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# A PROPOSAL ON AGENT-BASED PRODUCTION PLANNING IN INTEGRATED SUPPLY NETWORK

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**Abstract:** We propose models that focus on the improvement of flexibility in manufacturing supply networks by enabling a tighter information coupling between the various planning levels without tampering with the autonomy of enterprises which are geographically distributed. The problem is approached from the perspective of social network planning using a community of agents. These agents have unique properties which they exhibit at different planning levels. Characterization of agents in the models is discussed.

## 1. INTRODUCTION

The ability of a supply network to respond to changes in the socioeconomic environment in which it operates is greatly determined by the ease with which information is related to all participants in the supply network. Information latency in a supply network is affected by both the topology of the network and the level of autonomy of the various enterprises that make up the network (Fingar and Belini, 2006). In a manufacturing supply network with globally distributed autonomous enterprises operating in unique socioeconomic environments, there is need to coordinate the production planning activities in order to maximize resource utilization. One approach to solving production planning problems is by using the multiagent system paradigm which is amenable to interaction protocols based on social and economic models. The method preserves the autonomy of the supply network participants in an attempt to provide globally satisficing solutions (Schwartz, et. al., 2002).

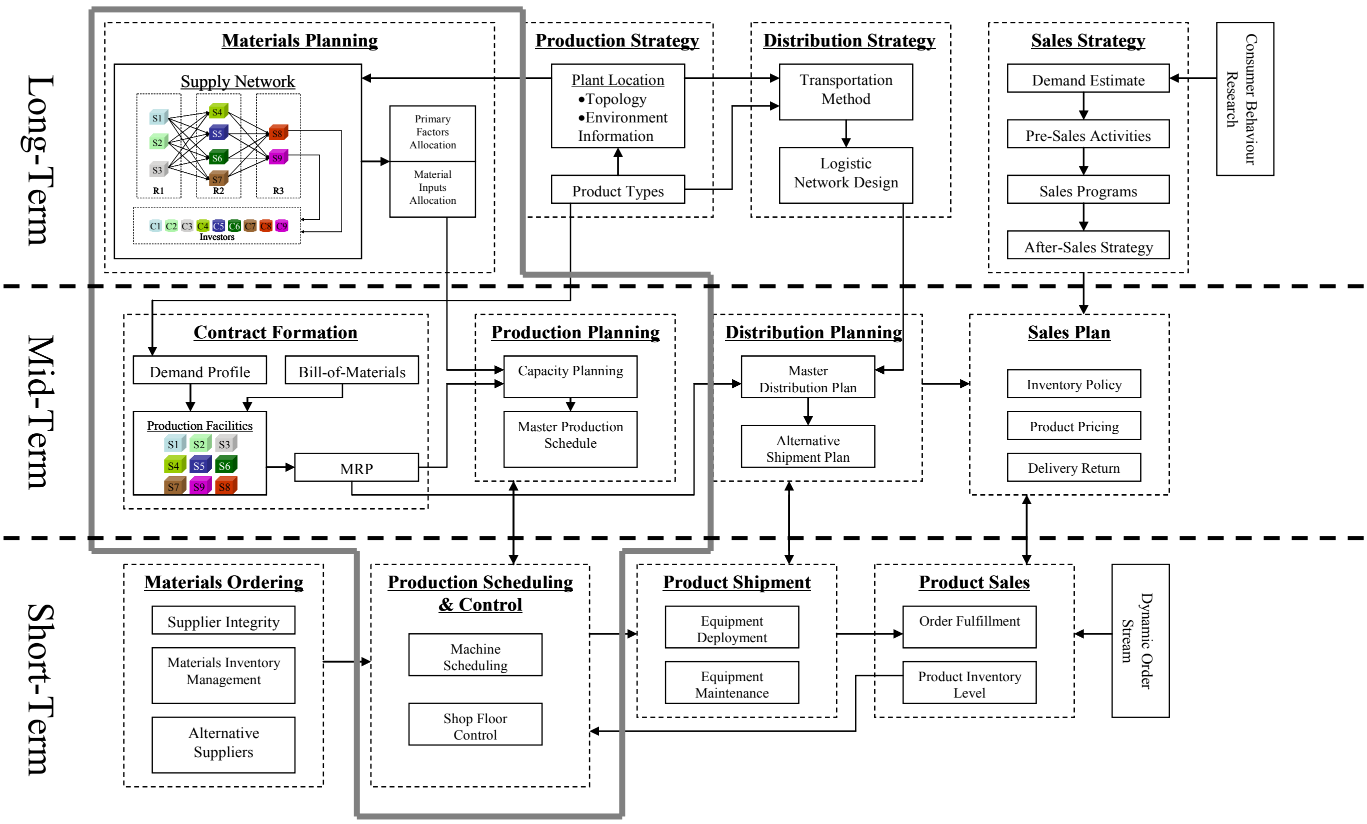


Fig. 1 Supply Network Activity Matrix

### *1.1 Supply Network Planning Activities*

In this work, we make use of the supply network planning activity matrix (Fleischmann and Meyr, 2004) as shown in Fig.1. The work presented in this paper covers the boxed out area of the figure. The various activities in the activity matrix are interdependent but planning such that the whole system will be optimally stable is quite a daunting task, hence the need to break down the planning process into activity groups. This helps planners to focus on an area of the supply network that require the most attention at a given period while monitoring the effects of performance improvement in such an area on the remaining activities in the network. Fig. 2 shows the type of information coupling that takes place during production planning in an integrated supply network.

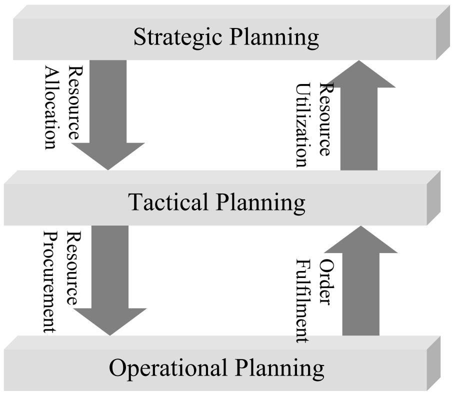


Fig. 2 Supply Network Information Coupling

## 2. STRATEGIC PLANNING AGENT

At the strategic level, aggregated planning is done to reduce complexity of the model by consolidating time, decision variables and data (Rohde and Wagner, 2005). We illustrate this planning process by using an example in (Opadiji and Kaihara, 2007(a)). Consider a manufacturing supply network made of enterprises operating in unique economic environments and represented by Fig. 3.

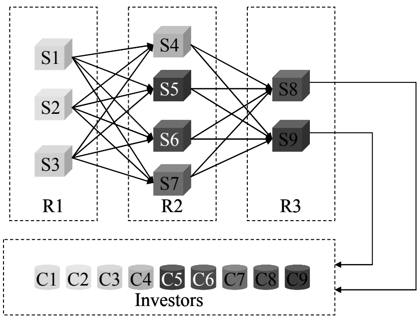


Fig. 3 Supply Network Model at Strategic Level

Let S1 – S9 represent the production enterprises in the supply network and C1 – C9 represent the proposed investment of management on each of these enterprises. The strategic objective is to redistribute production resources so as to maximize profits on the final products. In solving this problem, the agents are represented as trading agents operating in a competitive market environment. One can therefore apply the principles of a Walrasian market (Walras, 1954) in microeconomics to define the agents and formulate an interaction protocol which guarantees a Pareto-optimal solution in resource allocation among the trading agents under the conditions of the perfect competition markets. A model based on market-oriented programming (MOP) (Wellman, 1993) is presented as a suitable protocol for aggregated resource allocation in the supply network.

### *2.1 Agent Definition*

Investors (Consumer Agents):

These agents bid for market resources by solving a utility maximization problem:

$$\max U^c = R_c \prod_{i=1}^{k} g_i^{\alpha_i^c} \text{ for } \sum_{i=1}^{k} \alpha_i^c = 1 \qquad (1)$$

Subject to:

$$\sum_{i=1}^{k} p_i e_i^c \le B^c \qquad (2)$$

and $p_i > 0 \;\; for \;\; all \;\; p \subseteq P$ (3)

$R_c$ = consumption scale of consumer c

$\alpha_i^c$ = preference index of consumer c of good i

$e_i^c$ = endowment of consumer c of good i

$g_i$ = bid of good I by consumer c

An optimal bid formulation derived from a LaGrangean multiplier approach is given by:

$$g_i(p_i) = \frac{\alpha_i^c * B^c}{p_i} \qquad (4)$$

Production Enterprises (Supplier Agents):

Supply agents bid by solving a profit maximization problem:

$$\max \pi^s(P) = p_s g_s - \sum_{\substack{i=1 \\ i \ne s}}^{k} p_i g_i - \sum_{j=1}^{2} p_j h_j \qquad (5)$$

Subject to (technology constraint)

$$g_s(P) = R_s \prod_{\substack{i=1 \\ i \ne s}}^{k} g_i^{\beta_i^s} . \prod_{j=1}^{2} h_j^{\gamma_j} \;\; for \;\; \sum_{i=1}^{k} \beta_i^s + \gamma_1 + \gamma_2 = 1 \qquad (6)$$

The bidding function for the producer agent is:

$$g_i(p_i) = \left( \frac{p_i}{R_s \beta_i^s p_s} \right)^{\frac{1}{\beta_i^s - 1}} \qquad (7)$$

$\beta_i^s$ = technology index of good I for agent s

$\gamma_j$ = technology index of primary factor j (capital and labour)

$h$ = primary production factor j: {*K, L*}

### *2.2 Computing Optimal Resource Allocation*

The point of optimal resource allocation is defined by the price equilibrium point of the market where

$$\sum_{i=1}^{m} d_i^g = \sum_{i=1}^{m} s_i^g \;\; for \;\; all \;\; g \subset G \qquad (8)$$

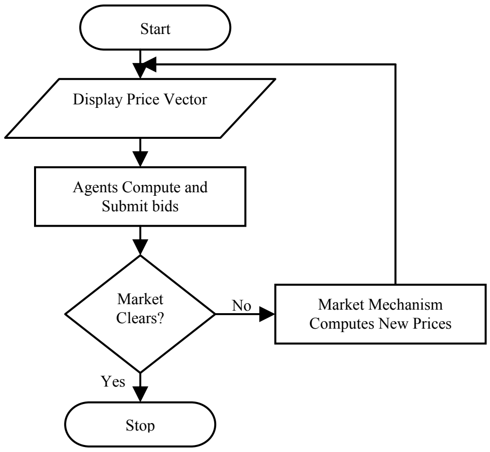


Fig. 4 Trading Protocol in MOP

Fig. 4 shows the process that leads to arrival at market equilibrium. The Agent parameters can be represented in a matrix for. For example, the supply network shown in Fig. 3 will have agent parameter matrices of the form shown in Fig. 5(a – d). Rows are agents (superscript) and columns are market commodities (subscript).

$$\begin{bmatrix} 0&0&0&0&0&0&0&0&0&\gamma_1^{11}&\gamma_2^{11}\\ 0&0&0&0&0&0&0&0&0&\gamma_1^{12}&\gamma_2^{12}\\ 0&0&0&0&0&0&0&0&0&\gamma_1^{13}&\gamma_2^{13} \end{bmatrix} \qquad \begin{bmatrix} 0&0&0&0&0&0&0&0&0&1&1\\ 0&0&0&0&0&0&0&0&0&1&1\\ 0&0&0&0&0&0&0&0&0&1&1 \end{bmatrix}$$

$$\begin{bmatrix} \beta_1^{21}&\beta_2^{21}&\beta_3^{23}&0&0&0&0&0&0&\gamma_1^{21}&\gamma_2^{21}\\ \beta_1^{22}&\beta_2^{22}&\beta_3^{23}&0&0&0&0&0&0&\gamma_1^{22}&\gamma_2^{22}\\ \beta_1^{23}&\alpha_2^{23}&\beta_3^{3}&0&0&0&0&0&0&\gamma_1^{23}&\gamma_2^{23}\\ \beta_1^{24}&\beta_2^{24}&\beta_3^{24}&0&0&0&0&0&0&\gamma_1^{24}&\gamma_2^{24} \end{bmatrix} \qquad \begin{bmatrix} R_1^{21}&R_2^{21}&R_1^{23}&0&0&0&0&0&0&1&1\\ R_1^{22}&R_2^{22}&R_2^{23}&0&0&0&0&0&0&1&1\\ R_1^{23}&R_2^{23}&R_3^{23}&0&0&0&0&0&0&1&1\\ R_1^{24}&R_2^{24}&R_4^{23}&0&0&0&0&0&0&1&1 \end{bmatrix}$$

$$\begin{bmatrix} 0&0&0&\beta_4^{31}&\beta_5^{31}&\beta_6^{31}&\beta_7^{31}&0&0&\gamma_1^{31}&\gamma_2^{31}\\ 0&0&0&\beta_4^{32}&\beta_5^{32}&\beta_6^{32}&\beta_7^{32}&0&0&\gamma_1^{32}&\gamma_2^{32} \end{bmatrix} \qquad \begin{bmatrix} 0&0&0&R_4^{31}&R_5^{31}&R_6^{31}&R_7^{31}&0&0&1&1\\ 0&0&0&R_4^{32}&R_5^{32}&R_6^{32}&R_7^{32}&0&0&1&1 \end{bmatrix}$$

$(a) \qquad\qquad (b)$

Fig. 4. (a)Technology indices (b) Utilization scale for Production Enterprises in regions R1, R2 and R3

$$\begin{bmatrix} 0&0&0&0&0&0&0&\alpha_8^{11}&\alpha_9^{11}&0&0\\ 0&0&0&0&0&0&0&\alpha_8^{12}&\alpha_9^{12}&0&0\\ 0&0&0&0&0&0&0&\alpha_8^{13}&\alpha_9^{13}&0&0 \end{bmatrix} \qquad \begin{bmatrix} 0&0&0&0&0&0&0&0&0&e_1^{11}&e_2^{11}\\ 0&0&0&0&0&0&0&0&0&e_1^{12}&e_2^{12}\\ 0&0&0&0&0&0&0&0&0&e_1^{13}&e_2^{13} \end{bmatrix}$$

$$\begin{bmatrix} 0&0&0&0&0&0&0&\alpha_8^{21}&\alpha_9^{21}&0&0\\ 0&0&0&0&0&0&0&\alpha_8^{22}&\alpha_9^{22}&0&0\\ 0&0&0&0&0&0&0&\alpha_8^{23}&\alpha_9^{23}&0&0\\ 0&0&0&0&0&0&0&\alpha_8^{24}&\alpha_9^{24}&0&0 \end{bmatrix} \qquad \begin{bmatrix} 0&0&0&0&0&0&0&0&0&e_1^{21}&e_2^{21}\\ 0&0&0&0&0&0&0&0&0&e_1^{22}&e_2^{22}\\ 0&0&0&0&0&0&0&0&0&e_1^{23}&e_2^{23}\\ 0&0&0&0&0&0&0&0&0&e_1^{24}&e_9^{24} \end{bmatrix}$$

$$\begin{bmatrix} 0&0&0&0&0&0&0&\alpha_8^{31}&\alpha_9^{31}&0&0\\ 0&0&0&0&0&0&0&\alpha_8^{32}&\alpha_9^{32}&0&0 \end{bmatrix} \qquad \begin{bmatrix} 0&0&0&0&0&0&0&0&0&e_1^{31}&e_2^{31}\\ 0&0&0&0&0&0&0&0&0&e_1^{32}&e_2^{32} \end{bmatrix}$$

$(c) \qquad\qquad (d)$

Fig.5. (c) Utility Matrices (d) Endowment Matrices for Investors in R1, R2 and R3

The results of the simulation will be a Pareto-optimal allocation of resources to the various enterprises. The resource allocated to each of the production enterprises at the strategic level will provide primal instruction in the form of a budget constraint when planning at the tactical level. This resource allocation table is shown in matrix from in Fig. 6.

$$\begin{bmatrix} g_{11} & g_{12} & \cdots & \cdots & g_{19} & K_1 & L_1\\ g_{21} & g_{22} & \cdots & \cdots & g_{29} & K_2 & L_2\\ \vdots & \vdots & \ddots & & \vdots & \vdots & \vdots\\ \vdots & \vdots & & \ddots & \vdots & \vdots & \vdots\\ g_{91} & g_{m2} & \cdots & \cdots & g_{99} & K_9 & L_9 \end{bmatrix}$$

Fig. 6. Production Resource Allocation Matrix

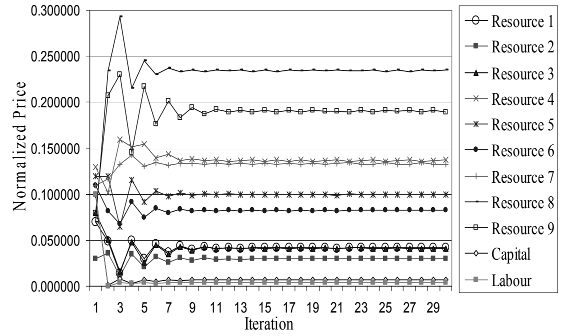


Fig. 7. Price Bids during Search for Equilibrium

Fig. 7 shows results of simulation using hypothetical data for the agent parameters. Variations in the prices of market resources affect the distribution of market resources hence the arrival at a Pareto-optimal allocation of resources at the point when the market prices stabilize in the graph shown. Fig. 8 depicts a Pareto-optimal allocation capital and labour.

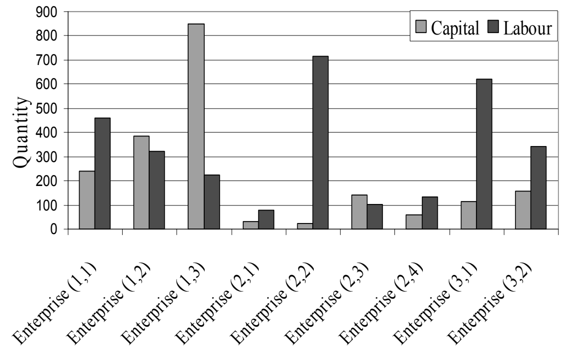


Fig. 8. Pareto-optimal Allocation of Capital and Labour

## 3. TACTICAL PLANNING AGENT

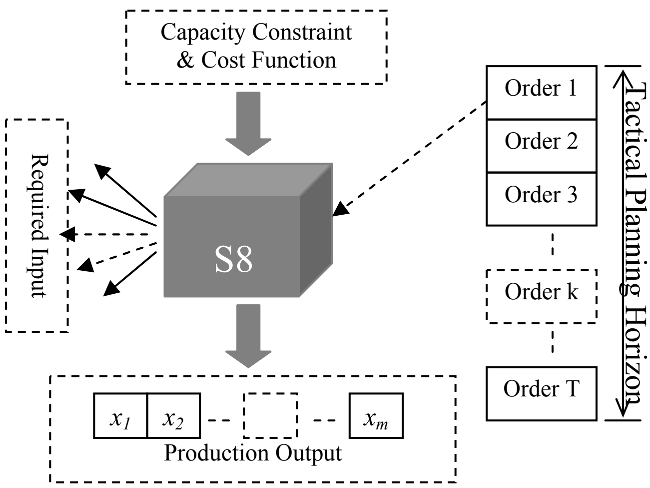


Fig. 9. Enterprise Agent Generating Tactical Plan

At the tactical level, decision variables for production plans become more concrete as some of the aggregated variables are unbundled and each enterprise agent must now generate its own tactical plan. The results obtained at the strategic level provide information in the form of tactical level constraints. We study the supplier selection problem for enterprises in a supply network given that each of the enterprises have procurement budgets for all their inputs. Consider a supply network depicted in Fig. 10.

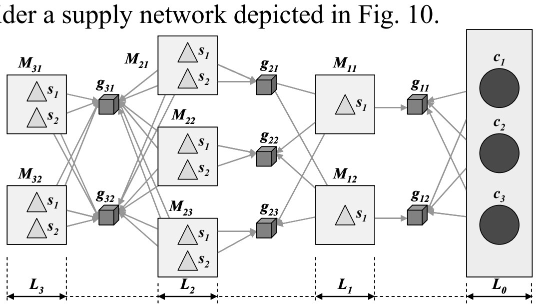


Fig. 10. Sample Supply Network at Tactical Level

The objective at this level is to obtain an allocation of input production resources for all the enterprise agents such that each of them will maximize their profits and the consumer agents will obtain the maximum value possible given their endowment of monetary resource. We define the agents in terms of their bidding tactics as follows:

### *3.1 Bidding Tactics of Agents*

Consumer Agents:

$$p_c(g) = p'(g) + \alpha_c \quad if \quad p(g) < p'(g) \tag{9}$$

*for*

$$g = \arg\max_{g \in G}(e_c^g - p_c(g)) \;\; s.t. \;\; (e_c^g - p_c(g)) \geq 0 \tag{10}$$

$p_c(g)$ = new bid price of consumer $c$ for resource $g$
$p'(g)$ = current market price for resource $g$
$g$ = bid quantity of resource $g$
$\alpha_c$ = bid adgustment constant for consumer $c$
$e_c^g$ = valuation of consumer $c$ for market resource $g$

Equation (9) is the price bidding tactic for the consumer agent. A consumer agent adjusts its bid price by a predetermined value $\alpha_c$ if its last bid price is not enough to make it win all the quantity of that input. It therefore bids above the current market price for that input. Equation (10) represents the quantity of an input a consumer agent will bid for at its current bid value. It bids such that it can get as much units as possible at the current bid price subject to its total valuation for that input.

Enterprise Agents

$$p^{i+1}(g_w) = \begin{cases} \max((p^i(g_w) + \beta_w), (\sum_{k=1}^{m_{l-1}} p_w^{i+1}(g_k^w) + c_w^k)); \text{ if } p_w^i(g_k^w) < p'(g_k) \\ p'(g_w) \quad \text{otherwise} \end{cases} \tag{11}$$

$$p_w^{i+1}(g_k^w) = \max(p'(g_k), p_w^i(g_k^w) + \alpha_w) \tag{12}$$

*for*

$$g_w = \operatorname*{argmax}_{g_w \in G_L \subset G}(\sum_{j=1}^{m_{l+1}} p_j(g_w^j)) \tag{13}$$

$$g_k^w = \operatorname*{argmax}_{g_k \in G_{L-1} \subset G}((p_w(g_k^w) + c_w^k)) \quad \forall \; k = 1,2..m_{l-1} \tag{14}$$

*s.t.*

$$(\sum_{k=1}^{m_{l-1}} p_w(g_k) + c_o^k) \leq p'(g_w) \tag{15}$$

$$g_k^w \leq \max(g_k^w(TPH)) \tag{16}$$

$$g_w \leq \max(g_w(TPH)) \tag{17}$$

$p^{i+1}(g_w)$ = new bid price for output resource $g_w$ of enterprise agent $w$
$\beta_w$ = sales bid price adjustment constant of enterprise agent $w$
$c_w^k$ = overhead cost of procuring resource $g_k$ for enterprise agent $w$
$p_w^{i+1}(g_k^w)$ = new bid price of enterprise agent $w$ for input resource $k$
$\alpha_w$ = input bid adgustment constant for enterprise agent $w$
$g_k^w$ = bid quantity of enterprise agent $w$ for market resource $g_k$
max( $g_k^w(TPH)$ ) = procuremen t estimate for market $g_k$ over TPH
$g_w$ = bid quantity of enterprise agent $w$ for output resource $g_k$
$m_{l-1}$ = total number of markets in input layer
$TPH$ = Tactical planning time span

Equation (11) is the price bidding function of the enterprise agent for its product (selling price). It updates this price whenever there is a change in the price of any of its inputs. The price bid for inputs is done in much the same way as in the case of a consumer agent as shown in equation (12). Equation (13) is the output quantity bid function. Equation (14) is the quantity bid function for inputs and is determined by the number of units the enterprise agent is willing to sell at that point in time. The equation shows how an enterprise agent selects the suppliers of an input by considering the allocation that will minimize its average overhead cost, i.e. the most input at the cheapest cost. The constraint of equation (15) is the non-negative profit constraint. Equation (16) is the input budget constraint imposed by the strategic plan and equation (17) is the output capacity constraint also imposed by the strategic plan of the enterprise.

### *3.2 Auction-Based Supplier Selection Algorithm*

The supplier selection algorithm used is based on the (m+1)st ascending bid auction (Walsh and Wellman, 2003). The trading mechanism is listed below:

- Step 1: Initialize all trading agents and virtual markets
- Step 2: Consumer agents send bids at current market price (Adjust bid if not winning)
- Step 3: Enterprise Agents inspect number of winning sales bid
- Step 4: Enterprise Agents check if there is enough inputs to meet winning sales bid (if not, adjust procurement bid upward and increment price for sales bid
- Step 5: Auctions compute new market price for all resources and posts bid results privately
- Step 6: If no bid revision for all agents auction clears else go to step 2
- Step 7: Terminate Auction

Sample results from simulation of the supply network in Fig. 9 are presented. First, the quantity bids, then the price bids of one of the enterprise layers and lastly, the selection of suppliers and allocated quantities.

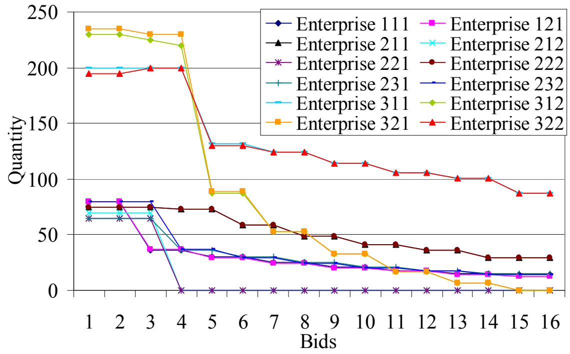


Fig. 11: Supply Quantity Bids for Enterprise Agents

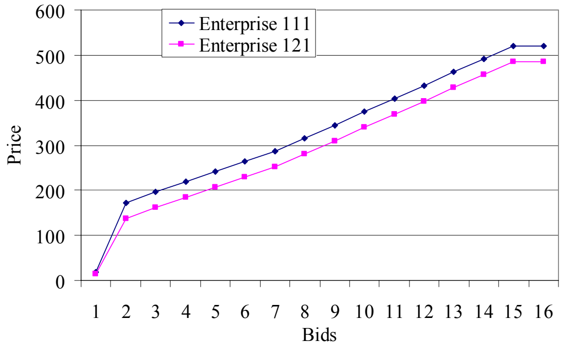


Fig. 12: Price Bids for Enterprise Agents in Layer L1

The inverse relationship between the prices of supply network resources and quantities distributed can be seen in Figs. 11 and 12.

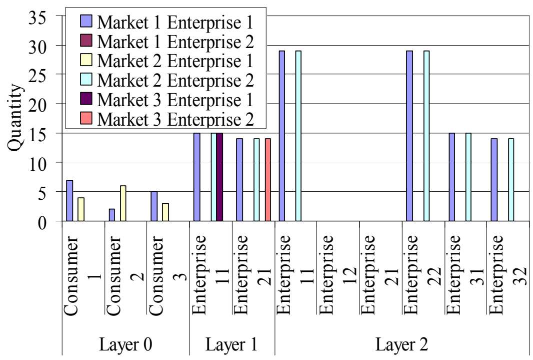


Fig. 13: Demand Allocation in the Supply Network

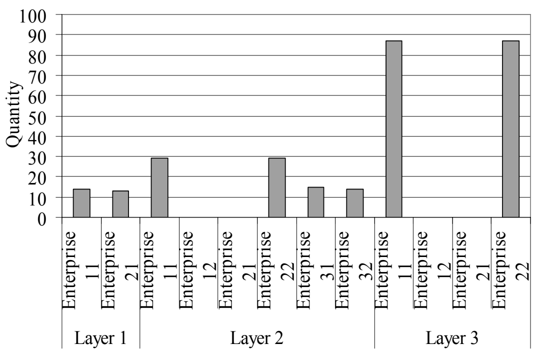


Fig. 14: Supply Allocation in the Supply Network

The results above show how the trading mechanism selects feasible enterprise agents in the supply network. Feasibility presupposes a situation in which a non-producing enterprise is not allocated any inputs in the market. Hence, in a given market, only feasible enterprise agents are selected. Privacy of bidding parameters ensures the autonomy of agents.

## 4. OPERATIONAL PLANNING AGENT

Planning at the operational level is strictly at the enterprise level with each enterprise having to program its production activities so as to meet the production objective planned for at the tactical level. The tactical level time horizon is divided into fine operational time-buckets for production shop floor scheduling and control. This research focuses on dynamic production scheduling so as to meet production objective subject to capacity constraints. To do this, the following scenario has to be defined for any particular production enterprise:

- Target production system, e.g., flow shop, job shop, open shop, etc.
- Scheduling objective and constraints – time-based or cost-based objectives, etc.
- Dynamic nature of production environment, e.g., capacity extension, scheduled maintenance, breakdowns, changing demand profile etc.

For any given enterprise, the dynamic production scheduling problem can also be addressed using the multiagent system paradigm. In essence, an enterprise subdivided into a community of agents which have the duty of interacting of improving the performance of the enterprise in a dynamic production environment. For the purpose of illustration of how this can be done, we assume a flexible job shop production system as in (Opadiji and Kaihara, 2007(b)) where the system is modelled as a federated community of agents as shown in Fig. 15.

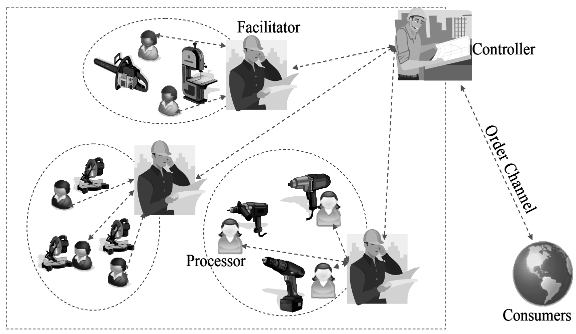


Fig. 15. Federated Agent Architecture

The enterprise is made of controller, facilitator and processor agents which interact to solve the production scheduling problem in a dynamic order environment defined as

$$\min\left(\sum_{i}^{N} \max C_i\right) \tag{17}$$

Subject to

$$\pi_i = P_i - C_i \geq 0; (for\ i = 1, \ldots, N) \tag{18}$$

$C_i$ is the processing cost of order $i$, $\pi_i$ is expected profit from order $i$ and $P_i$ is expected payment from fulfilling $i$.

This problem is modelled such that only profitable orders are scheduled and the production agents are supposed to schedule to fulfill as many orders as possible. In proposing a solution methodology for this problem, the production floor reinforcement learning mechanism is proposed to enable adaption of the production system to the changing order environment. The goal is to fulfil as many profitable orders as possible within the available system capacity. Fig. 16 shows an example of simulation results obtained as dynamic orders are processed in an enterprise with a flexible job shop production system. Some of the orders were not processed because they did not meet the non-negative profit constraint.

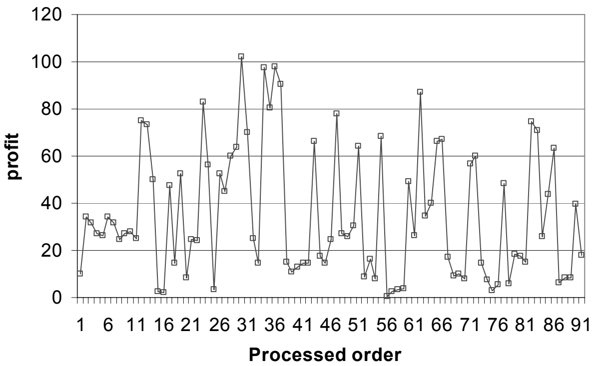


Fig. 16. Profit Variation with Dynamically Processed Orders in a Flexible Job Shop Production System

The result of this planning process will be the total number of fulfilled orders and the profit accrued to the enterprise within the planning period. This result is sent as a feedback to the tactical level for the next tactical planning horizon.

## 5. CONCLUSION

The agent-based production planning model proposed is a multi-level approach to production planning. In the short-run, the agent-based adaptive scheduling allows for greater flexibility in a production system in response to continuously changing product order and shop floor environments. The mid-term (tactical) planning methodology proposed is aimed at improved decision making for supplier selection in response to the different demand estimates over the tactical planning time span. This is carried out by taking into account operational performance of enterprise production system in the preceding planning phases. Also, the modelling of enterprises as agents allows for the incorporation of learning mechanism that aids decision making in the long run. The long-term planning model based on competitive market mechanism makes it possible to factor in the effects of macroeconomic variables in the different economic environments in which the enterprises are located.

From the work done so far on the proposed model, we have found the competitive market representation of a supply network to be a simple yet robust way of addressing the aggregate planning problem at the strategic level of supply network planning. The MOP algorithm adopted has also been found to be more efficient than some of the existing algorithms implemented for obtaining equilibrium points in competitive markets (Kaihara and Fujii, 2004). The tactical level work is based on the (m+1)st auction protocol which allows multiple units of a product to be traded in a market. While this approach does not guarantee arrival at the optimal solution, the existence of an equilibrium point means that we can generate a solution which can be improved upon depending on the values of the bidding parameters of trading agents. We have also done some work on the operational level model involving adaptive production scheduling using federated agent architecture. The next phase of the work involves provision of inter-level communication infrastructure which will allow for simulation of supply networks where agents integrate plans generated at different planning levels. Also, as a point of focus for future research activities, a robust learning scheme is needed to aid the supply network in responding better to dynamic environment.

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