

# Autonomous Trading Agents for Supply-Chain Management

Wolfgang Ketter

Erasmus School of Economics

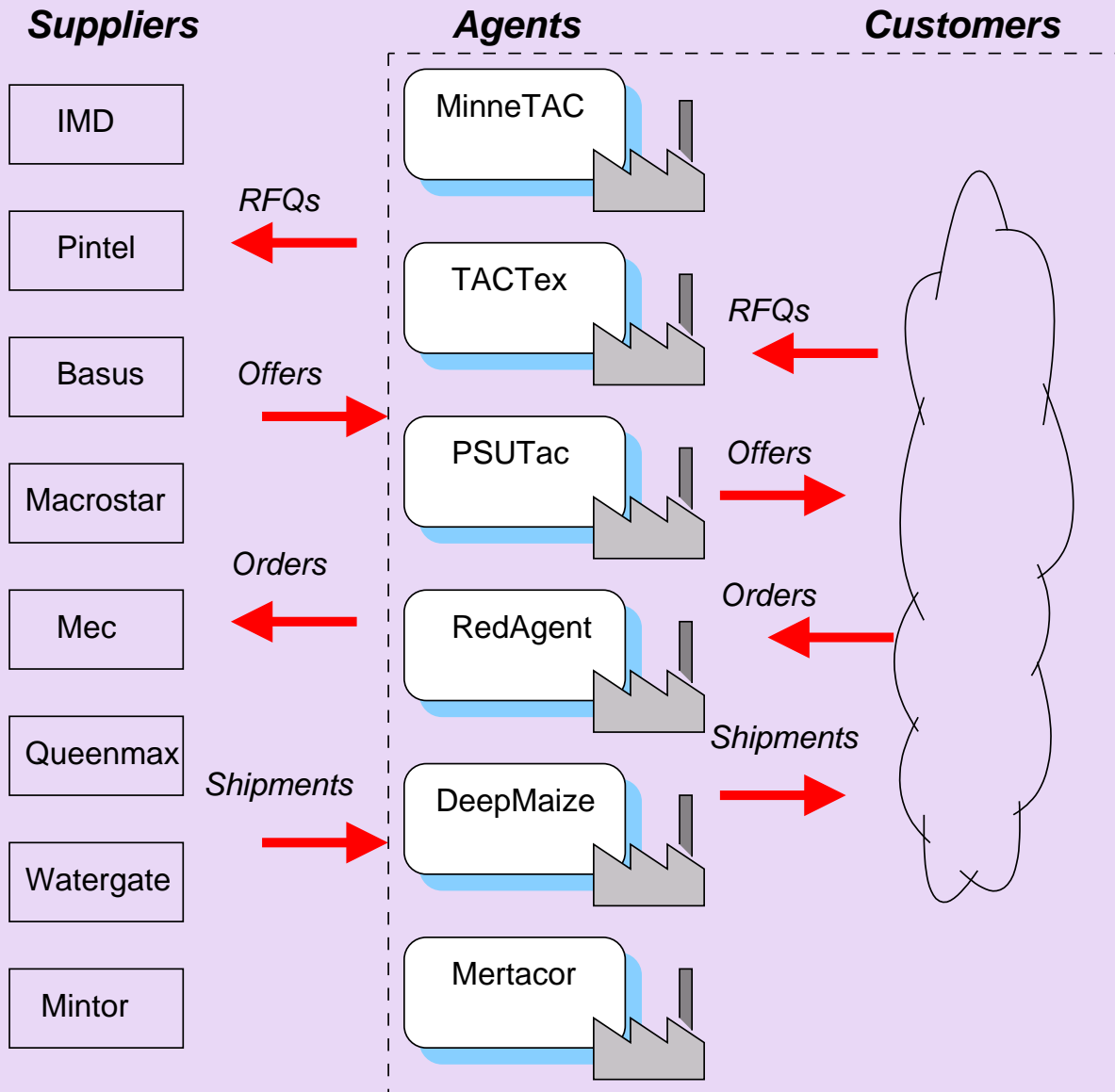
Erasmus University

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# Overview

- Trading Agent Competition for Supply Chain Management (TAC SCM)
- MinneTAC
- Economic Regimes
- Future Work and Conclusions

# TAC SCM - Scenario



# Static vs. Dynamic Practices

- Today's supply chains are mostly static, relying on fixed, long-term trading partners. Not always optimal!
- Dynamic management allows for finding better matches between suppliers and customers as market conditions change.
- This is the goal of the Supply-Chain Management Trading Agent Competition (TAC SCM).

# TAC SCM - Implications in the Real Business World

- Markets are changing quickly - Organizations that have the ability to meet changing market demands in a timely and cost-effective manner will prosper.
- Decreased cost and performance improvement can be provided through new algorithms for procurement of components, production, and sales management.
- The algorithms can be used to provide information to a human decision maker.

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- MinneTAC
- Economic Regimes
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# MinneTAC - Design Challenges

- Clean separation of infrastructure from decision processes.
- The design must support multiple independent developers pursuing their own lines of research.
- We need to be able to configure agents with different combinations of decision process implementations.
- Controllable generation of experimental data.

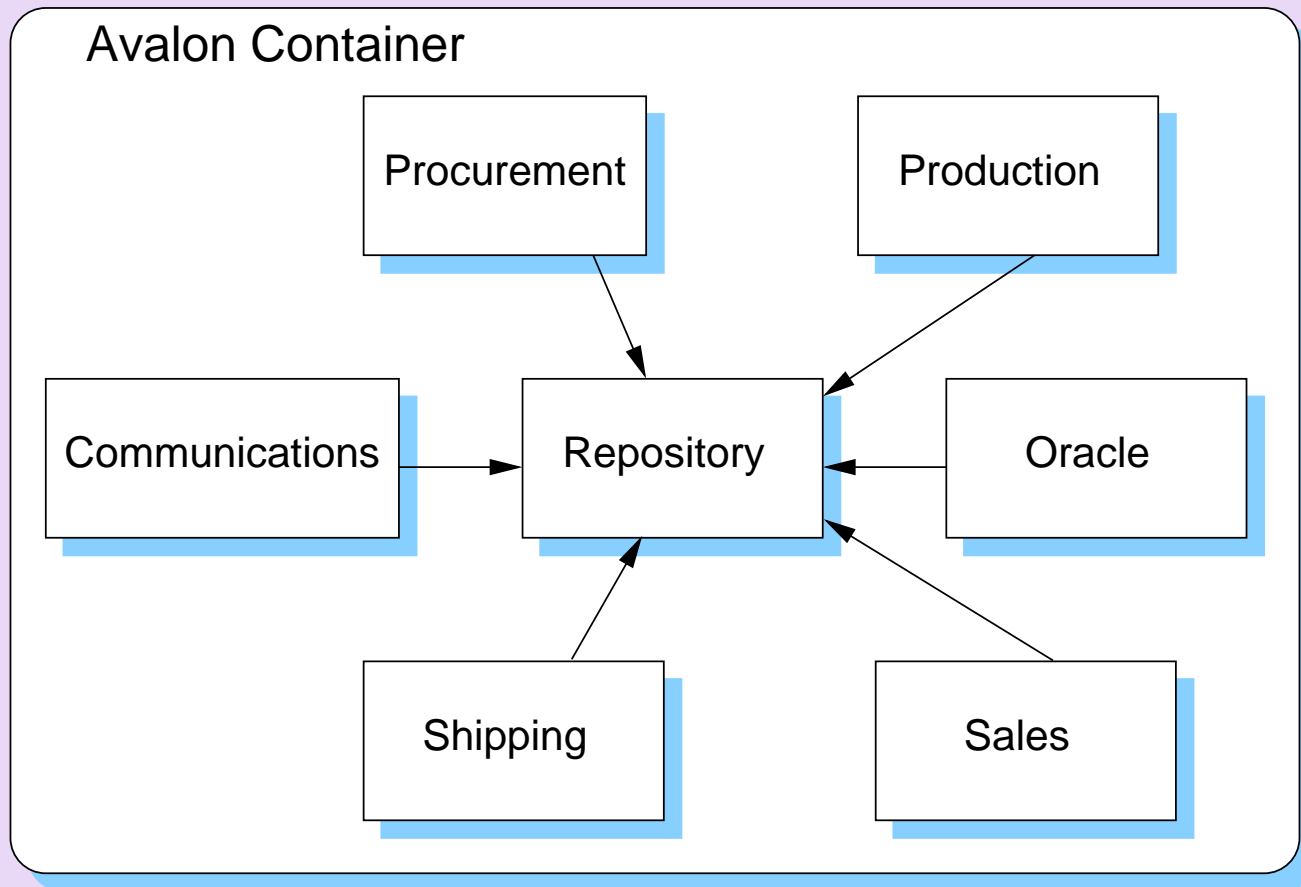
# MinneTAC - The Design

We chose an component-oriented approach.  
Two pieces form the foundation of MinneTAC:

- Apache Excalibur component framework
- “Dummy agent” distributed by the TAC SCM game organizers

J. Collins, W. Ketter, and M. Gini. “Flexible decision control in an autonomous trading agent.” submitted to Electronic Commerce Research and Applications, 2007.

# MinneTAC - Architecture



Arrows indicate API dependencies.

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- MinneTAC
- **Economic Regimes**
- Future Work and Conclusions

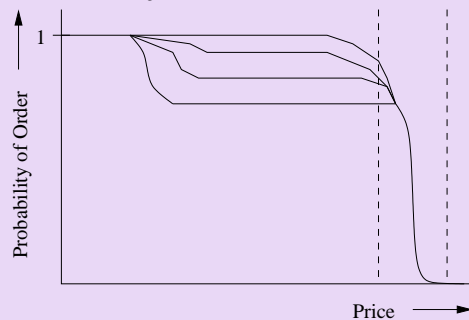
# Motivation Economic Regimes

- Economic theory suggests that economic environments exhibit 3 dominant market patterns: scarcity, balanced, and over-supply.
- We call these distinguishable conditions *economic regimes*.
- The long term objective of our work is to show how knowledge of current and anticipated regimes can enable an agent to make better operational and strategic decisions.

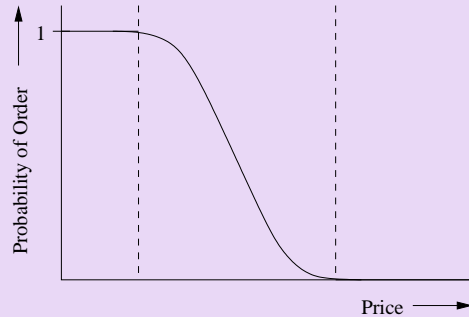
Work done with John Collins, Maria Gini, Alok Gupta, and Paul Schrater.

# Relationship between Prices, Order Probability, and Regimes

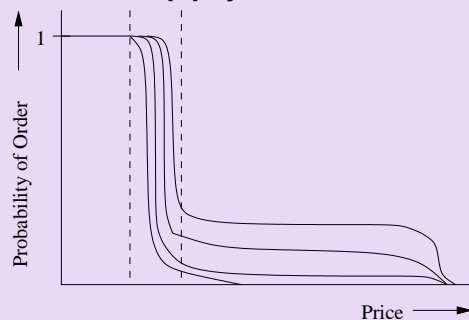
Scarcity:



Balanced:

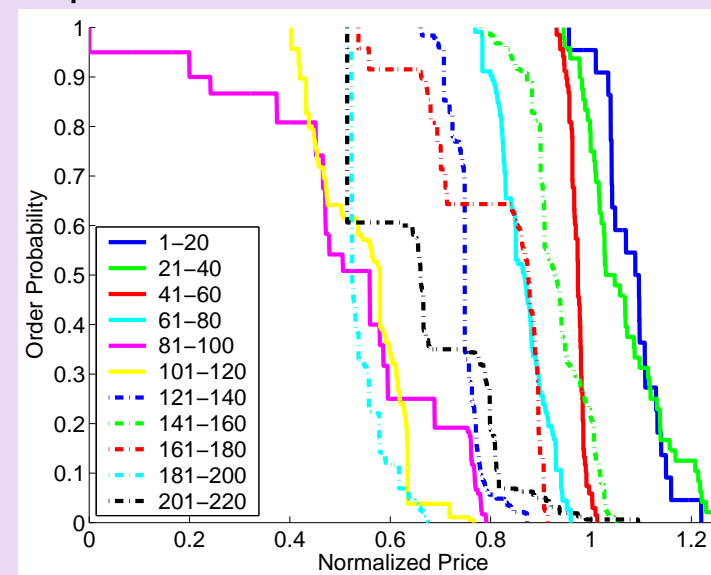


Over-supply:



Reverse cumulative density function represents probability of order.

Experimental:



# Use Regime Prediction For Sales Strategies

1. Allocation (Strategic Decision):
  - Optimal product mix, given resource constraints.
  - Allocation of parts, production capacity, and finished goods over time (multiple sales cycles).
2. Pricing (Tactical Decision):
  - Find the best prices to move the desired inventory.

# Proposed Approach

1. Off-line Regime Training
2. Real-time
  - (a) Regime Identification and Prediction
  - (b) Sales Pricing

# Estimating Price Density Functions

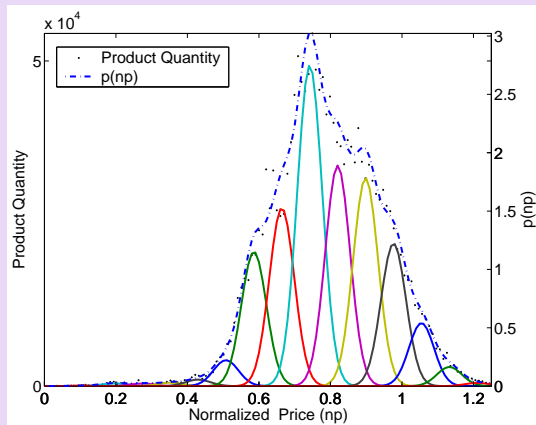
We estimate price density functions using a Gaussian mixture model (GMM)

$$p(\text{np}) = \sum_{i=1}^N p(\text{np}|\zeta_i) P(\zeta_i)$$

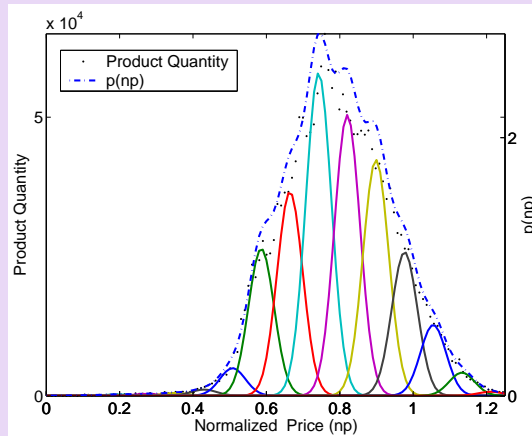
where

- $p(\text{np})$  is the density of the normalized price (np).
- $p(\text{np}|\zeta_i) = N[\mu_i, \sigma_i](\text{np})$  is the  $i$ -th Gaussian of the normalized price density from the GMM.
- $P(\zeta_i)$  is the prior probability of the  $i$ -th Gaussian. We determine it using the EM-algorithm.

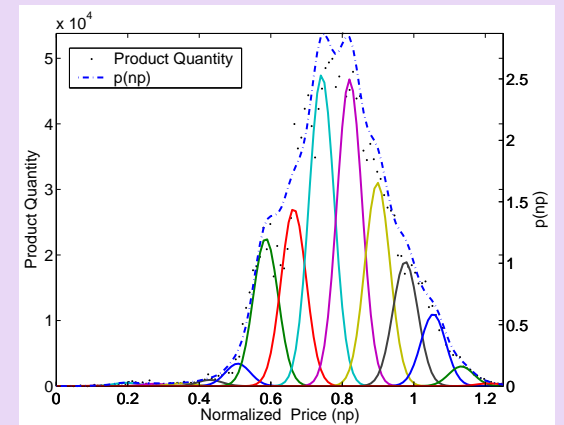
# Examples of Estimated Price Density Functions



Low Market



Medium Market



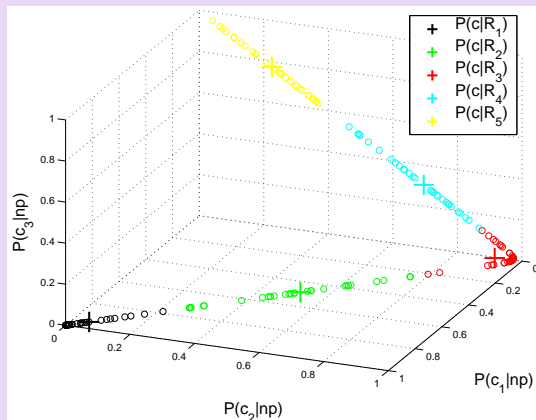
High Market

# Definition of Regimes

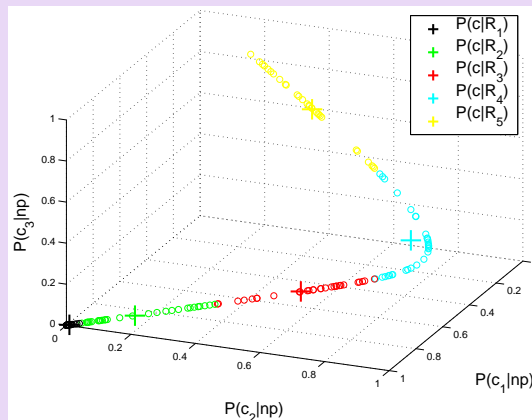
1. We compute at each price  $np_j$  the N-dimensional vector

$$\vec{\eta}(np) = [P(\zeta_1|np), P(\zeta_2|np), \dots, P(\zeta_N|np)]$$

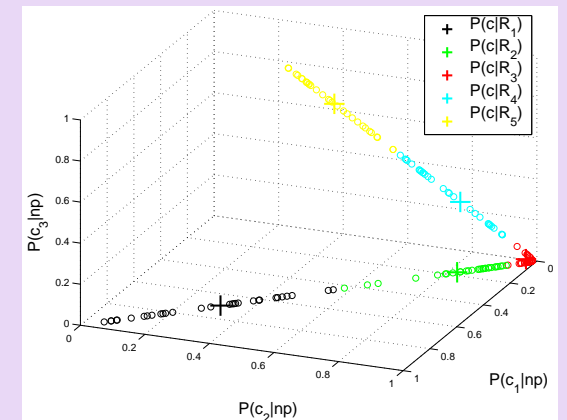
2. We cluster these vectors using k-means.
3. The center of each cluster corresponds to a regime  $R_k$ .
4. We compute the posterior probability  $P(R_k|np)$



Low Market



Medium Market



High Market

# Proposed Approach

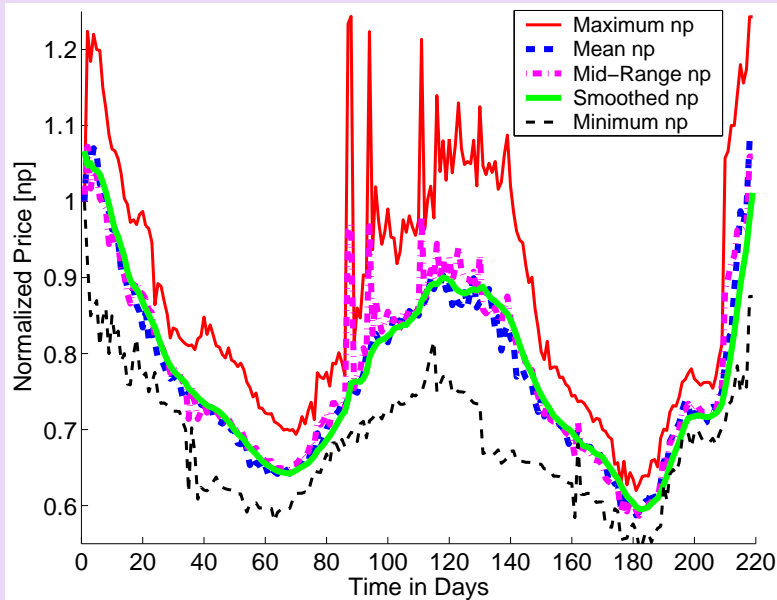
1. Off-line Regime Training
2. Real-time
  - (a) Regime Identification and Prediction
  - (b) Sales Pricing

# Information Available in the Customer Market

Every day each agent receives:

1. Requests for Quotes (RFQs): computer type, number of computers, due date, reserve price.
2. A price report which includes the lowest and highest price paid per computer type from the previous day.

# Real-time Identification of Dominant Regime

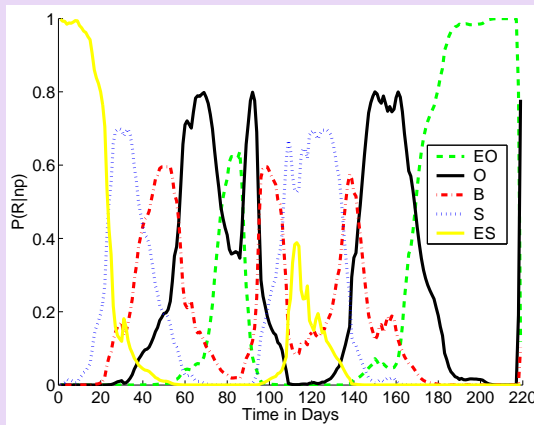


Daily price report  
3717@tac3 – low  
market: Minimum and  
maximum order  
prices.

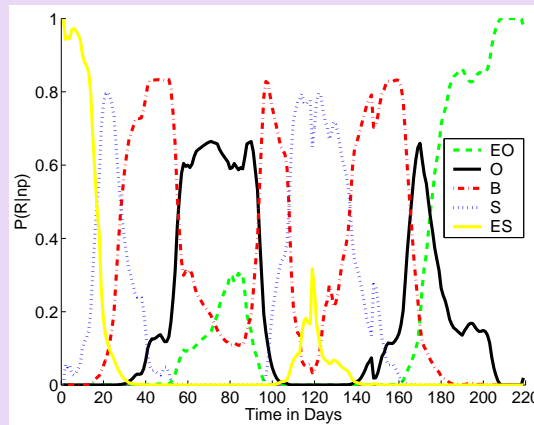
1. Every day we estimate the current regime by calculating the smoothed mid-range normalized price  $\widetilde{np}_{day}$  based on the daily price report.
2. We select the regime which has the highest probability, i.e.

$$\operatorname{argmax}_{1 \leq k \leq M} \vec{P}(R_k | \widetilde{np}_{day}).$$

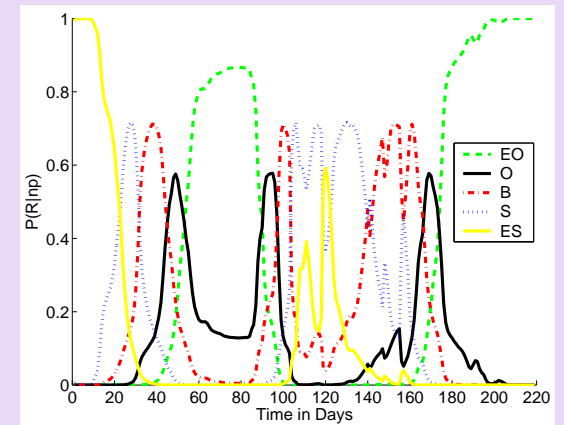
# Regime Probability – Real-time



Low Market



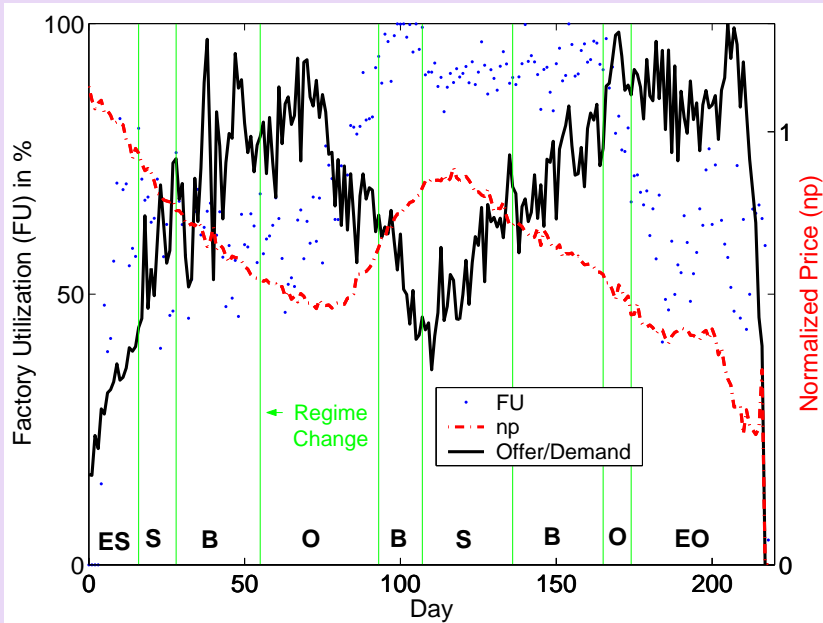
Medium Market



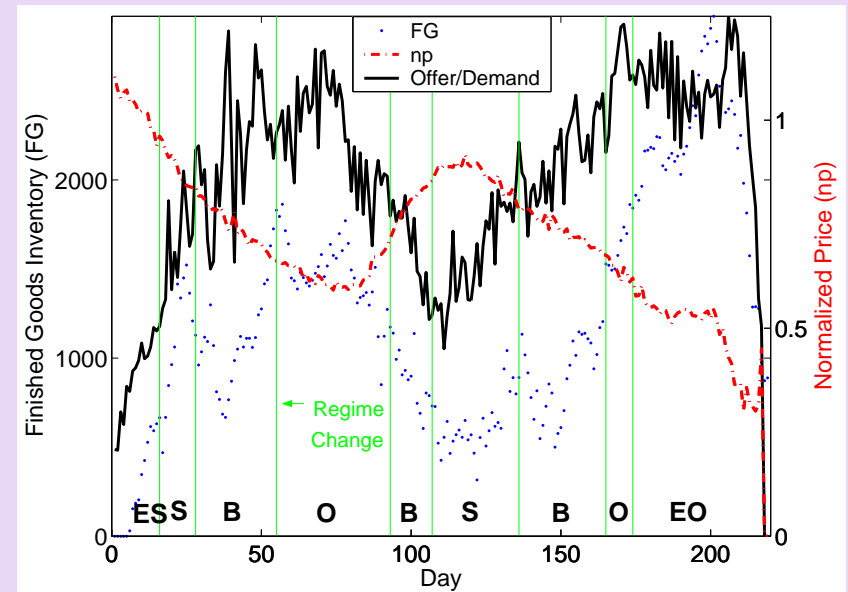
High Market

$\vec{P}(R_k | \widetilde{np}_{day}) \quad \forall k = 1, \dots, M$  calculated online for game 3721 @tac3.

# Regime Market Parameters



Factory Utilization (FU)



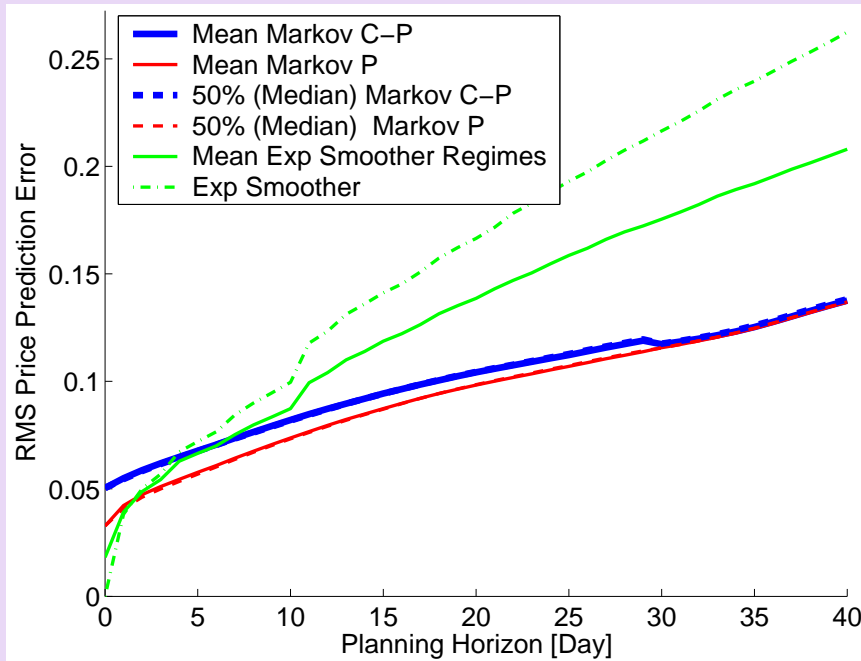
Finished Goods Inventory (FG)

Game 3721tac3 - medium market segment: Ratio offer/demand, **normalized prices**, and **regime transitions**.

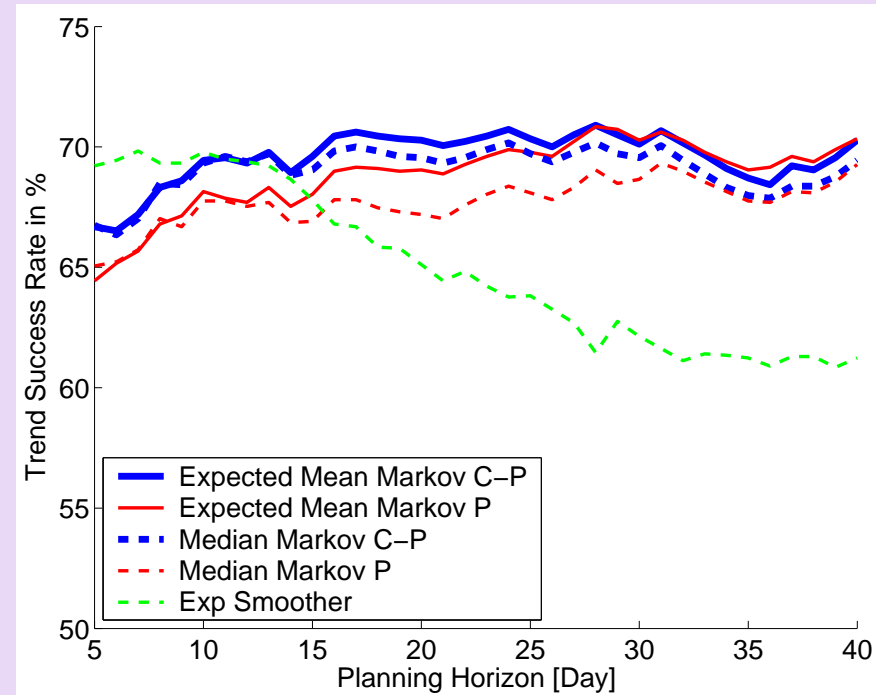
# Online Prediction of Regimes

We model the prediction of the next regime as a Markov prediction process: The posterior regime probabilities are predicted for current and future days based on yesterday's smoothed mid-range normalized price  $\widetilde{np}$ .

# Evaluation of Price and Trend Prediction



Price Prediction

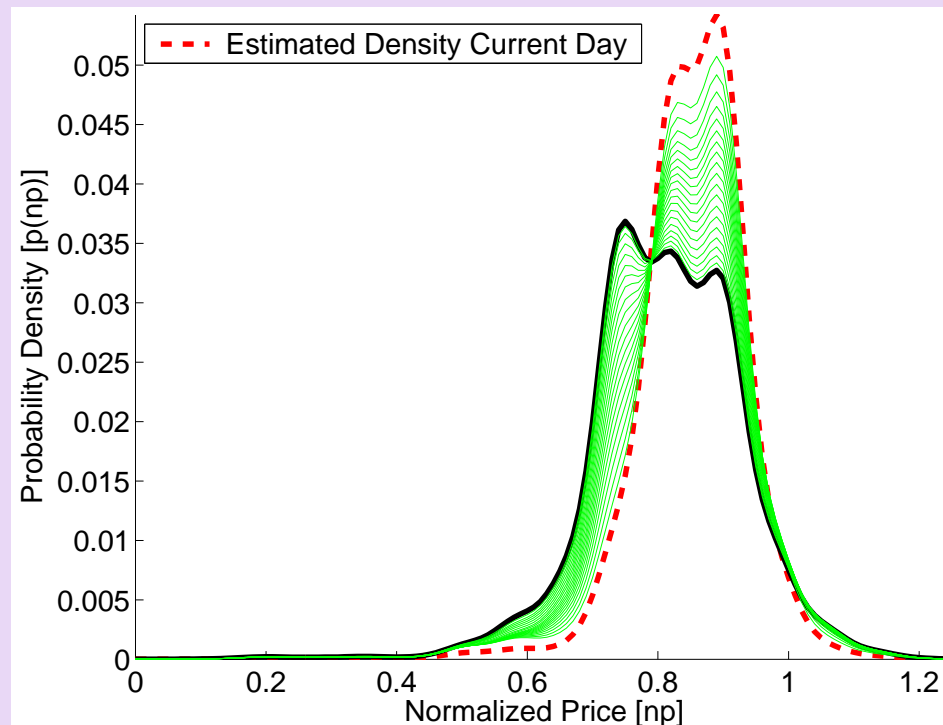


Trend Prediction

# Prediction of Price Density

$$p(\widehat{np}_{t+n} | \widetilde{np}_{t-1}) = \sum_{j=1}^N P(\zeta_{j,t+n}) p(np | \zeta_j)$$

Sample  $np$  from 0 to 1.25 in increments of 0.01



# Prediction of Order Probability

$$P(\text{order}|\text{np}) = 1 - CDF(\text{np})$$

where

$$CDF(\text{np}) = \int_0^{\text{np}} p(\text{np}') \text{dnp}'$$

In TAC SCM  $\text{np}_{max} = 1.25$ ,

so that  $CDF(\text{np}_{max}) = 1$ .

# Proposed Approach

1. Off-line Regime Training
2. Real-time
  - (a) Regime Identification and Prediction
  - (b) **Sales Pricing**

# Optimizing sales quotas (1)

To optimize profits over time, an agent needs to know:

- Current and future prices
- Its own costs
- Available inventory and production capacity

If per-unit profit for good  $g$  sold on day  $d$  at price  $price_{d,g}$  is  $\Phi_{d,g}$ , then total profit over a horizon  $h$  is

$$\Phi = \sum_{d=0}^h \sum_{g \in \mathcal{G}} \Phi_{d,g} A_{d,g}$$

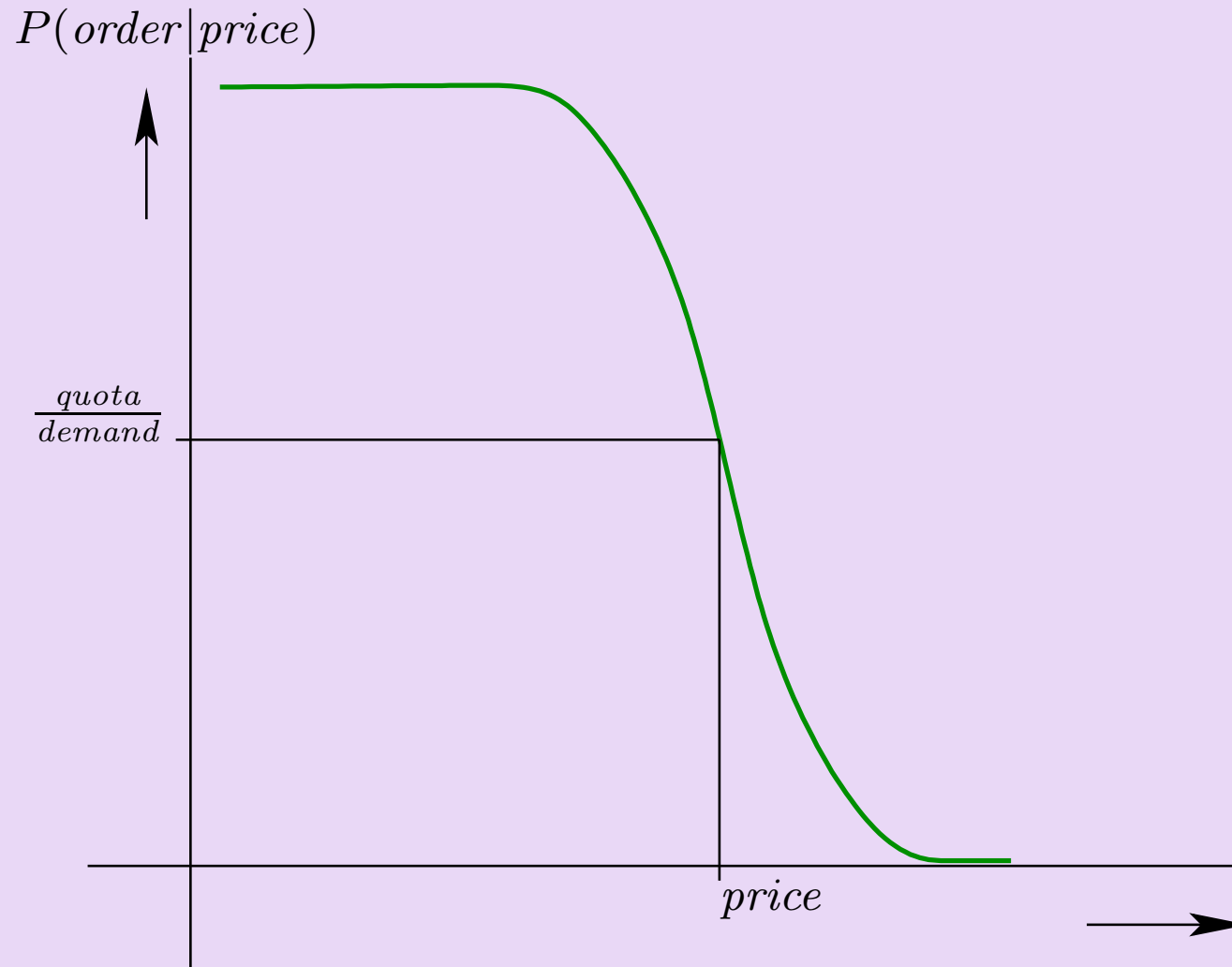
# Optimizing sales quotas (2)

LP solver can optimize total profit, subject to:

- Sales quotas cannot exceed expected demand
- Uncommitted finished-goods and raw-materials inventories
- Inventories are augmented by expected deliveries and components available from suppliers over the planning horizon  $h$
- Quotas not satisfied from finished goods are constrained by factory capacity

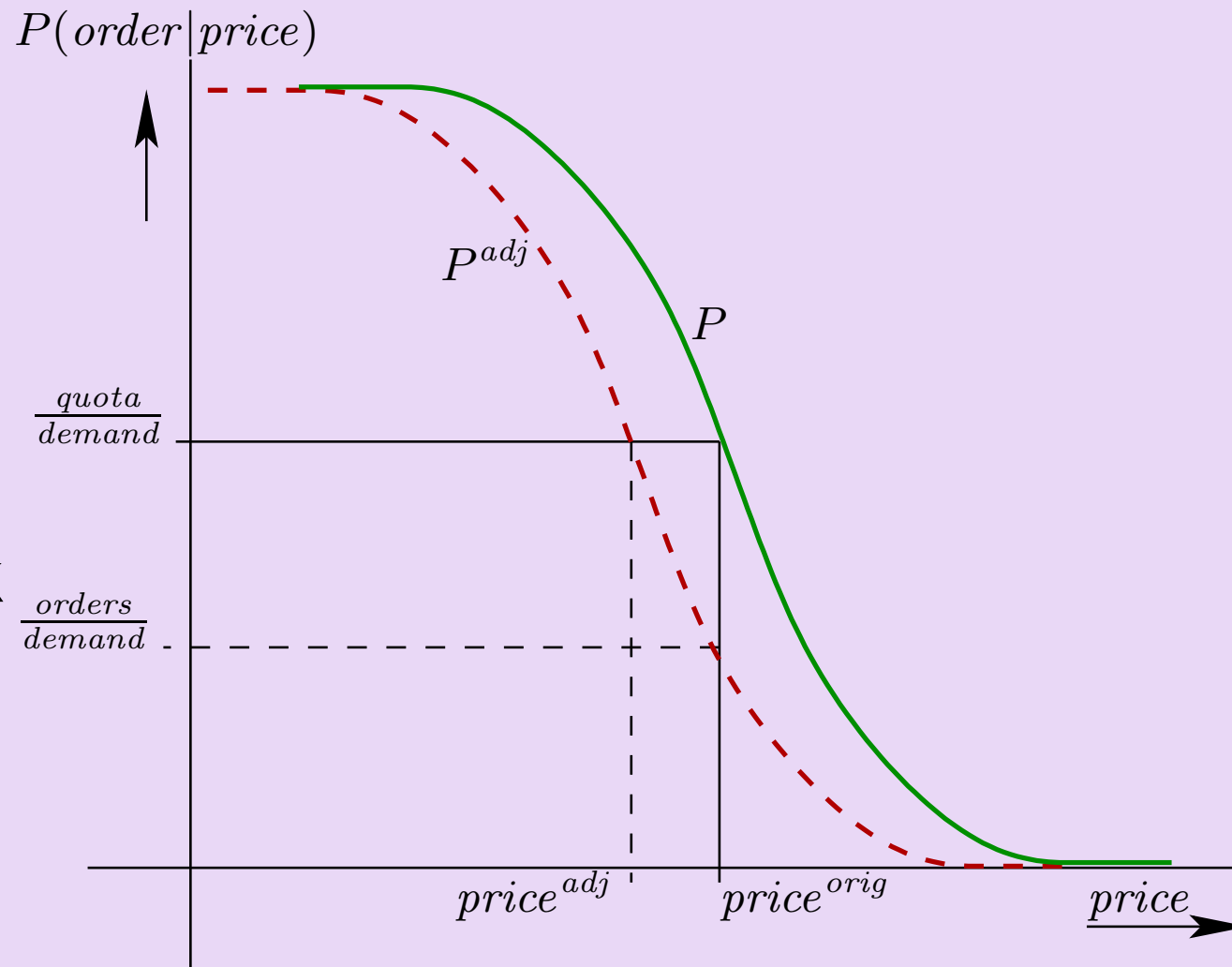
# Setting sales prices

To sell our quota, we set prices using our order probability model.



# Tuning sales prices

The pricing model is approximate. We tune it using feedback from actual orders.



# Mean Profit Results using Different Versions of MinneTAC

Strategic: Tactical: Agent:	Mean Profit / Standard deviation (in \$M)			
	Price-Follower	Regimes	Combo	Regimes
	Linear	Linear	Linear	Regimes
MinneTAC	1.347/3.703	1.813/4.017	1.780/4.536	2.117/3.764
TacTex06	8.752/5.682	8.873/5.600	8.399/5.173	9.205/5.385
DeepMaize06F	8.839/4.629	8.713/4.846	8.403/4.710	8.318/4.181
PhantAgent06	8.049/5.422	7.991/5.384	7.895/5.326	8.173/5.437
Maxon06F	4.243/4.516	3.767/4.288	3.808/4.254	4.019/4.181
Rational05	0.739/4.912	0.669/4.692	0.710/4.692	1.305/4.527

Experimental setup with controlled market conditions and different variations of MinneTAC for order probability, price and price trend predictions. Each column is an average of 23 games.

# Application Areas Economic Regimes

- Identification of economic regimes:
  - Strategical decision making
  - Tactical decision making
- Price and price trend forecasting.
- Forecasting of economic regimes shifts:
  - Wholesaler (e.g. book store).
  - Production plant (e.g. Daimler-Chrysler).
- Automated supply-chain management, e.g.,
  - i2
  - SAP

# TAC SCM - Finals 2006

- TacTex - University of Texas, USA - Winner
  - Good Procurement
  - Good Sales
- MinneTAC - Univ. of Minnesota, USA
  - Average Procurement
  - Good Sales
- PhantAgent - Univ. of Bucharest, Romania
- DeepMaize - Univ. of Michigan, USA
- Maxon - Applied Univ. of Gelsenkirchen, Germany

# Future Work - Economic Regimes

- Dynamic model selection between the different price prediction approaches.
- Develop procurement strategies that take advantage of regime forecasting.
- Implement and evaluate approach in other application domains, e.g.,
  - Stock market
  - Amazon
  - eBay

# Supply-Chain Simulation

- Tease apart subtle interactions and effects that would never be visible among the noise of the real world.
- Try ideas for things like pricing and inventory control that you could never risk in the real world.
- Run a whole year's interactions in an hour, change the setup, and run the year again.
- Provide a real good understanding of challenges that one is likely to face in a real environment.

# LARGE - Learning Agents Research Group at Erasmus (I)

- Interdisciplinary research group spanning the fields of artificial intelligence, behavioral science, computer science, economics, information systems, operations research, and software engineering.
- Primary objective: Research, develop, and apply autonomous intelligent agents to support human decision making capabilities in the area of business networks, electronic markets, and supply-chain management.

# LARGE - Learning Agents Research Group at Erasmus (II)

## Sample Projects:

- Research on decision support tools and advanced technologies aimed at significantly increasing enterprise supply chain agility.
- Highly personalized agents that facilitate information gathering and optimize human decision making.
  - Significantly enhance bounded rationality of humans with the help of multi-agent systems.
- Form an Erasmus TAC SCM team

# References

## **TAC SCM**

<http://www.sics.se/tac/page.php?id=1>

**MinneTAC** <http://tac.cs.umn.edu/>

**LARGE** <http://large.rsm.nl>

## **This Presentation**

<http://www.ketter.ws/research/talks>

# Conclusions

- Supply-Chain Simulation TAC SCM.
- Autonomous Trading Agents.
- Identification and Prediction of Economic Regimes.
- New way of predicting prices and price trends.
- LARGE - Learning Agents Research Group at Erasmus.

## **Questions and Research Opportunities**

email: `wketter@rsm.nl`

URL: `http://www.ketter.ws`