

# **CAP6671 Intelligent Systems**

## **Lecture 7:**

### **Trading Agent Competition: Supply Chain Competition**

Instructor: Dr. Gita Sukthankar

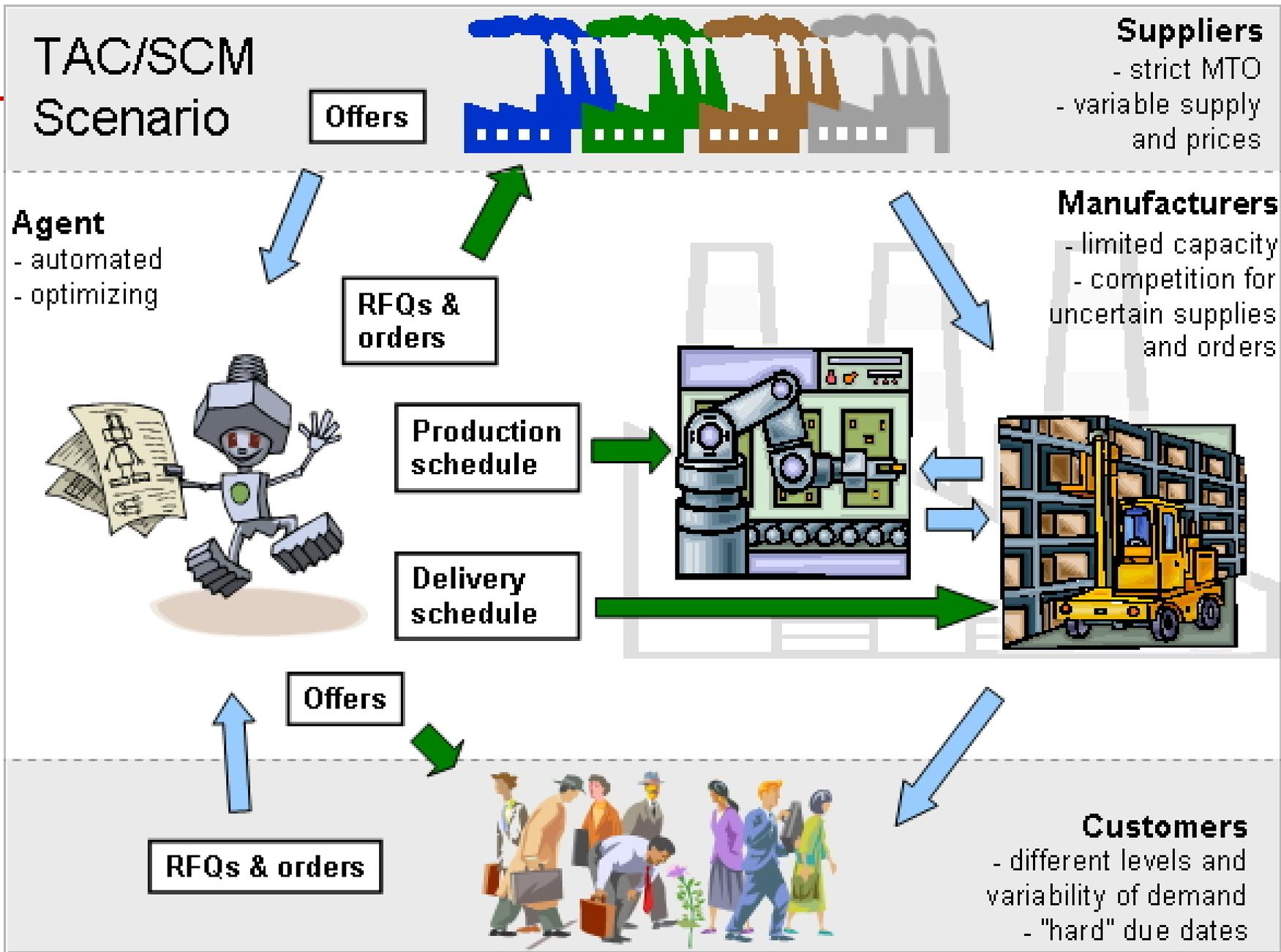
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Schedule: T & Th 9:00-10:15am

Location: HEC 302

Office Hours (in HEC 232):

T & Th 10:30am-12



# Why is this interesting/difficult?

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- Competitive setting more rigorously tests model
- Use of prediction in decision-making
- Supply chain management is an important problem
- Must make complicated decisions in rapid-time frame (each day 15 seconds)
- Clever use of abstraction makes problem easier

# What are the limitations?

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- Simulator creates world using:
  - Linear models
  - Simple distributions
  - Small number of known parameters.
- TAC Agent makes its prediction by calculating probable values of the same parameters used by the simulator.
- Prediction of events in the real world requires a much larger number of (unknown) parameters and a multi-modal distribution

# Game overview

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- A simulated economy consisting of computer manufacturers, customers, and component suppliers
- Six teams per game compete as manufacturers
- Customers and suppliers controlled by a game server
- One game lasts for 220 simulated days, each lasting 15 seconds (about 1 hour)
- Simulator includes:
  - Manufacturers
  - Suppliers
  - Customers
  - Factories

# TAC Agent Tasks

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- Function as manufacturer
- Buy components from suppliers
- Manage a factory that assembles and delivers computers
- Sell computers to customers

# Supplier Interaction

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- Manufacturers send Requests for Quotes (RFQs) on component deliveries
- Suppliers respond with offers
- Manufacturers accept or reject offers
- Suppliers deliver components

# Customer Interaction

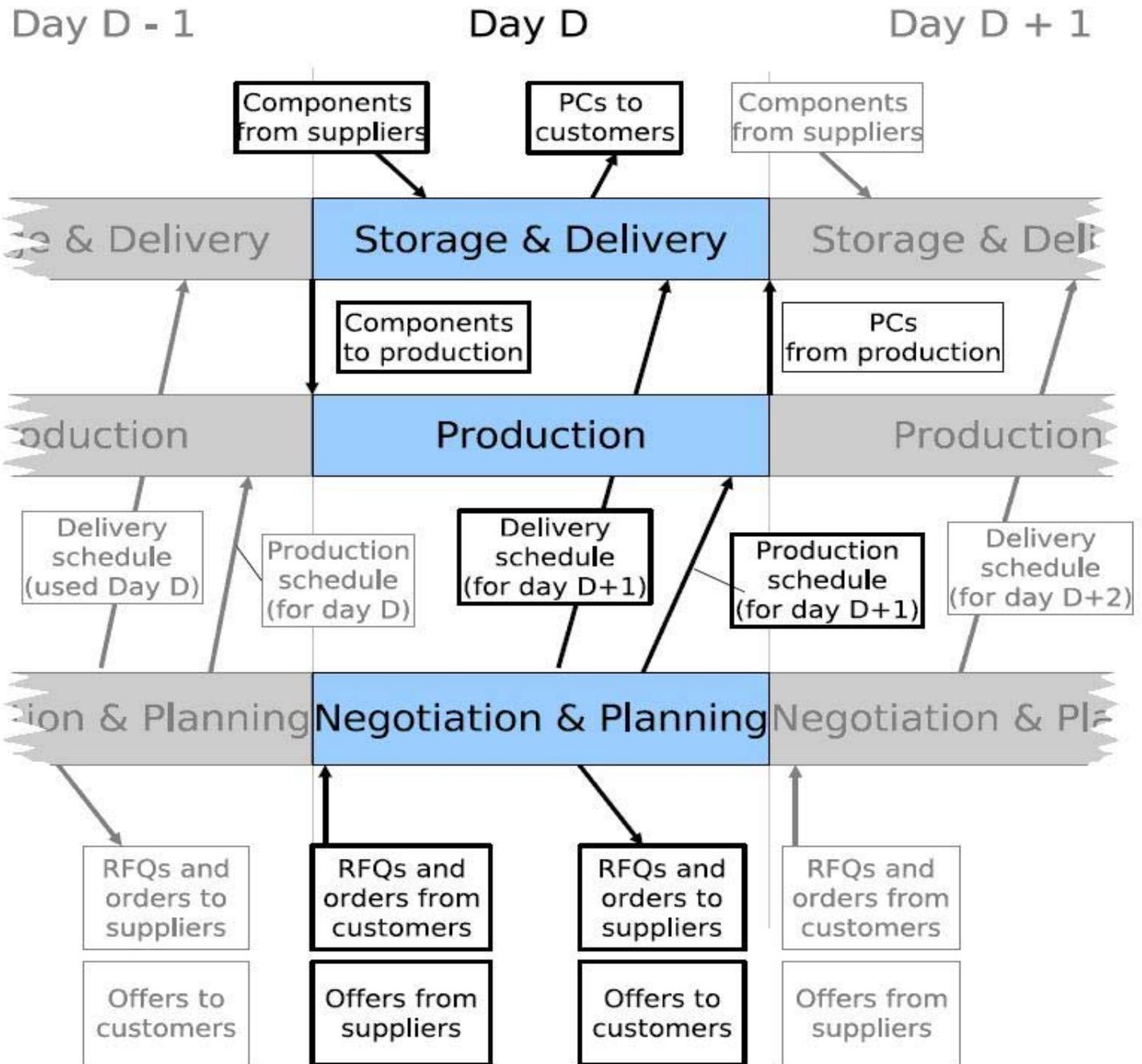
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- Customers send RFQs on computers to each Manufacturer
- Each manufacturer responds with an offer
- The lowest offer results in an order (thus a first price sealed bid reverse auction)
- The winning manufacturer delivers the computers

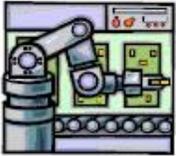
# Factory Interaction

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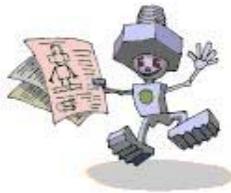
- Factory has limited production capacity
- Manufacturer receives inventory report each day
- Each day, manufacturer sends next day's production schedule
- Manufacturer also sends next day's delivery schedule
- Simplified version of real-life problem since you only have to dictate schedule 1 day in advance



**Inventory**



**Assembly Line**



**The Agent**

Component	Base price	Supplier	Description
100	1000	Pintel	Pintel CPU, 2.0 GHz
101	1500	Pintel	Pintel CPU, 5.0 GHz
110	1000	IMD	IMD CPU, 2.0 GHz
111	1500	IMD	IMD CPU, 5.0 GHz
200	250	Basus, Macrostar	Pintel motherboard
210	250	Basus, Macrostar	IMD motherboard
300	100	MEC, Queenmax	Memory, 1 GB
301	200	MEC, Queenmax	Memory, 2 GB
400	300	Watergate, Mintor	Hard disk, 300 GB
401	400	Watergate, Mintor	Hard disk, 500 GB

SKU	Components	Cycles	Market segment
1	100, 200, 300, 400	4	Low range
2	100, 200, 300, 401	5	Low range
3	100, 200, 301, 400	5	Mid range
4	100, 200, 301, 401	6	Mid range
5	101, 200, 300, 400	5	Mid range
6	101, 200, 300, 401	6	High range
7	101, 200, 301, 400	6	High range
8	101, 200, 301, 401	7	High range
9	110, 210, 300, 400	4	Low range
10	110, 210, 300, 401	5	Low range
11	110, 210, 301, 400	5	Low range
12	110, 210, 301, 401	6	Mid range
13	111, 210, 300, 400	5	Mid range
14	111, 210, 300, 401	6	Mid range
15	111, 210, 301, 400	6	High range
16	111, 210, 301, 401	7	High range

# Customer RFQs

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- Computer type (1 of 16)
- Quantity (1 – 20)
- Due date (3 – 12 days in the future)
- Reserve price (.75 – 1.25 times base)
- Penalty (.05 - .15 daily for up to 5 days)
  
- Only the high/low prices announced

# Customer Demand

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- 3 segments: low, mid, high
- Each segment's state: demand  $D$ , trend  $t$ 
  - $D$  in  $[25, 100]$  for low, high,  $[30, 120]$  for mid
  - $T$  in  $[\cdot95, 1/\cdot95]$
- Number of RFQs is Poisson( $D$ )
- $D$  is multiplied by  $t$  each day
- $t$  follows a random walk

# RFQs to suppliers

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- Each manufacturer can send 5/day
- Quantity, due date, reserve price
- Supplier offers a price
- Alternatives: reduced quantity, later date
- Manufacturer must accept offer next day, 10% down payment
- Reputation tracks fraction accepted

# Supplier Capacity

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- Daily capacity follows a random walk that reverts to 500
- Suppliers produce at full capacity as long as they have sufficient orders
- Delivery dates can be pushed back; latest orders given priority, no notice given
- Manufacturer agent must be robust to these supplier failures and be able to get orders to customers in a timely fashion without incurring penalties.

# Supplier RFQ handling

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- Determine capacity needed for current orders
- Consider groups of RFQs in order of *reputation* (fraction of offered components accepted)
- Add new demand to capacity used, determine prices, remove RFQs based on reserve prices
- If insufficient capacity, divide up available, make partial offers, then consider late offers
- Determine price for each offer and make offers

# Supplier Pricing

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$$P_{d,i} = P_c^{base} \left( 1 - \delta \left( \frac{C_{d,i}^{avl'}}{i C_d^{ac}} \right) \right)$$

- $d$  is curr
- $i$  is days in future
- Delta = .5
- $C^{avl'}$  is available capacity
- $C^{ac}$  is total capacity

# Factory

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- Production schedule gives number of each computer to produce, must have enough components and cycles
- Delivery schedule lists each order to ship
- Deliveries can be early, but payment is on time
- Storage cost: about .1 - .2% per day
- Interest: 3-6% over the game, double for debt

# Challenges in TAC SCM

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- Planning, scheduling, optimization
- Incomplete information
- Limited time for decisions
- Multiagent interactions
- Adapting to opponent behavior

# Agent Tasks

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1. Requesting components from suppliers (RFQ)
2. Deciding which offers from suppliers to accept
3. Bidding on RFQs from customers to request components
4. Sending the daily production schedule to the factory
5. Delivering completed computers

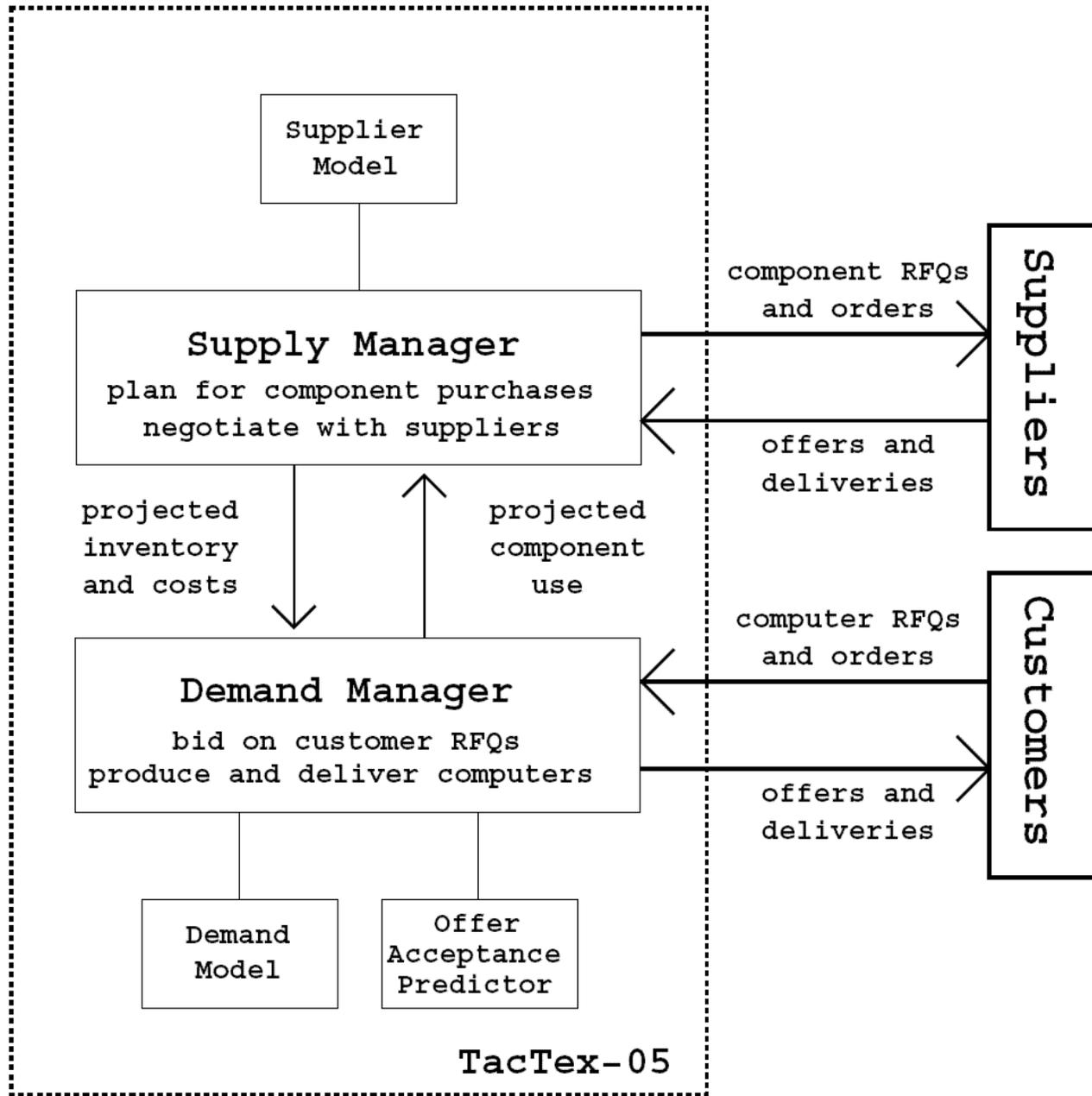
# What approach would you use?

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# Their Approach

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- Handle decision-making like a control problem
- Include prediction into the system rather than just making the controller purely reactive



# Method

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- Record info from server and update prediction modules
- Supply manager
  - Input: supplier component offers
  - Output: which components to buy
  - Update: projected future inventory, replacement costs
- Demand manager
  - Input: customer RFQs, current orders, projected inventory, and replacement costs
  - Output: accepting RFQs, production schedule
  - Updates: future customer demand, future component use
- Supply manager
  - Determines future deliveries needed to maintain inventory
  - Uses Supplier Model to predict future component prices
  - Decides what RFQs need to be sent

# Predicting Customer Demand

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- Bayesian approach adapted from DeepMaize
- Keep distribution over demand and trend
- Update distribution based on observation
- Then update according to trend
- Can predict future demand

# Bayes Filter Reminder

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- Prediction

$$\overline{bel}(x_t) = \int p(x_t | u_t, x_{t-1}) bel(x_{t-1}) dx_{t-1}$$

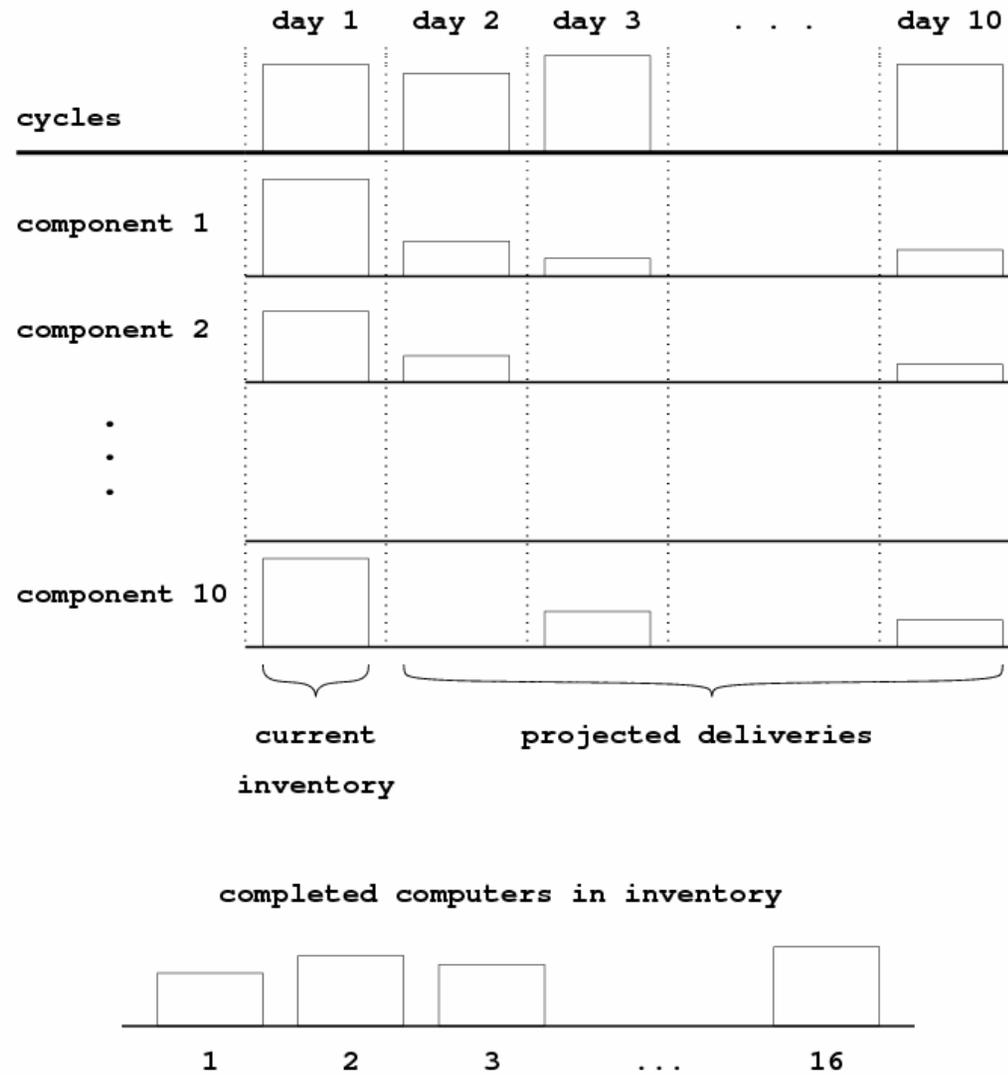
- Correction

$$bel(x_t) = \eta p(z_t | x_t) \overline{bel}(x_t)$$

# Production Algorithm

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- Greedy works well (similar to LP)
- Given orders, future inventory, costs
- Choose order with most profit
- Try to produce as late as possible
- Take from inventory if needed
- Push back due date and mark late if needed



# Produce, Deliver, Bid

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- First handle orders that are due
- Then apply to other orders and RFQs
- Extract tomorrow's deliveries, production
  - Deliver only if due or extra inventory
  - Fill in gaps in tomorrow's production
- Record predicted future component use

# Experiments with Predictions

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- Demand prediction accuracy has little impact
- Acceptance predictions somewhat important - but shape of distribution not so much
- Supply price predictions very important
- Better to wait to order, even if supply prices increase slightly

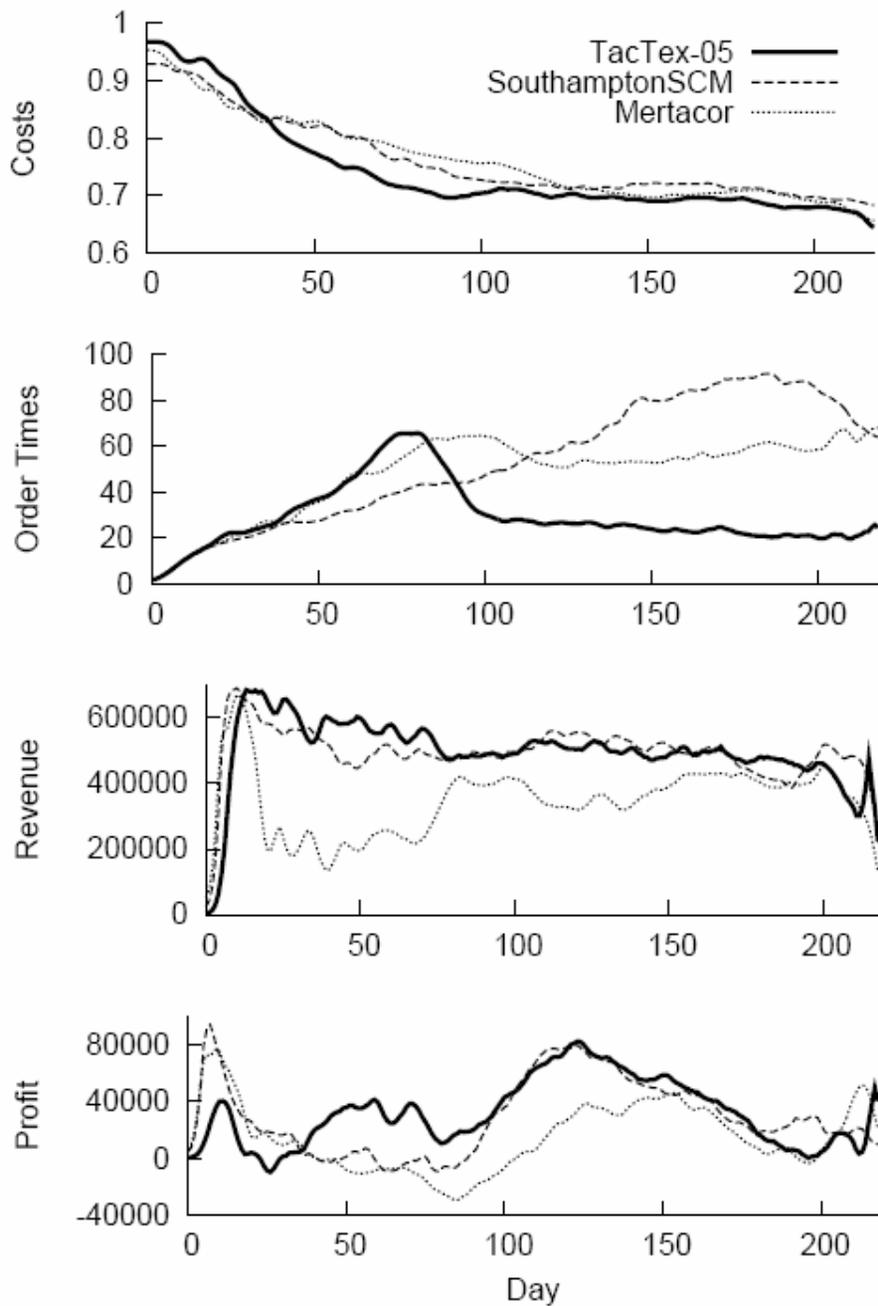
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<i>Exp. #</i>	<i>Description</i>	<i>Score</i>	<i>Util.</i>	<i>Revenue</i>	<i>Costs</i>	<i>Win %</i>
0	no changes	\$7.28M	83%	\$104.7M	\$94.5M	-
1	no component price prediction increase	-1.42	+3%	+3.51	+4.79	23%
2	no computer price change prediction	-3.51	-1%	-4.50M	-.70M	0%
3	no particle filter	-1.97	-7%	-10.05M	-8.03M	0%
4	no particle filter or prediction	-3.93	-6%	-10.99M	-6.83M	0%
5	heuristic price change prediction	-1.74	0%	-1.14M	-.64M	13%

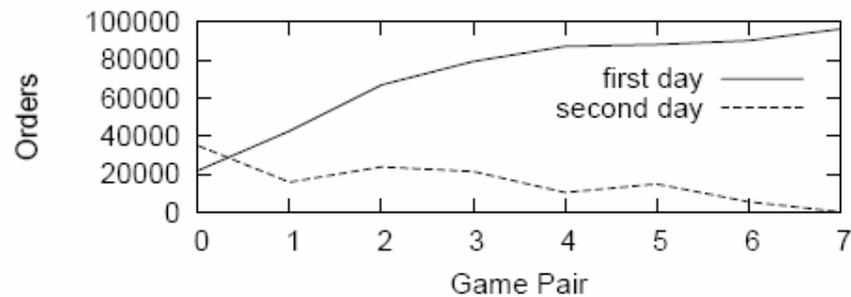
# Adaptation

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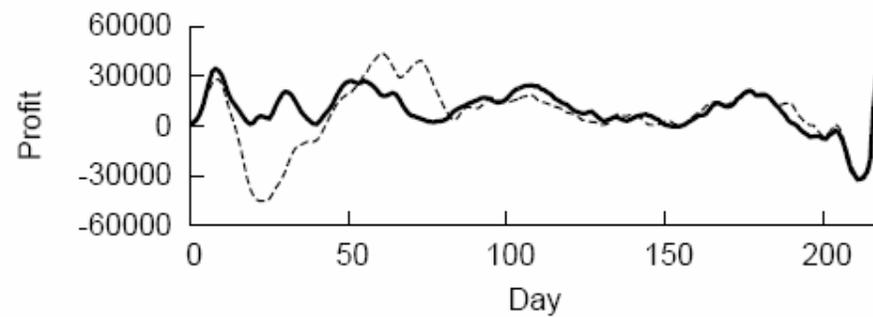
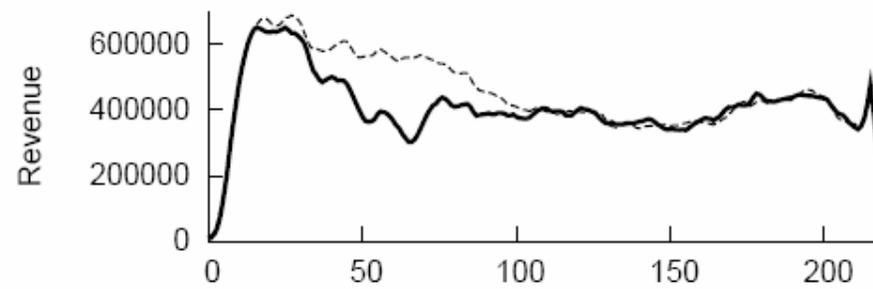
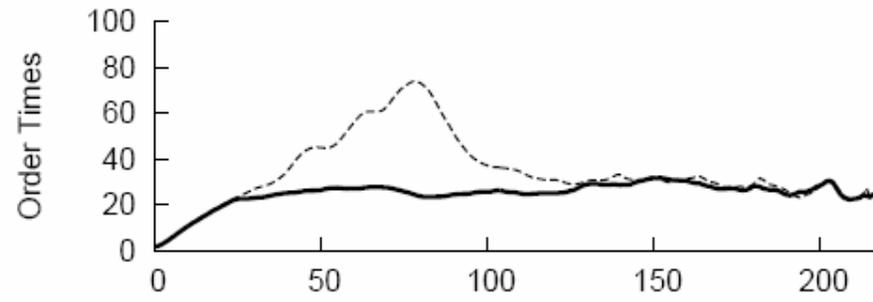
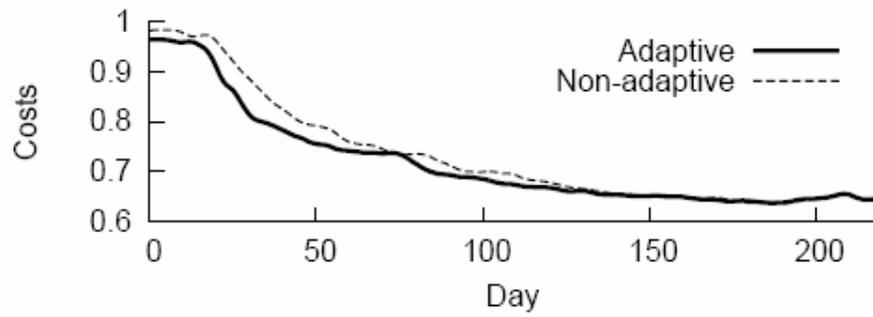
- First day ordering
  - Most agents hardcode orders
  - Can predict prices on first day, later
  - Order if cheapest on first day
- End of game bidding
  - Opponents often have surplus or shortage
  - Can save computers or sell early



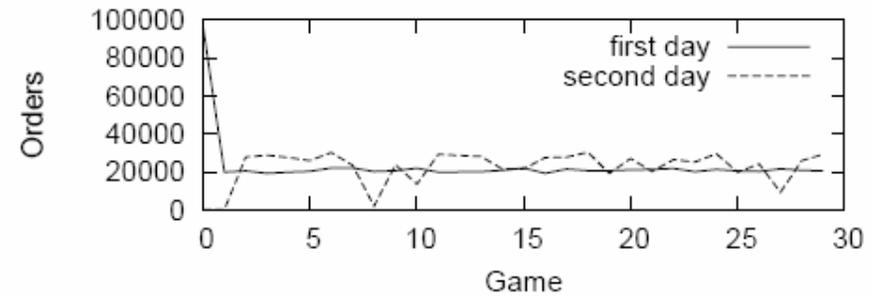
Results – final day of competition



Initial orders – competition



Results – experiment



Initial orders – experiment

# Future Work

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- Improve prediction accuracy
  - Possibly with learning
  - Adapt predictions during competition
- Make better use of supply price predictions
  - Wait to order if possible
- Predict *future* computer prices
  - Sell computers now or save for later

# References

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- Most of the slides here are directly from D. Pardoe and P. Stone's talk  
<http://www.cs.utexas.edu/~pstone/Papers/bib2.html/>