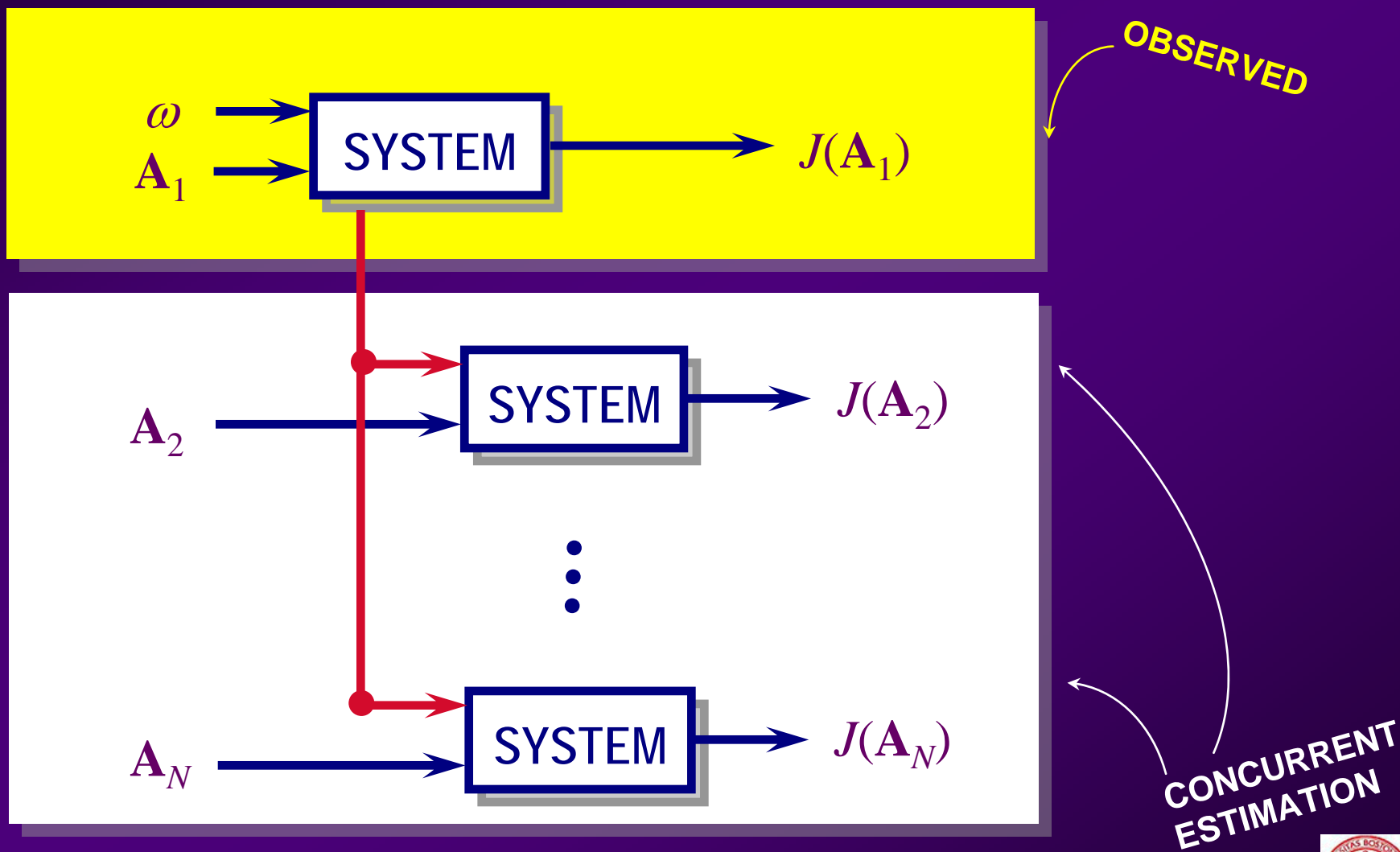
Because structural knowledge of *nominal system dynamics* is also used

- **Constructability Theory:** Conditions under which this is possible and methods for constructing perturbed sample paths
- **Performance Analysis:**  $\Delta J(t+\delta; \theta, \Delta\theta) = f[\Delta J(t; \theta, \Delta\theta), x(t; \theta); \theta, \Delta\theta]$
- **Perturbation Analysis:** Obtaining unbiased, consistent estimators for  $\frac{dJ}{d\theta}$



# BACK TO THE *BUFFER ALLOCATION* PROBLEM

ALLOCATION VECTOR:  $\mathbf{A} = [K_1, \dots, K_N]$



# “LET’S CONTROL EVERYTHING” IN THE 1980’S...

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Anonymous referee comments for 1983 papers on  
Supervisory Control:

*(courtesy W.M. Wonham)*

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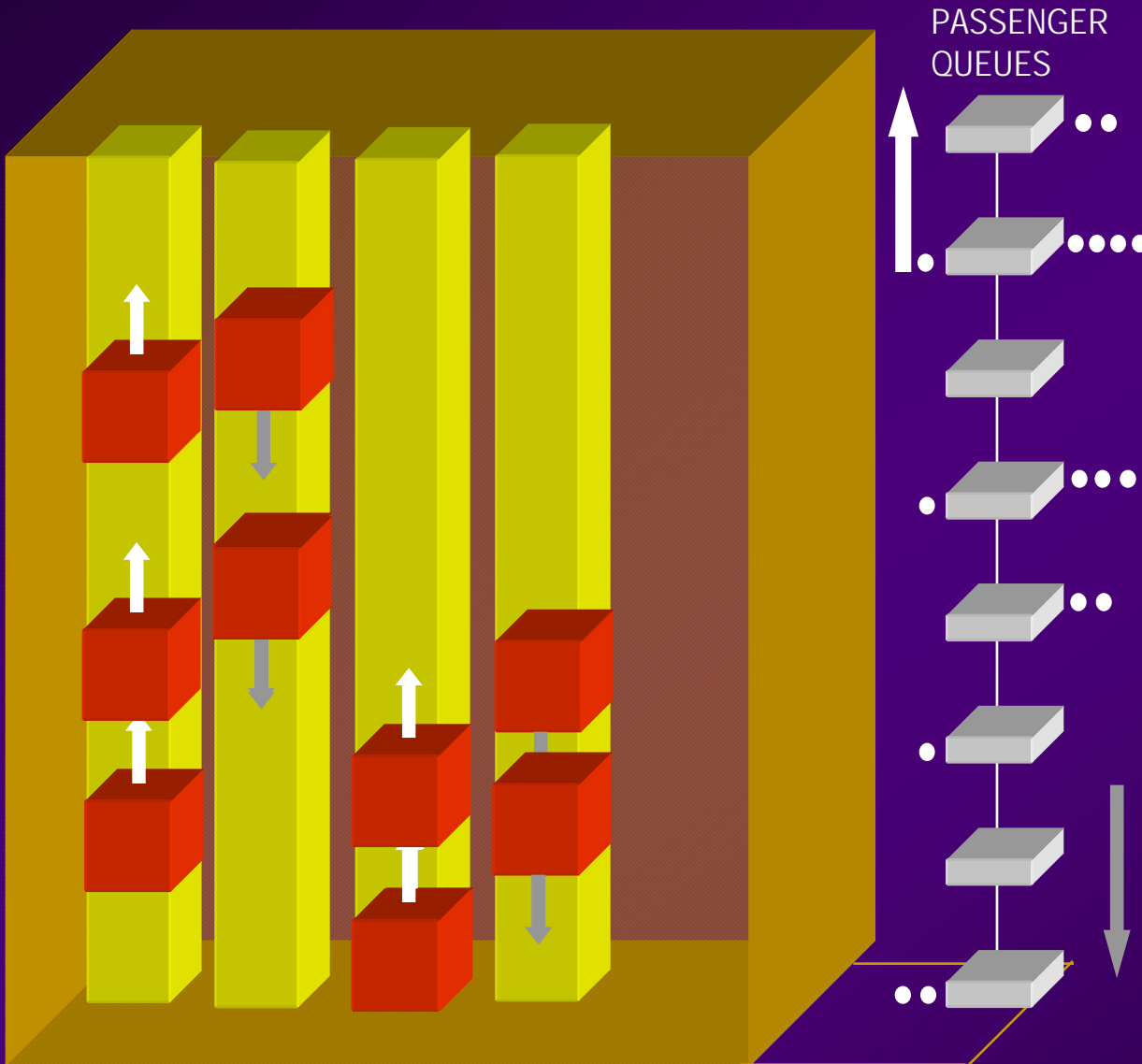
- *Automatica* (reject)  
“Automata have no place in control engineering”
  - *Math. Systems Theory* (reject)  
“FSM and regular languages are nothing new at best and trivial at worst”
  - *SIAM J. Control and Optimization* (accept)  
“If it’s optimal control we’ll take it”
- 

*W.M. Wonham’s conclusion:*

“Crossing cultural divides can be a chilly business”



# ELEVATOR DISPATCHING CONTROL



**COMPLEXITY:**  
Huge state space,  
Movement constraints,  
incomplete state info.,  
etc.

$\sim 10^{50}$

## *PROBLEM (OTIS Elevator, circa 1987)*

- How should an elevator respond to calls?
- At each floor: *STOP, GO, or SWITCH DIRECTION?*
- *Goal: Reduce waiting times and preserve fairness over all floor response times*

Can you outperform existing patented elevator dispatch control?

Challenge posed to...

- A Computer Scientist
- A Control Engineer





## How would you proceed ?

Computer  
Scientist

Build a database...

... collect data...

... *design a user interface...*

Control  
Engineer

Build a model...

... formulate control/optimization problem...

*Does a solution exist?*

...*and, if so, is it unique?*

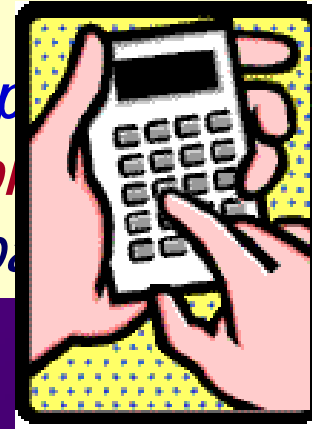


2 weeks later, they are ready to propose...

Computer  
Scientist

\$0.5M, 6-month project

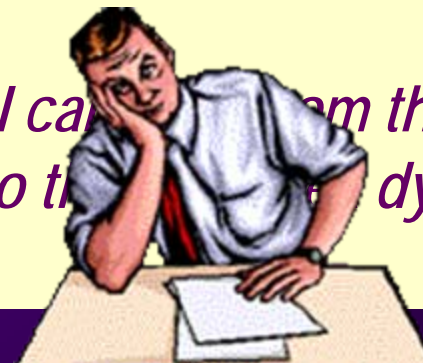
*Will deliver a database-driven Expert System using AI methods and a java-based full-computer simulation running on a LAN with agent-based HLA-compatibility*



Control  
Engineer

\$50K, 1-year project

*Let me investigate what insight I can gain from the system dynamics, and seek a solution to the dynamic optimization problem...*



6 months later: *Can you outperform existing technology?*

Computer  
Scientist

Success!... Expert system finds solutions... not always good, but that's because we need a faster CPU for the neural net training... Need \$200K more to upgrade.

Control  
Engineer

Well, here is an algorithm that improves performance by 20%...

But I can prove convergence of my solution to the optimal only "in probability" -- not "with prob. 1" ...



2 years later:

Computer  
Scientist

Still adding rules to the Expert System and training the neural net...

*...but that User Interface is a real beauty!*

Control  
Engineer

Algorithms developed now outperform existing solutions by 30%...

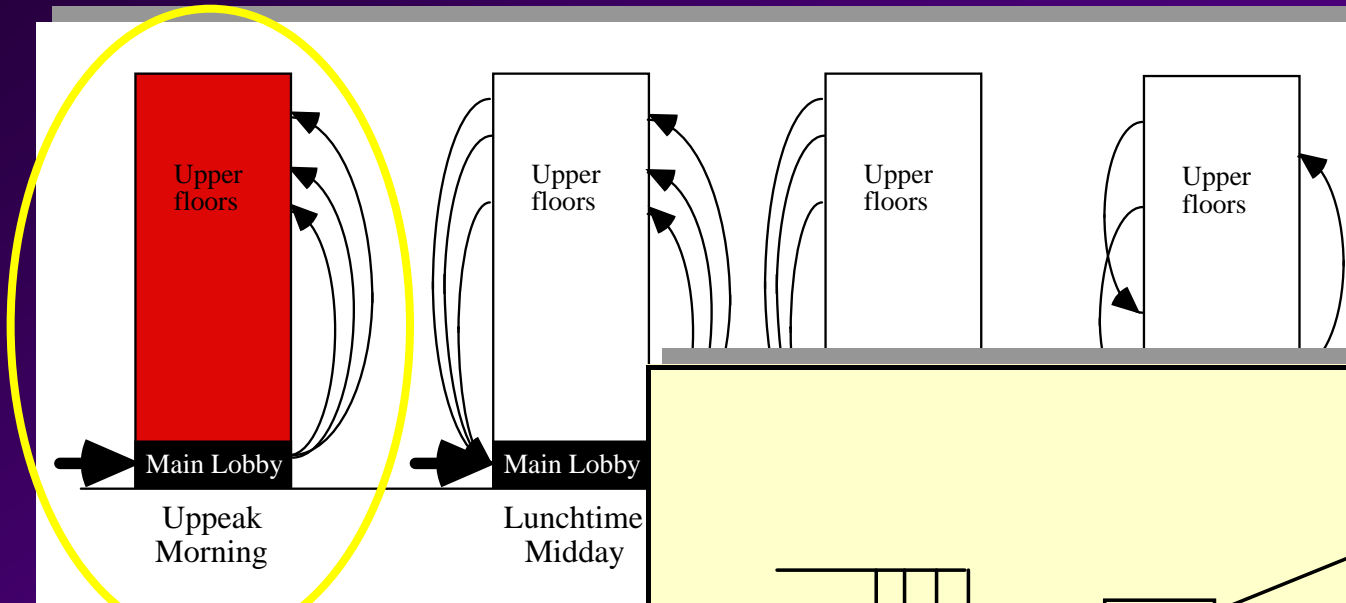
...Asking for \$0.5M to add...

*java-based full-colored GUI running on a LAN with agent-based HLA-compatible interoperability*

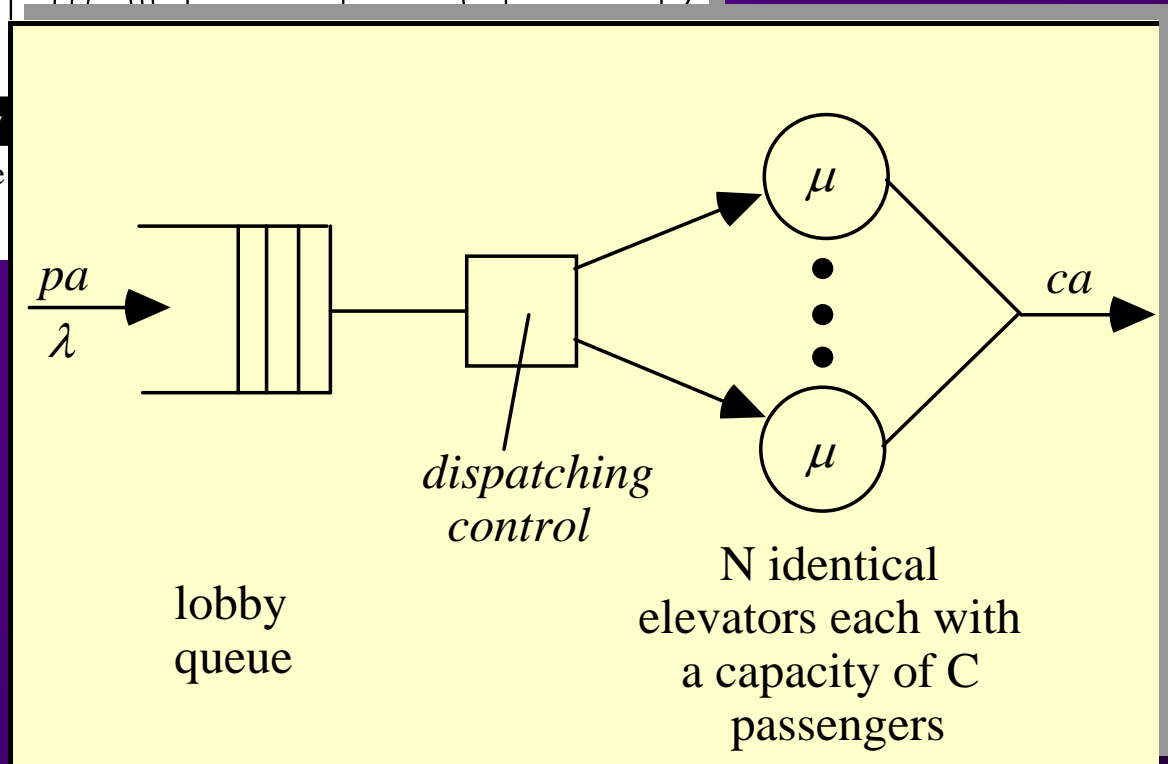


*A glimpse of the Control  
Engineer's approach...*



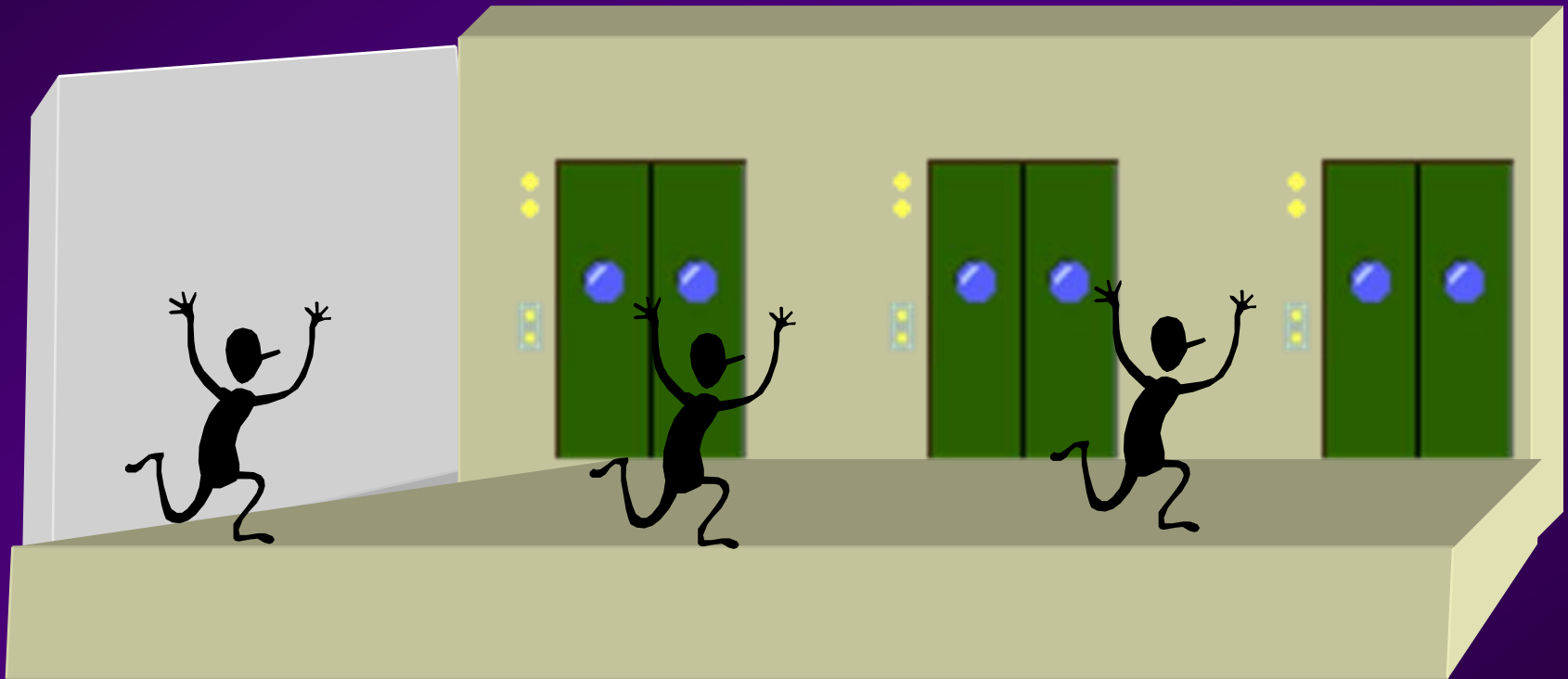


**UPPEAK DISPATCHING CONTROL PROBLEM:**

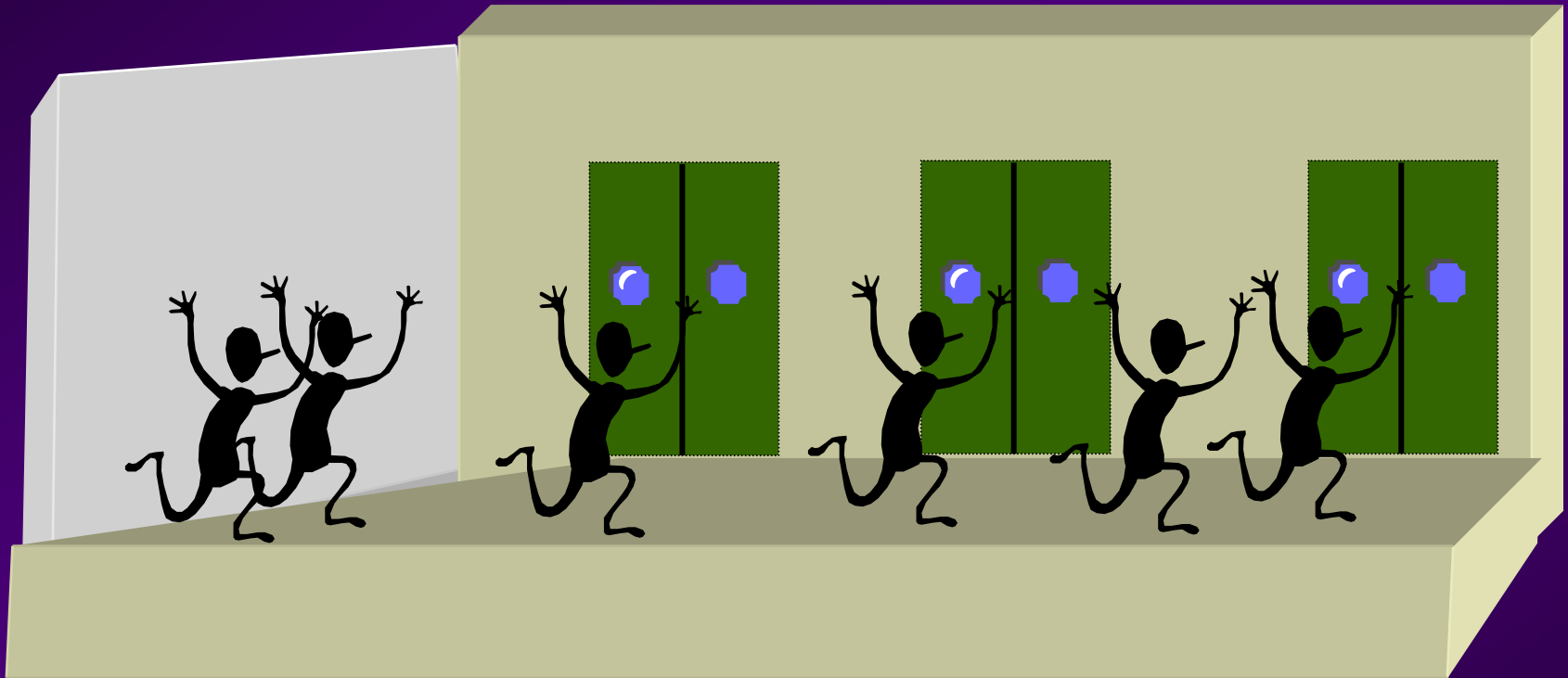


# HOW **NOT** TO CONTROL...

3 elevators available at lobby...



Each person takes one and goes



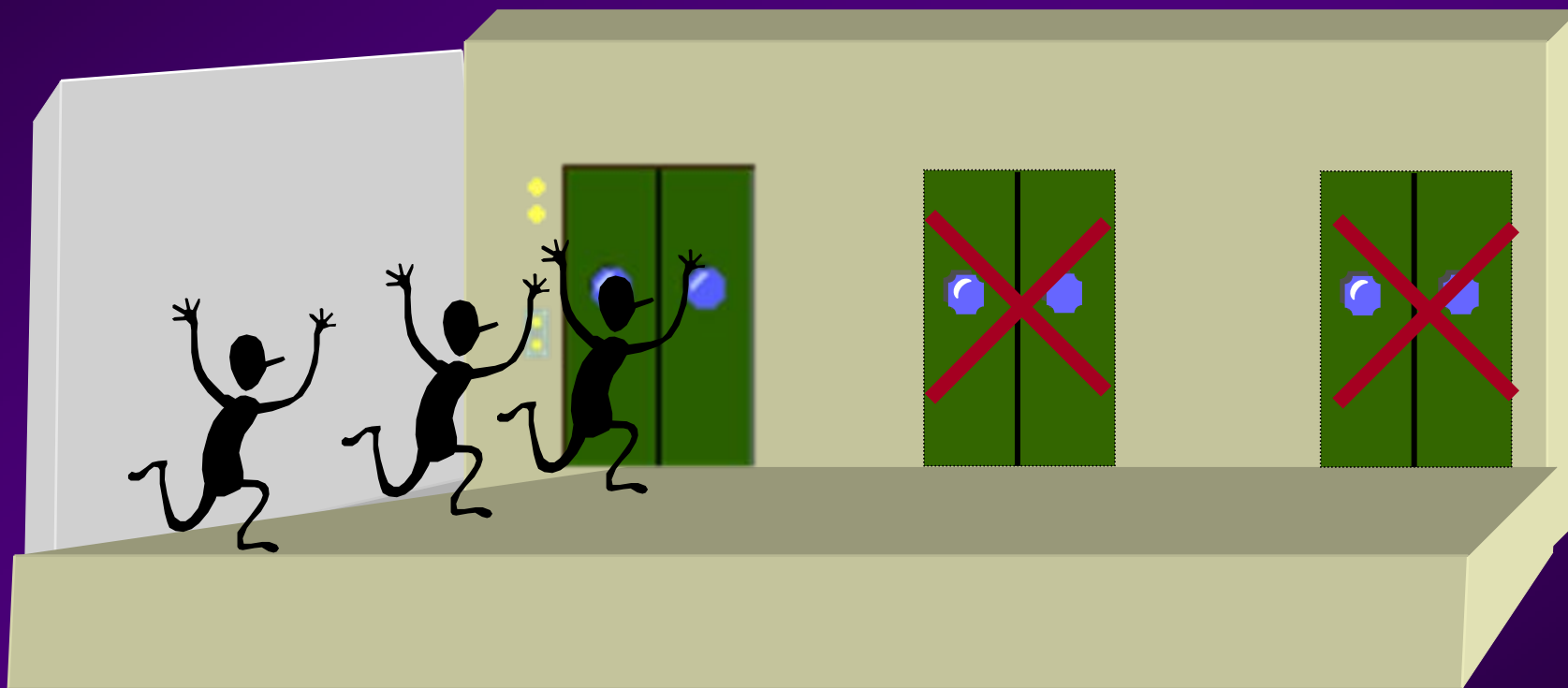
Long waiting results...



# A BETTER WAY TO CONTROL...

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Force only 1 of the 3 elevators to be available



# ELEVATOR DISPATCHING

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Can formally show (TCST, 1997) that a Markov Decision Problem formulation leads to a *threshold-based optimal policy* minimizing average waiting time.

Threshold parameters depend on

- *passenger arrival rate*
- *car service rate*

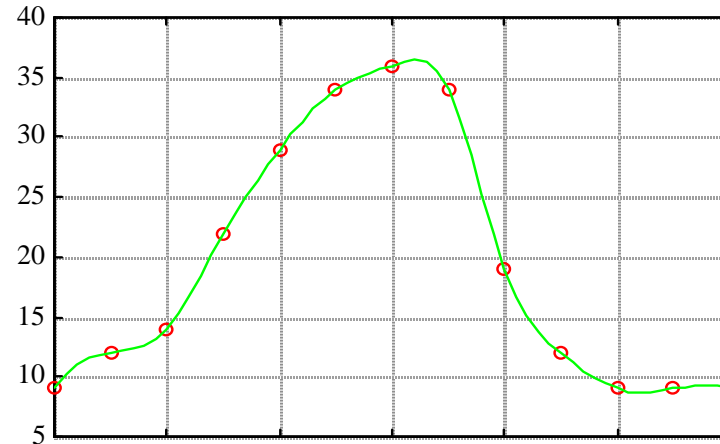
## *CONTROLLER:*

- Load one car at a time
- Dispatch this car when

*number of passengers inside car  $\geq \theta(\lambda, \mu)$*



Variation in  $\lambda$  over 12  
5-min. intervals for  
1 hour uppeak traffic  
(courtesy B. Powell, OTIS Elevator)



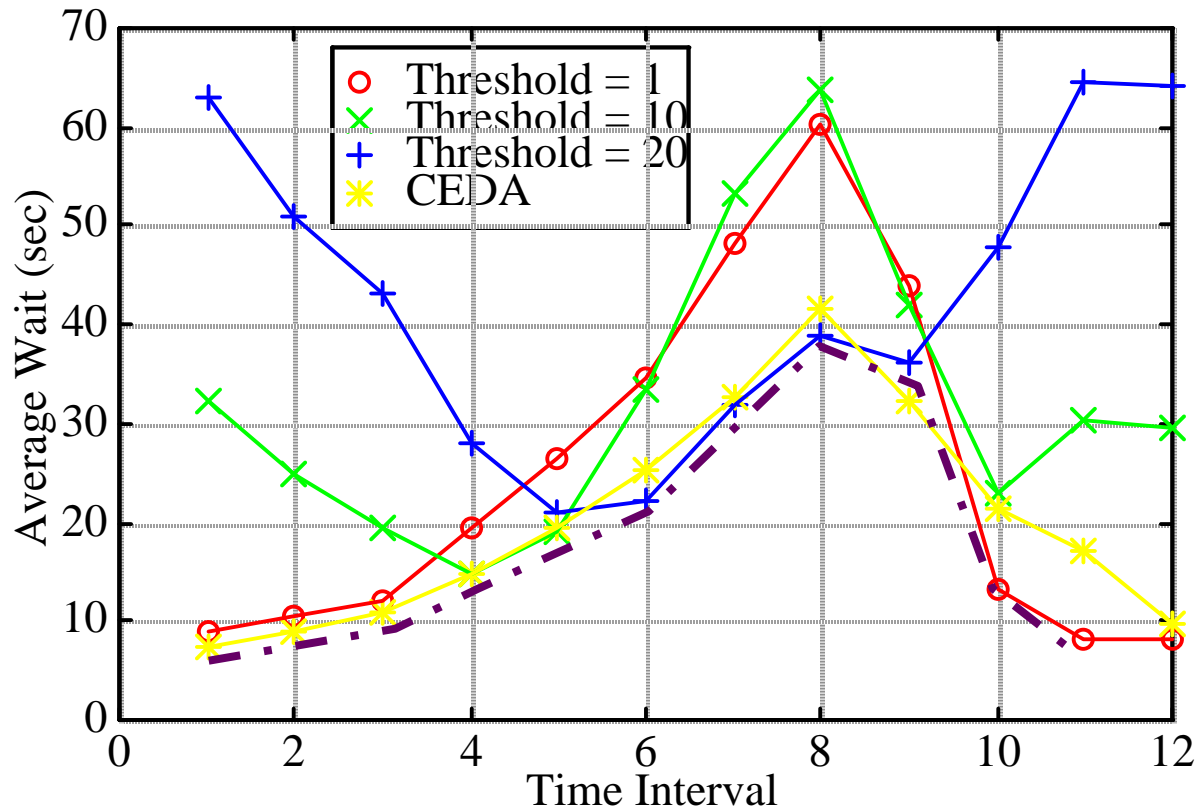
## PROBLEM:

- How to determine 12 thresholds, one for each 5 min. interval of fixed traffic rate?
- How to automatically adjust them on line?

## CONCURRENT ESTIMATION APPROACH:

- Choose any set of 12 thresholds  
(one for each 5-min. interval)
- Observe system under given thresholds
- Apply Concurrent Estimation to “*learn*” effect of all other feasible thresholds  
(*i.e., infer performance under hypothetical threshold values*)
- Optimize thresholds





**CEDA:**  
*Concurrent  
Estimation  
Dispatching  
Algorithm*

**RAPID  
LEARNING**

How fast did the **CEDA** learn optimal thresholds?

- Approximately 5 uppeak periods to converge (i.e., 5 real days)

# THE FUTURE

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- *COMPLEXITY*
  - *HYBRID SYSTEMS*
  - *COMPUTATIONAL CHALLENGES*
  - *NEW OPTIMIZATION METHODS*
- 

*OPPORTUNITIES...*

- *MIXED INITIATIVE CONTROL OF AUTOMA-TEAMS (MICA)*



# THREE FUNDAMENTAL *COMPLEXITY LIMITS*

**$1/T^{1/2}$   
LIMIT**

**NP-HARD  
LIMIT**

**one order increase**

Tradeoff between **GENERALITY** and **EFFICIENCY**  
of an algorithm

[*Wolpert and Macready, 1997*]

INFO.  
SPACE

**NO-FREE-LUNCH  
LIMIT**



# THREE FUNDAMENTAL *COMPLEXITY LIMITS*

$1/T^{1/2}$   
LIMIT

NP-HARD  
LIMIT

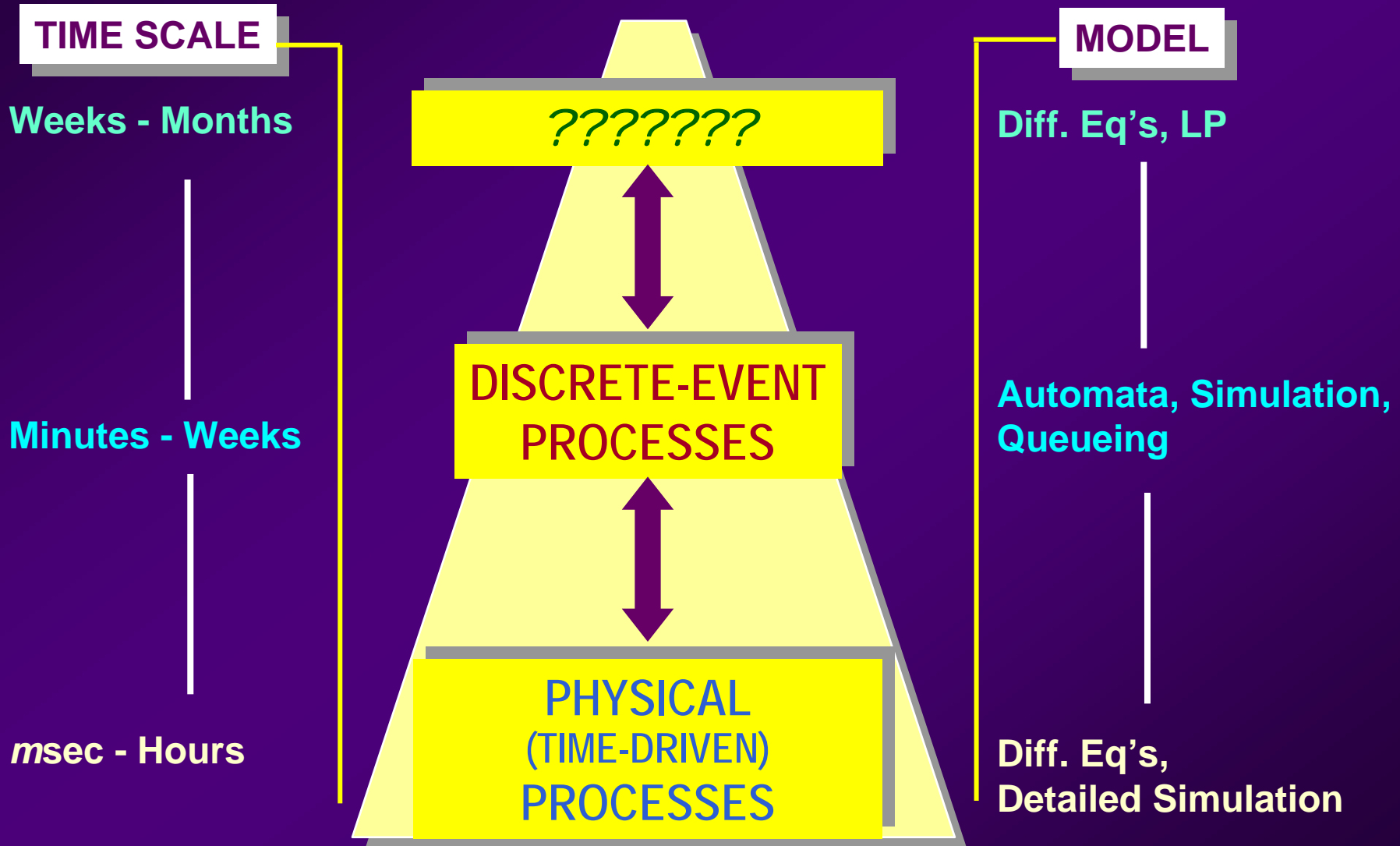


NO-FREE-LUNCH  
LIMIT

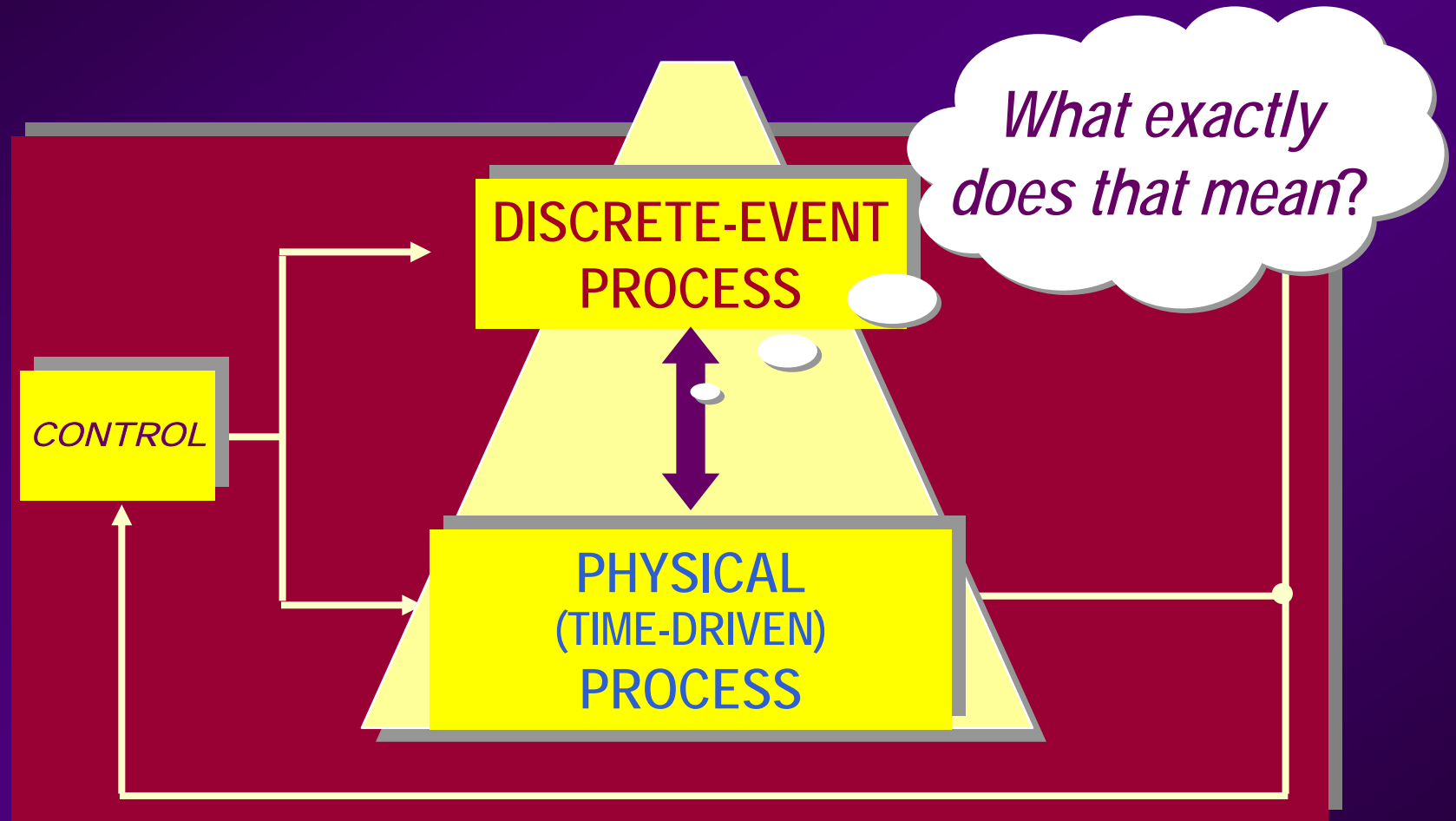




# HIERARCHICAL DECOMPOSITION OF COMPLEX SYSTEMS



# HYBRID SYSTEMS



# **HYBRID** SYSTEMS IN MANUFACTURING

Manufacturing system integration (*ALCOA, 1997*) :

- How to integrate '*process control*' with '*operations control*' ?
- How to improve product *QUALITY* within reasonable *TIME* ?



## PROCESS CONTROL

- Physicists
- Material Scientists
- Chemical Engineers
- ...

**Time-Driven World**

## OPERATIONS CONTROL

- Industrial Engineers, OR
- Schedulers
- Inventory Control
- ...

**Event-Driven World**



# ACKNOWLEDGEMENTS

*Thanks to several co-workers whose contributions are reflected in this talk...*

*... All 13 Former  
+ Current PhD Students...*

*...Colleagues...*

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<b>Wei-Bo Gong</b>	<b>Xiren Cao</b>
<b>Yorai Wardi</b>	<b>Ted Djaferis</b>
<b>Young Cho</b>	<b>Doug Looze</b>
	<b>Felisa Vazquez-Abad</b>

*...and Sponsors...*

**NSF, AFOSR, AFRL, DARPA, NASA,  
EPRI, ARO, UT, ALCOA, NOKIA, GE**



*TO CONCLUDE...*

*...LET'S APPLY  
CONTROL PRINCIPLES  
LIKE **FEEDBACK**, etc.  
IN EVERYTHING...*

*...BUT...*



# LET'S NOT GET CARRIED AWAY EITHER...

