# Agent-based Fuzzy Constraint-directed Negotiation Mechanism for Planning and Scheduling in Supply Chain

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***Abstract***— *This paper presents an agent-based fuzzy constraint-directed negotiation mechanism for planning and scheduling in supply chain. The supply chain scheduling problem is modeled as a set of fuzzy constraint satisfaction problems (FCSPs), interlinked together by inter-agent constraints. For converging each distinct firm's interests, the conflicts among the set of FCSPs are resolved through negotiation by iteratively exchanging offers/counters with limited sharing of their perspectives and preferences. During the negotiation, proposing offers/counter-offers takes not only firm's self-interest and preferences but also opponents' perspectives into consideration. By sharing perspectives between agents to gradually uncovering the intent of opponents, consensus can be obtained and the quality of consensus can be guaranteed at satisfactory level. Experimental results suggest that the proposed approach obtains a superior solution for supply chain scheduling than other negotiation models in a fully distributed processing.*

***Keywords***— Supply Chain Planning and Scheduling, Fuzzy Constraint-directed Negotiation, Fuzzy Constraint Satisfaction Problem, Multi-Agent System.

## 1 Introduction

Facing with global economic downturn and intense competition, firms have to rapidly respond to the variations in market situation. Business entities (suppliers, manufacturers, distributors, retailers and customers) are urged to integrate their operations into multi-layer supply chain for product/service provision [1]. However, supply chain usually handles multiple projects concurrently with shared components, facilities, and capacities governed by distinct firms. Collaborating with supply chain partners in planning and scheduling in a cost effective manner is the key to survive in today's fierce market competition.

Since the supply chain environment in nature is distributed, autonomous, and heterogeneous, agent-based approaches which are characterized by decentralization of computation and information processing are particularly attractive for supply chain modeling and problem solving [2, 3]. To ensure the global performance with limited interaction among agents, a mediator or a third party agent is used in some systems for coordination. Negotiation processes can be facilitated by a mediator which helps the parties understand their needs, suggests possible agreements and/or supports them in the implementation of the agreement. But, agents may have to share sensitive strategic information that should not be revealed to competitors or even to a third party agent, to the mediator for coordination.

So, instead of coordinating with a third party agent, coordination/negotiation in a fully distributed environment for privacy concern has been addressed in some agent-based approaches. Those papers address the dynamic nature of supply chain and emphasize the flexibility and responsiveness. Two popular and fully distributed negotiation models, contract net protocol (CNP) and market-based protocol, have been proposed for these purposes [4]. The CNP can rapidly produce a feasible solution to overcome the frequently changes in supply chain. With simplified negotiation protocol, however, agents with very limited interaction and information sharing can only make their decisions independently and optimize their local objectives in a myopic way. Accordingly, more sophisticated negotiation mechanism is needed and thus bringing us to a market-based approach. Market-based approaches employ a bargaining or auction process characterized by iterative bidding among agents. During the bidding process, agents will adjust bids according to the direction of surplus and deficit of demand. The bids which imply the degree of competition can be used to resolve the conflicts caused by contention and improve the system performance. But the bid indicates only the demand that is in high or low contention, not where the contention can be resolved. Thus, the process might oscillate and not achieve the convergence. It also affects the quality of solution.

Accordingly, facilitating the convergence and guaranteeing the system performance in supply chain are the critical challenges and they are highly influenced by the level of information sharing [5, 6, 7, 8] as well. To cope with these problems, this paper proposes an agent-based fuzzy constraint-directed negotiation mechanism (AFCN) in a fully distributed environment.

In AFCN, a supply chain problem is modeled as a set of fuzzy constraint satisfaction problems (FCSPs), interlinked together by inter-agent constraints. Each FCSP represents the firm's perspectives and issues in supply chain. Constraints which are characterized by non directional, declarative, and intuitive properties are closely related to the real-world problem descriptions. Besides, the subjective, imprecision and qualitative knowledge (e.g., human cognition, preferences, or even opponent's perspectives) which are frequently used for business decision making in supply chain can easily be coped

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by fuzzy constraints with the levels of consistency. Fuzzy constraints also can be used to rank the solutions by specifying the possibilities prescribing to what extent the solutions are suitable. Additionally, it even provides a measure of similarity between solutions and opponents' counteroffers and a basis for the selection of multi-objective decision from a set of feasible alternatives. Thus, AFCN can be a practical and effective methodology for the supply chain problem modeling.

To coordinate supply chain parties, the conflicts among set of FCSPs are resolved through AFCN negotiation protocol by iteratively exchanging offers/counters with limited sharing of their perspectives. For converging each distinct firm's interests in supply chain, proposing an offer/counteroffer takes not only firm's self-interest and preferences but also opponents' perspectives into consideration. In a proposed offer/counteroffer, it indicates not only the region of acceptable solutions and preference degrees but the possibility of conflicts in the region. For each FCSP, incremental propagation eliminates the redundant decision values and infeasible combination of solutions. According to the ranking of solutions by fuzzy constraints, the set of feasible solutions can be further restricted in a preferred region with an acceptable/controlled threshold. It supports agent to quick response the changes in the environment and promises the proposed offers/counteroffers to be focused within the interest/attention area.

By sharing limited information among agents to incrementally uncovering the intention of opponents, consensus can be obtained and the quality of solution can be guaranteed at a satisfaction level as well. Moreover, the framework of AFCN also provides flexibility to incorporate negotiation strategies, such as self-interested, cooperative, and win-win, for various global performance measures.

The remainder of this paper is organized as follows. Section 2 introduces the theoretical basis for modeling supply chain planning and scheduling problem as a distributed fuzzy constraint satisfaction problem (DFCSP). Section 3 then presents an agent-based fuzzy constraint-directed negotiation mechanism in detail. Then, Section 4 provides the experimental results to show the effectiveness of the proposed approach followed by conclusions in Section 5.

## 2 Modeling Supply Chain Planning and Scheduling as DFCSP

During the process of production/service provision from acquiring material to deliver to the end customers, it passes through the stages of raw material supply, intermediate supply, manufacturing, distribution, and retail. This paper focuses on the stage of manufacturing in supply chain. The supply chain project scheduling problem, as shown in Figure 1, is to schedule multiple projects in a network of manufacturers and suppliers (or contractors). Each project involves a set of tasks or operations with complex precedence relationships in which the task can be performed by a set of alternative suppliers. Suppliers differ from each other in terms of resource capacity, processing times, and costs of performing tasks. The process of project planning and scheduling specifies how the suppliers are selected from alternatives and tasks are scheduled. The problem is multi–objective in nature. For example, manufacturers wish to optimize the scheduling performance as well as to minimize the operation cost. On the other hand, the suppliers are more inclined to maximize the utilization and profit.

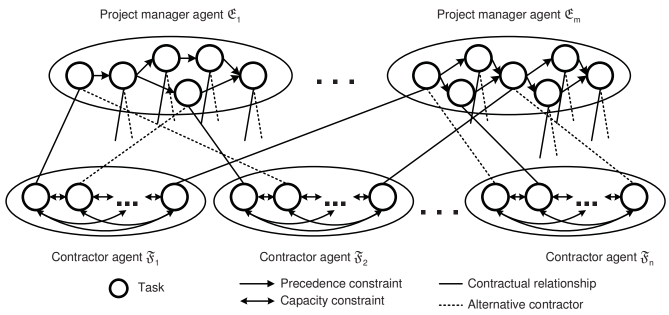


Figure 1: Supply chain project scheduling with m project agents and n contractor agents.

The problem can be represented as a triple $(\mathfrak{E}, \mathfrak{F}, \mathfrak{I})$, where $\mathfrak{E}$ is a set of $m$ project manager agents (PAs) for the manufacturers, $\mathfrak{F}$ is a set of $n$ contractor agents (CAs) for the suppliers, and $\mathfrak{I}$ is a set of inter-agent constraints between two class of agents. Each PA consists of a chain of tasks which are specified further by precedence constraints, including the processing time on the set of alterative suppliers for each task, due date, arrival (release) date, and tardiness cost. Each CA consists of capacity constraints and processing cost. Thus, the problem can be modeled as a distributed constraint satisfaction problem (DFCSP) in that coming up to a mutually acceptable solution between two classes of agents is the same as uncovering a consistent solution satisfying all the constraints in a distributed fuzzy constraint network specifying the fuzzy relationships inside each agent and between agents. Adapted from [9], a distributed fuzzy constraint network (DFCN) can be defined as below.

**Definition 1**
*A distributed fuzzy constraint network* $(\mathcal{U}, \mathbf{X}, \mathbf{C})$ *for a supply chain project scheduling problem* $(\mathfrak{E}, \mathfrak{F}, \mathfrak{I})$ *can be defined as a set of* $m+n$ *fuzzy constraint networks* $\{\mathfrak{N}_1, \ldots, \mathfrak{N}_{m+n}\}$, $\mathfrak{N}_l$ *representing an agent* $l \in \{\mathfrak{E}, \mathfrak{F}\}$, *where*

- $\mathcal{U}_l$ *is a universe of discourse for an FCN* $\mathfrak{N}_l$;
- $\mathbf{X}_l$ *is a tuple of non-recurring objects of agent* $l$;
- $\mathbf{C}_l$ *is a set of fuzzy constraints which involves a set of internal fuzzy constraints existing among objects in* $\mathbf{X}_l$, *and a set of external fuzzy constraints* $\mathfrak{I}_l$ *between agent* $l$ *and opponent agents;*
- $\mathfrak{N}_l$ *is connected to other FCNs by a set of external fuzzy constraints* $\mathfrak{I}_l$;
- $\mathcal{U}$ *is a universe of discourse;*
- $\mathbf{X} = \left(\cup_{l=1}^{m+n} \mathbf{X}_l\right)$ *is a tuple of all non-recurring objects;*
- $\mathbf{C} = \left(\cup_{l=1}^{m+n} \mathbf{C}_l\right)$ *is a set of all fuzzy constraints.*

In Definition 1, a set of $\mathbf{X}_l$ of agent $l$ is corresponded to its beliefs, its knowledge of the environment (tasks, resources, etc.), and any other attitudes (desires, intentions, opponents' response, etc.). A set of fuzzy constraints $\mathbf{C}_i$ for project agent $\mathfrak{E}_i$ is corresponding to a set of restrictions (e.g. precedence

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constraints), objectives (e.g. flowtime, operating cost) and inter-agent constraints between project agent $\mathfrak{E}_i$ and related contractor agents; $\mathbf{C}_k$ for contractor agent $\mathfrak{F}_k$ is corresponding to a set of restrictions (e.g. capacity constraints), objectives (e.g. utilization) and inter-agent constraints between contractor agent $\mathfrak{F}_k$ and related project agents.

By Definition 1, a consistent solution of a DFCSP for scheduling is an instantiation of all time allocation of the tasks such that all the constraints of the agents are satisfied at a degree of membership function. No agent knows about other agents' feasible solutions and possible agreements a priori. An agent negotiation mechanism is to explore potential agreements and then to move the negotiation toward a globally beneficial solution.

## 3 Agent-based fuzzy constraint-directed negotiation mechanism

Fuzzy constraint-directed approach has been demonstrated in [10, 11, 12, 9, 13] as an effective framework for agent negotiation. During the negotiation, each agent plans the solution by solving its own FCSP, and exchanges the proposals among the agents for resolving the inconsistency of time allocation of activities. As a proposal cannot be accepted by its opponents, a counter-proposal will be made according to the negotiation strategies which consider alternative solutions at the same constraint satisfaction level or offer a solution with a lower constraint satisfaction level. Exchanging proposals and counter-proposals will continue until termination conditions (e.g., achieving a consensus or a failure) are met.

In the proposed negotiation mechanism, the process of proposing a offer/counter-offer in an agent is regarded as the inference process for solving its own FCSP. The process includes the following steps: opponent responsive state evaluation, internal state update, behavioral state determination, set of feasible solutions generation, prospective solution selection and offer/counter-offer generation. The process of proposing an offer $\mathbf{A}^*_{i,j}$ with the FCN $\mathfrak{N}_{i,j} = (\mathcal{U}_{i,j}, \mathbf{X}_{i,j}, \mathbf{C}_{i,j})$ for the task $j$ in project manager agent $\mathfrak{E}_i$ in a negotiation round is described as follows.

While receiving the counter-offer $\mathbf{B}_{i,j}$ over negotiation issues $\mathbf{I}_{i,j} \in \mathbf{X}_{i,j}$ from opponent agents, the opponent responsive state $\sigma_{i,j}$, which indicates the difference between current self-interest and opponents' perspectives, is obtained by

$$\sigma_{i,j} = 1 - ((\widehat{D}_{i,j} - D_{i,j})/(\widehat{D}_{i,j})), \tag{1}$$

where $D_{i,j}$ is the distance between the offer $\mathbf{A}'_{i,j}$ generated in last round and the latest counter-offer $\mathbf{B}_{i,j}$ and $\widehat{D}_{i,j}$ is the basis of distance for normalizing which is obtained at the first negotiation round.

The distance $D$ between an offer $\mathbf{A}$ and a counter-offer $\mathbf{B}$ over set of issues $\mathbf{I}$ is obtained from

$$D = \frac{1}{N_I}\sqrt{\sum\nolimits_{k=1}^{N_I} \mathcal{L}(A^k, B^k)^2}, \tag{2}$$

where $\mathcal{L}$ is a distance measure for two fuzzy set, $A^k$ and $B^k$ is the fuzzy set for the offer $\mathbf{A}$ and counter-offer over issue $I^k \in \mathbf{I}$, respectively.

As none of the counter-offers can be accepted by the project manager agent $\mathfrak{E}_i$, agent $\mathfrak{E}_i$ has to decide the behavioral state to proposal alternative solutions in the current preferred region or offer a solution with a lower constraint satisfaction level. The internal states of agent and the opponent responsive state are involving to determine the behavioral state. In this manner, the internal states include the satisfaction level $\rho_{i,j}$ for task $j$ and degree of tightness in solution space $\delta_{i,j}$. The aggregated satisfaction value $\rho_{i,j}$ for task $j$ indicates the satisfaction level for the current prospective solution $\mathbf{S}'_{i,j}$ and is obtained by

$$\rho_{i,j} = \Psi(\mathbf{S}'_{i,j}) = \frac{1}{N_G}\sum\nolimits_{k=1}^{N_G} \mu_{\mathbf{C}_k}(\mathbf{S}^k_{i,j}), \tag{3}$$

where $\mathbf{S}'_{i,j}$ is the prospective solution of task $j$ obtained in last negotiation round, $\Psi(\mathbf{S}'_{i,j})$ denotes the aggregated satisfaction value for the prospective solution, $\mu_{\mathbf{C}_k}(\mathbf{S}^k_{i,j})$ is the satisfaction degree of the fuzzy constraint $\mu_{\mathbf{C}_k}$ over goal $\mathbf{G}$.

The tightness of solution space $\delta_{i,j}$ indicates the remaining feasible solution space between the aggregated satisfaction value $\rho_{i,j}$ and the acceptable threshold $\epsilon'_{i,j}$ and is obtained by

$$\delta_{i,j} = 1 - (\rho'_{i,j} - \epsilon'_{i,j}), \tag{4}$$

where $\rho'_{i,j}$ is the aggregated satisfaction value, and $\epsilon'_{i,j}$ is the threshold of aggregated satisfaction determined in last negotiation round.

According to the internal state and the opponent responsive state, the level cut $\tau$ for the desire of concession $\mathbf{V}$ obtained by

$$\tau = (\mu_\rho(\rho'_{i,j}) \wedge \mu_\delta(\delta'_{i,j}) \wedge \mu_\sigma(\sigma_{i,j}))^{W_c}, \tag{5}$$

where $\mu_\rho(\rho'_{i,j})$, $\mu_\delta(\delta'_{i,j})$, and $\mu_\sigma(\sigma_{i,j})$ denote the desire of concession according to the degree of tightness, aggregated satisfaction and degree of difference, respectively; $W_c$ denotes the weight associated with the desire of concession.

Then, the behavioral state regarded as the threshold of aggregated satisfaction $\epsilon_{i,j}$ is obtained from

$$\epsilon_{i,j} = \epsilon'_{i,j} - \Delta\epsilon = \epsilon'_{i,j} - \mathcal{D}(\mathbf{V}_\tau), \tag{6}$$

where $\epsilon'_{i,j}$ is the threshold of aggregated satisfaction obtained from last negotiation round, and $\Delta\epsilon$ is the concession value transformed from the fuzzy set of the desire of concession $\mathbf{V}$ with $\tau$ level cut. $\mathcal{D}$ is the defuzzification method.

To evaluate and generate the offer and counter-offer, an agent has to plan its prospective solution first. Each agent can only plan the prospective solution from its individual area of interests limited by the threshold of aggregated satisfaction $\epsilon_{i,j}$. That is, a set of feasible solution $\mathfrak{P}_{i,j}$ for task $j$ in agent $\mathfrak{E}_i$ can be defined as

$$\mathfrak{P}_{i,j} = \left\{\mathbf{S}_{i,j} \mid (\mathbf{S}_{i,j} {\in_\alpha} \mathbf{\Pi}_{i,j}) \wedge (\Psi(\mathbf{S}_{i,j}) \geq \epsilon_{i,j})\right\}, \tag{7}$$

where ${}_\alpha\mathbf{\Pi}_{i,j}$ is the solution set with $\alpha$ level cut, $\Psi_{i,j}(\cdot)$ is the aggregated satisfaction value, and $\epsilon_{i,j}$ is the threshold of aggregation satisfaction degree of objectives.

Given the counter-offer $\mathbf{B}_{i,j}$ and the feasible solution set $\mathfrak{P}_{i,j}$, the prospective solution $\mathbf{S}^*_{i,j}$ is generated by solution selection method

$$\mathbf{S}^*_{i,j} = \arg_{\mathbf{S}}(\max_{\mathbf{S}\in\mathfrak{P}_{i,j}} \mathcal{H}(\mathbf{S}, \mathbf{B}_{i,j})), \tag{8}$$

where $\mathcal{H}$ is a utility function to evaluate the appropriateness between the feasible schedule $\mathbf{S}$ and the counter-offer set $\mathbf{B}$ in

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which the utility function $\mathcal{H}$ can be defined by

$$\mathcal{H}(\mathbf{S},\mathbf{B}) = \frac{1}{N_I}\sqrt{\sum\nolimits_{k=1}^{N_I} (\mathcal{P}(S_k)^{w_p} \wedge \mathcal{S}(S_k, B_k)^{w_s})^2}, \quad (9)$$

where $\mathcal{P}$ is a satisfaction function over the issue $I_k$, and $\mathcal{S}$ is a similarity function (a distance measure) between the solution $\mathbf{S}$ and the counter-offer $\mathbf{B}$; $w_p$, and $w_q$ denote the weight associated with the satisfaction and the similarity of the solution of task, respectively.

For the task $j$, given the feasible solution set $\mathfrak{P}_{i,j}$ and the prospective solution $\mathbf{S}^*_{i,j}$ which involves a set of values $\{\mathbf{S}^1_{i,j}, \mathbf{S}^2_{i,j}, ..., \mathbf{S}^{N_I}_{i,j}\}$ for $N_I$ issues, the offer $\mathbf{A}^*_{i,j}$ for task $j$ is a tuple of fuzzy set $\{A^1_{i,j}, A^2_{i,j}, ..., A^{N_I}_{i,j}\}$ in which each fuzzy set $A^k_{i,j}$ for issue $I^k_{i,j} \in \mathbf{I}_{i,j}$ is the marginal particularized possibility distribution

$$A^k_{i,j} = Proj_{X^k_{i,j}}(\mathfrak{P}_{i,j} \cap \overline{\Pi}_{X^1_{i,j}} \cap ... \cap \overline{\Pi}_{X^{k-1}_{i,j}} \cap \overline{\Pi}_{X^{k+1}_{i,j}} \cap ... \cap \overline{\Pi}_{X^{N_I}_{i,j}}), \quad (10)$$

where $\overline{\Pi}_{X^k_{i,j}}$ is the cylindrical extension of $\Pi_{X^k_{i,j}}$ in the space $(\mathbf{X}^1_{i,j}, ...\mathbf{X}^{N_I}_{i,j})$, $\Pi_{X^k_{i,j}} = \mathbf{S}^k_{i,j}$, and $\mathbf{X}^k_{i,j}$ is the object of issue $I^k_{i,j}$ for task $j$.

Meanwhile, when project manager agent $\mathfrak{E}_i$ receives a counter-offer $B_{i,j} = \{B^1_{i,j}, B^2_{i,j}, ..., B^{N_I}_{i,j}\}$ for the task $j$, the opponent agents' preferred solution $\widehat{\mathfrak{P}}_{i,j}$ can be obtained by

$$\widehat{\mathfrak{P}}_{i,j} = (\overline{B}^1_{i,j} \cap ... \cap \overline{B}^{N_I}_{i,j}), \quad (11)$$

where $\overline{B}^k_{i,j}$ is the cylindrical extension of $B^k_{i,j}$ in the space $\mathbf{X}_l$. Each element $\widehat{\mathfrak{P}}$ represents a solution preferred by opponent agents and the membership degree of each element represents the acceptability of solution for all opponent agents.

The project manager agent $\mathfrak{E}_i$ will accept the counter-offer $B_{i,j}$ proposed by its opponent as an agreement if

$$(\mathfrak{P}_{i,j} \cap \widehat{\mathfrak{P}}_{i,j}) \neq \{\}, \quad (12)$$

The negotiation process for task allocation will be terminated when the project manager agent reach an agreement with one of contractor agents or the project manager agent or all of their contractor agents withdraws the negotiation. A project manager agent will terminate the negotiation when each of tasks in project is assigned to a contractor agent or the project manager agent withdraws the negotiation while failing to reach agreement. And the supply chain planning/scheduling process will be terminated when all of project manager agents are termination.

## 4 Experiments

To demonstrate the utility of the proposed model for project planning and scheduling problem in supply chain, the experiments are meant to compare AFCN with centralized heuristic (CTR) [14], conventional CNP (CNP) [15], modified CNP (MCNP) [4], market-based auction CNP (MA-CNP) (i.e., extended from CNP) and market-based auction MCNP (MA-MCNP) (extend from MCNP) (i.e., extended from MCNP) in terms of the number of project managers over makespan, total operating cost, and computational time.

The experiment was implemented on a Pentium M PC with 0.8 GHz running windows XP and 256 MB RAM. In the experiment, each project has a linear sequence of tasks, and each task is then specified by its precedence constraints, required resources, processing time and tardiness cost. Each supplier is specified by its unique capacity and processing cost. The total operating cost is the sum of the total processing cost and tardiness cost of each project. For simplicity, the number of tasks per project is identical at five, alternative suppliers for a task are identical at three, and 50 instances are generated for each number of project managers. Figures 2 to 4 show the performance comparisons over makespan, total operating cost, and computational time, respectively.

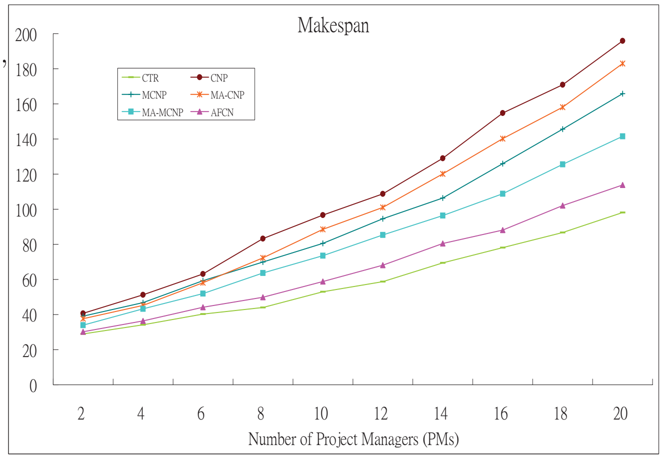


Figure 2: Makespan of various negotiation mechanisms over a number of project managers.

The conventional CNP supports one PA to assign a task at a time and another PA can start only after the PA finishes selecting CAs for all its tasks. In this form of negotiation model, a large number of slacks will be generated since that the conflicts among PAs cannot be coordinated. Each PA's performance highly depends on the order of contracting.

Instead of one PA assigning a task, MCNP supports multiple PAs to contract tasks to multiple CAs simultaneously. In the manner, PAs propose the whole time window of task and price to CAs. CAs resolve the conflicts among tasks according to the urgency of task be completed and the price of the task. It reduces the possibility of violating the due date of the PAs and decreases the tardiness when a project is delayed.

Since the simplicity of negotiation protocol, the single-shot negotiation models (CNP and MCNP) have the best time efficiency in Figure 4. With very limited information sharing and myopic decision-making, however, the global performances can easily get trapped at local optima and are highly unstable. It also can be observed in Figures 2 and 3, these models worse results than other approaches over makespan and total operating cost.

For reflecting the service preference in PA and the task contention in CA, MA-CNP and MA-MCNP incorporate the market-based auction mechanism [16] which is characterized

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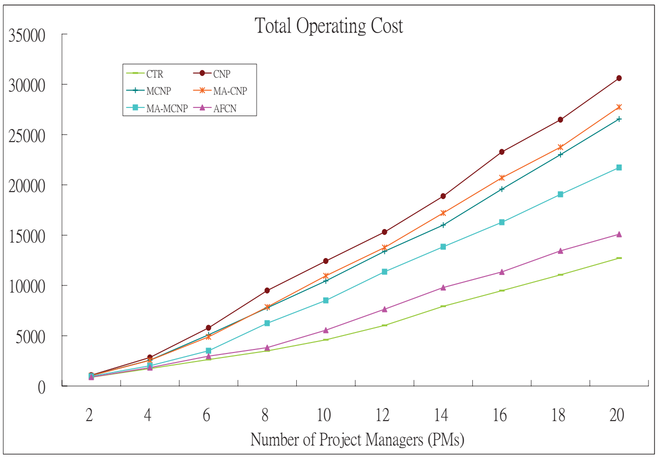


Figure 3: Operating cost of various negotiation mechanisms over a number of project managers.

by iterative bidding among agents. Agents will adjust the prices of bid according to the direction of surplus and deficit of demand. Task allocation processing in CA can be adjusted iteratively according to time boundary and the updating price of tasks. In this way, MA-MCNP with iterative bidding have better makespan and total operating cost than the single-shot negotiation models. However, due to the characteristic of protocol in MA-CNP, MA-CNP even worse than MCNP over makespan and total operational cost when the number of project managers is larger than 8 in Figure 2 and 3, respectively.

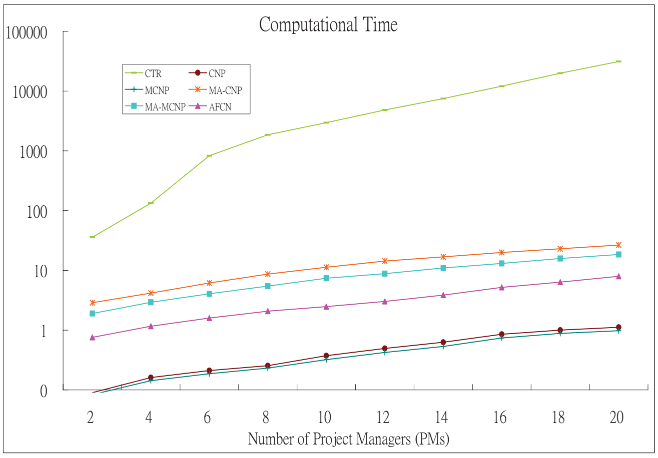


Figure 4: Computational time of various negotiation mechanisms over a number of project managers.

However, the price of task proposed by CA indicates the contention degree of the desired time slots of task, but not indicates where the contention can be resolved. PA might blindly increase price but the schedule of task can not be improved (overpricing). Besides, sharing full of task's time boundary in PA is not practical in reality.

In AFCN, PA generates the offer not only considers how much suppliers can provide this service, but how pressing the task be finished. Instead of the bid information in the market-based mechanism, the negotiation information in the AFCN varies not only depending on the particular combination of task demands/resource contracts, but the objectives and preferences of agent. Both of PA and CA proposes offers/counter-offers which involve the current feasible time slots of task with preference and price. The time slots with preference in offer/counter-offer indicate not the current time boundary of task, but the time window for conflict-free. According to time slots with preference from PA, CA can arrange the task allocation efficiency and can response the conflict in counter-offer directly. Meanwhile, CA generates the counter-offers considering not only the tasks of PAs are satisfied but the profit obtained in the transaction. Based on the counter-offers from CA, PA can avoid requiring the high contention area in CA or can abort lower quality service of suppliers. Thus, PA can bid the desired time slots to preferred suppliers with controllable budget.

In Figure 2 and 3, it can be observed that the AFCN has superior performance than other approaches in makespan and total operating cost. Meanwhile, AFCN performs better in time efficiency than that of market based mechanism. Additionally, as the problem size is increasing, the performance improved by the AFCN grows more significantly.

## 5 Conclusions

We have presented an agent-based fuzzy constraint-directed negotiation protocol for project planning and scheduling in supply chain. Constraint modeling gives a more direct fusion to the real-world problem descriptions and the impreciseness of knowledge in supply chain can easily be represented by fuzzy constraints with the levels of consistency as well. Experimental results suggest that the AFCN indeed can provide a practical and efficient framework for supply chain planning and scheduling.

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