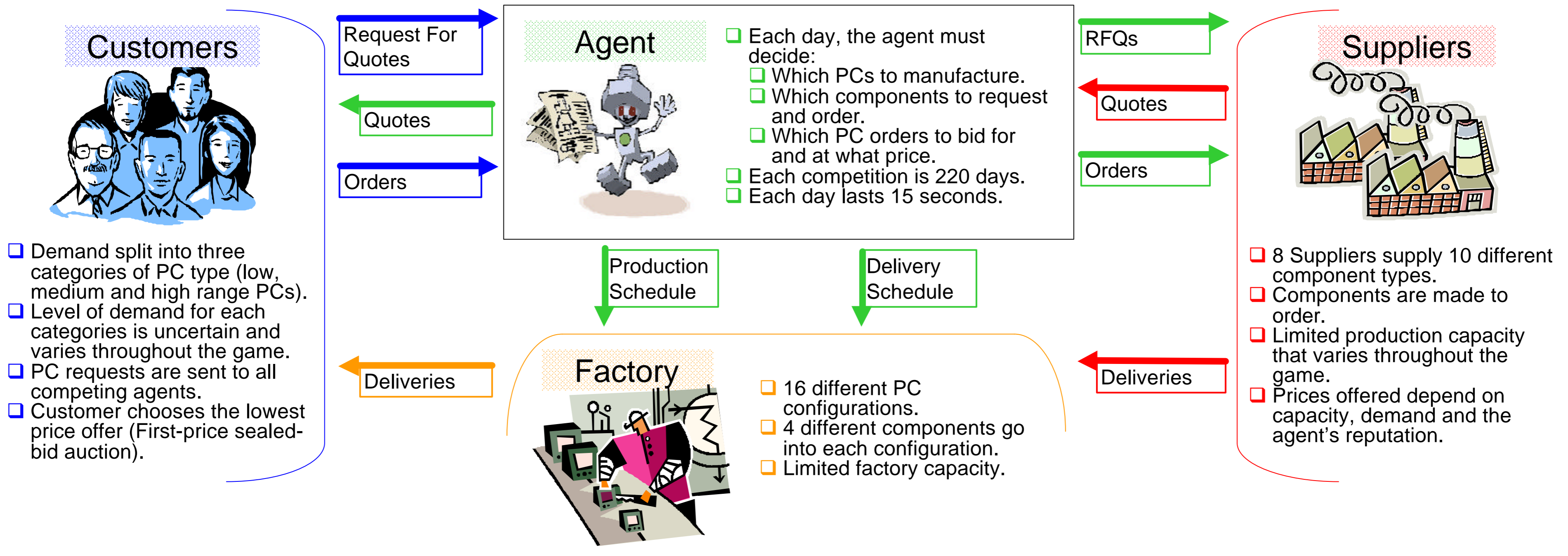


Applying constraint-based optimisation and online learning for trading and scheduling in a simulated supply chain

Trading Agent Competition – Supply Chain Management

- Today's supply chains are essentially static, relying on long-term relationships among key trading partners.
- More flexible and dynamic practices offer the prospect of better matches between suppliers and customers as market conditions change.
- TAC SCM captures many of the challenges involved in supporting dynamic supply chain practices.
 - Develop an agent that manages a supply chain dealing with the manufacturing of PCs.
 - 6 agents compete against each other for supplies and customers orders.
 - Variable and uncertain customer demand and supply availability.

- Constraint programming has been applied to many aspects in supply chain management such as product scheduling, inventory management, etc.
- But problems are often treated as isolated, well-defined and static, where as in practice, all aspects interact, the problem is dynamic and uncertain, and frequently there are other agents competing for scarce resources.
- TAC SCM is an excellent test-bed for such problems as all decisions are subject to significant uncertainty, caused partly by the game parameters, and partly by the presence of other agents acting in the game.
- In this poster we describe an agent that we have developed for the game, concentrating on the problem of deciding what offers to make to customers.



Customer Offer Constraint Model

Problem:

- Each day the agent receives a set of request for quotes from customers containing, product ID, quantity, reserve price, due date and quantity.
- What requests do we bid on, and at what price, such that profit is maximised?
- This gives a dynamic optimisation problem involving constraints and uncertainty, in 220 stages. Each stage needs a response in approximately 10 seconds. We have implemented a model in OPL for this problem.

Inputs:

- Each day the current days RFQs are input to the model, along with:
 - Bill of materials – $bom_{i,j}$ which is a binary matrix with a row for each product i , column for each component j . The value 1 indicates that a component is used in the product.
 - The number of processing cycles required to build each product i ($cycles_i$).
 - Expected inventory levels of each component j at time t ($inv_{t,j}$).
 - Non-committed factory capacity for each day t in the planning horizon (cap_t).
 - Range of price/probability pairs from which to choose selling price. $price_{i,p}$ = the price of product i that has a probability of acceptance of $prob_p$.
 - Component costs for each component j based on average paid by agent over last 10 days ($cost_j$).

Decision Variable:

- For each request r , choose whether or not to bid, and select a price from the range of input prices p , that are being learnt and updated throughout the game. $bid_{r,p} \in \{0,1\}$

Objective Function:

- Maximise the profit, where the profit of request r is calculated by subtracting from the selling price of product i the cost of components. This is multiplied by the probability that the offer will be accepted by the customer.

$$(1) \quad profit = \sum_{r=1}^m profit_r$$

$$(2) \quad profit_r = bid_{r,p} \times prob_p \times quantity_r \times (price_{r,p} - \sum_{j=1}^m cost_j \times bom_{i,j})$$

Constraints:

- Ensure that we will be able to schedule any new orders we receive with existing orders such that the factory capacity for each day in the current horizon is not exceeded (3,4).
- We know the current amount of components available and by ordering components in advance we also know how much of each component will be arriving at each day. This allows us to add a constraint for availability of supplies (5,6).
- No offer made should exceed the reserve price of the request (7).

$$(3) \quad \sum_{i=1}^n prod_{t,i} \times cycles_i \leq cap_t \quad (4) \quad prod_{t,i} = \sum_{p=1}^x quantity_r \times bid_{r,p} \times prob_p$$

$\forall r \text{ where } product_r = i, due date_r = t$

$$(5) \quad \sum_{k=1}^t comp_{k,j} \leq \sum_{k=1}^t inv_{k,j} \quad (6) \quad comp_{t,j} = \sum_{i=1}^n prod_{t,i} \times bom_{i,j}$$

$$(7) \quad bid_{r,p} \times price_{r,p} \leq reserve_r$$

Online Learning of Offer Prices

- In order to reason about what offers to make to customers our agent maintains prices that correspond to different probabilities of success in winning contracts using an online learning approach.
- By keeping track of the ratio of offers accepted to those made, the prices can be updated iteratively to move closer to the target probability.
- This range of price/probability pairs is then used as input to the constraint model.

Supply Procurement

- Demand and order trends are monitored to determine future expected component needs.
- Components are ordered in advance and in an attempt to maintain a buffer level based on expected customer orders.
- Recent market reports are examined to determine reserve price to use for component requests.

Scheduling Production and Deliveries

- Confirmed sales are produced in order of ascending due date (tie-break on largest profit) until all available production capacity and supplies are used.
- Orders not produced in the current schedule are provisionally scheduled for being produced the day before they are due to be delivered.
- If there is spare capacity and supplies, build, in random blocks of 5, up to 100 of each product for storage in inventory.
- Orders are delivered when ready.

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