A Trust Mechanism for Decentralized Economic Scheduling

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***Abstract*— This paper presents a *decentralized negotiation protocol* for *cooperative economic scheduling* in a supply chain environment. For this purpose we designed autonomous agents, which maximize their profits by optimizing their local schedule and offer side payments to compensate other agents for lost profit or extra expense if a cumulative profit is achievable.**

To further increase their income the agents have to apply a randomized local search heuristic to prevent the negotiation from stopping in locally optimal contracts. We show that the welfare could be increased by using a Simulated Annealing like search strategy. Unfortunately, a naïve application of this strategy makes the agents vulnerable to exploitation by untruthful partners. We develop and test a straightforward mechanism based on trust accounts to protect the agents against systematic exploitation. This "Trusted" Simulated Annealing mechanism assures truthful revelation of the individual opportunity cost situation, as a basis for the calculation of side payments.

I. Introduction

Real-life supply chain management (SCM) is closely related to problems caused by the diverging interests of the actors (enterprises) and the distributed structure of the underlying optimization (scheduling) problems. One way to address this constellation is to employ holonic multi agent system (MAS), mapping the process structure onto single agents [12]. To deal with the systems' agency problems, like the unwillingness of actors to reveal sensitive but (in terms of system optimization) valuable information, incentive compatible mechanisms to avoid exploitation by competitors have to be implemented in the decentralized supply chain optimization system. We propose a holonic MAS for SCM, which addresses the revelation issue by introducing a trust account mechanism to avoid individual long term exploitation. We directly integrate the trust mechanism into the schedule optimization procedure, similar to [30]. Each agent - operating a single production facility - optimizes its own return by finding a yield maximizing internal schedule. To avoid opportunity and penalty cost due to overcapacity, processing bottlenecks or late delivery, agents are additionally enabled to negotiate delivery times and "outsourcing contracts" based on prices calculated depending on their production load, giving reason to talk about economic scheduling. This negotiation has to be seen as a second inter-agent schedule optimization process, leading to a social contract equilibrium of the MAS. Due to fact that the calculation of these negotiated prices cannot be directly controlled by the contract partners, a trust protocol fosters the agents' truthful bidding. After depicting the theoretical foundations of our holonic MAS, we deliver a detailed description of the combined trust and scheduling protocol. In the description of our experimental results the usefulness of the mechanism is demonstrated by applying it to settings with purely selfish, altruistic and mixed agent "strategic worlds", using the individual income distribution and the global welfare as benchmarks.

II. Literature Review

Mainly three research areas are relevant for our model from the theoretical point of view. Firstly, there is the topic of scheduling problems, especially economic scheduling problems. We modified the well known job-shop scheduling problem (JSSP) making it decomposable to interdependent weighted job interval scheduling problems (WJISP). to analyze our trust mechanism. Secondly, we have to address the dynamic selection of players' strategies in value networks. Such evolving strategies are traditionally described in connection with equilibrium building processes employing evolutionary game theory. Fictitious play (FP) with its iterated application of strategies depending on learned response patterns, seems to be especially suitable to tackle with this aspect of agent-based SCM. As third point trust and reputation mechanisms in MAS literature have to be inspected to find out which type trust-(reputation) model is appropriate to our SCM application.

A. Economic Scheduling and the Weighted Job Interval Scheduling Problem

The WJISP was gradually introduced by the work of [20], [27], [26], [17] and [31]. It is defined as the scheduling of a set of jobs, subject to *release dates* and *due dates* on a single machine, which can process at most one job at a time. The objective is to minimize the weighted number of late jobs, or equivalently to maximize the weighted number of early jobs [24]. This problem is shown to be NP-hard if the tasks are assumed not to be preemptive [18]. The application of meta-heuristics like genetic algorithms (GA), tabu search (TS) and simulated annealing (SA) is very common for JSSP solutions [40] [47] [38]. Sevaux and Dauzère-Pérès apply a GA with different types of encoding and crossover operators to the WJISP [35] [36]. They are able to further improve a initial solution found by lagrangean relaxation (LR) [9].

In addition Wan and Yen [42] develop a TS meta-heuristic for the WJISP, which is especially capable to deal with lager problem instances. Erlebach and Spieksma [11] propose a greedy algorithm to tackle with the WJISP which has an expectedly short runtime, granting a satifactory approximation to the exact WJISP solution, which could be for example achieved by using a Branch and Bound method [3]. Inserting a idle job into given job sequences can be seen as a subproblem of the WJISP which has high relevance in real single machine interval scheduling problems [23]. Koulamas therefore proposes a heuristic, which enables a production planner to optimally insert idle time into a predefined job sequence.

Elendner [10] proposes the application of a combinatorial auction (CA) for job allocation in a WJISP context, where the owner of a single machine tries to optimize the return offering production capacity to resource buyers, which submit at least one bid. Under the assumption of superadditive preferences [41] of the buyers with respect to the items, Elendner shows that the CA winner determination problem can be expressed as a WJISP. In the economic interpretation of the WJISP the job weights are interpreted either as returns gained by their execution or additional costs resulting from their non-execution.

Conen [7] introduces an economically augmented job shop scheduling problem (EJSP), which comprises valuation information. This formulation enables the decentralized optimization of scheduling processes making use of the advantages of holonic multi-agent manufacturing systems, especially the protection of sensitive private information, like the production systems' load or the profit margin. Similar to Elendner, Conen assigns prices to the jobs, incuring the WJISP weights. Contrary to Elendner, Conen maps the EJSP to a winner determination problem of a CA, calling the entire problem class combinatorial job shop auction problem. Based on this mechanism Conen is able to prove the existence of equilibria, where prices are coherent with the proposed economic scheduling procedure [8]. The efficiency in the holonic system of self-interested agents is measured by the ability to establish Walrasian equilibria, giving the agents the possibility to maximize their individual utility with respect to the given prices [1].

B. *Fictitious Play*

In FP settings players believe that their opponents have a fixed but unknown mixed strategy. At each stage of the game, each player counters with a best reply under the belief that other players are employing a mixed strategy represented by the empirical distribution of his opponents past actions. According to [25] FP can be used as an optimization objective to exploit the behavioral paradigm of competition in connection with SA or GAs. Unfortunately the convergence behavior of the classic FP is very slow [43] resulting in the design of new FP variants using randomized strategies [14]. A similar approach is proposed by [16], while using actions with exponential weighted proportion according to their historic utility. Due to the fact FP even works in 'one-against-all' multi-player games [33] and can additionally be coupled with coordination games, in which players receive no return, if they fail to coordinate [34], FP seems to be a suitable formulation method for myopic learning strategies in MAS SCM.

C. *Trust and Reputation Management*

Besides sociological, psychological, behavioral and philosophical dimensions of trust [5] the cognitive aspect of human rationality has a formative impact on trust in the artificial intelligence domain. In this context Castelfranchi and Falcone characterize trust "basically as a mental state, a complex attitude of an agent x towards another agent y about the behavior/action α relevant for the result g" [6]. According to Mui et al. [29] trust and reputation stand in a reciprocity relationship defined as a 'mutual exchange of deeds', where trust is 'a subjective expectation an agent has about another's future behavior based on the history of their encounters' and reputation denotes the 'perception that an agent creates through past actions its intentions and norms'. Based on this definition, trust between agents in computational models can be established by accounting the historic behavior of the agents. Mostly, reputation factors consists of direct and indirect reputation component representing the agents own perception of its prospective contract partner or the interaction cognition reported by other agents respectively [28].

Reputation-based trust models are increasingly popular in Peer-to-Peer (P2P) and E-commerce oriented applications [48], [49]. Xiong and Liu [46] offer a coherent adaptive trust model for quantifying and comparing the trustworthiness based on a transaction-based feedback system. In this model trust is simply expressed as a metric including the feedback in terms of satisfaction, the number of transactions, the credibility of the feedback calculated by other peers' opinion and a transaction and community context factor. Mostly, reputation models are implementing simple mechanisms for trust accounting, providing a sufficient transparency of the mechanism for the reviewing peers to guarantee the incentive compatibility effect.

Jurca and Faltings [22] identify three problems for P2P truthful reputation reporting in competitive software agent trading models: First, by reporting information the agent provides a competitive advantage to other agents, second by reporting positive ratings, the agent slightly decreases its own reputation with respect to the average reputation of the other agents and consequently the agents could be tempted to give negative reputation ratings to improve their own situation. By implementing a combined trading and side payment scheme employing reputation-information trading agents these downsides are compensated in the Jurca and Faltings model. Tran and Cohen [39] present a reputation model using Reinforcement Learning (RL) to adjust sellers and buyers prices and / or quality according to the perceived product quality. In addition buying agents are allowed to explore the market in order to discover new reputable sellers.

In a more game theoretic view on trust in MAS [4] shows that trust can emerge as a self-organizing phenomenon in a complex dynamical system. For this purpose the model assumes the existence of a trustworthiness property in an extended version of the continuous-cooperation N-player prisoners dilemma (CN-PD) as extension of evolutionary strategies in the iterative prisoner dilemma introduced by Axelrod [2]. Choosing a mainly system-oriented aspect Huberman and Wu study the endogenous dynamics of discounted reputation in a system consisting of firms with long horizons that provide goods and services with varying levels of quality, and large numbers of customers. Besides well defined equilibria regimes of instability, oscillating reputation can be identified for several parameter constellations [19].

Applying reputation and trust mechanisms in SCM Padovan et al. [30] implement an electronic market employing a simple reputation mechanism based on direct and indirect reputation in order to exclude fraudulent participants form negotiation. The implementation of centralized and decentralized trust mechanisms in a market organized along the value chain, integrating risk premiums for potential loss in contracts, leads to improved system reliability for both cases. In a similar model Eymann et al. [12] use genetic algorithms to vary agents behavior. By analyzing decentralized coordination in the supply chain, they instruct their agents to take information about the reputation of a potential transaction partner into consideration and use it to choose the appropriate partner. Franke et al. [15] analyze the impact of direct discounted reputation on supply webs. In this model, strong reputation stimulates the formation of monopolies and stable supply chains. The well known supply chain specific bullwhip-effect is observed to antagonize this reputation effect.

Sabater [32] presents a 'SuppWorld' scenario with a market structure, having agents acquire the input products for a manufacturing process, while aiming to maximize their revenue. Using different negotiation tactics and enabled to form coalitions for the exchange of reputation information, they act in a simulative economy with raw material and money entrance. Relying on the REGRET system, which takes a individual (direct) and a social (indirect) view of reputation into account Sabater introduces a ontological meaning enabling a differentiation of reputation with respect to crucial aspects of the supply chain like delivery on time or quality reliability [21] [37] and evaluates systemic the impact of reputation on the SCM framework.

III. Description of the Negotiation Model

A. Simplifying Assumptions

Immediate delivery: Our negotiation model assumes delivery time at supplier and availability time at customer to be identical. Although unrealistic, this assumption can easily be relaxed by introducing intermediary logistics agents for storage or transport. The negotiation protocol does not have to be altered with respect to a potentially different internal scheduling calculus applied by these agent types. While storage agents may apply a direct multi-resource extension of the WJISP for pricing of scarce storage space, for transport agents the model is more involved since vehicle routing decisions always require sequence dependent setup times when modeled as scheduling problems.

Closed model with deterministic jobs: We assume every task to be known to the agents, i.e. they only renegotiate existing contracts. However, the extension to a dynamic model with emerging tasks is straightforward: Whenever a new service or product request has to be priced, the agent's WJISP defined by its current portfolio of $2n$ contracts gets extended by two additional contracts. Whenever the customer's willingness to pay is higher than the additional cost incurred by solving the $n+1$ task WJISP' compared to the original WJISP, the new contract should be accepted.[1]

Unlimited compensation budgets: We assume each agent to have unlimited financial resources for side payments. Since the side payments only serve to compensate for economic value generated by relaxing the agent's scheduling constraints or to collaboratively escape suboptimal plans, the sheer number of recontracting steps applied keeps the probability of a persistant financial loss very low. Of course, this only holds as long as there are no defecting agents or vulnerability to defection is limited by trust accounts.

Each job is composed by a number of sub-tasks that have to be executed sequentially (other inputs are not critical): Although we adopted this classical job shop scheduling assumption for our multi-agent scheduling model, it is very unrealistic to assume one single predecessor agent in most applications. The relaxation requires the WJISP's release times to be defined as the maximum of all contract times over all suppliers. Although it is clear that only renegotiation of the most restricting contract (defining this maximum) may have impact on the WJISP's total cost, it might be more efficient to simultaneously renegotiate with all suppliers.

Static costs for task outsourcing: Currently we assume an outsourcing option to be available for all tasks and every agent at all times, meeting whatever deadline the customer will require. While this simplification reduces the problem's complexity[2] it is true that in most economies for almost any product or service a substitute will be available at any time for a price below infinity. Nevertheless, the price for a substitute strongly depends on the time interval between request and required delivery. Extending our model towards negotiations with providers of outsourcing options instead of assuming static values for each task will therefore be a high priority.

B. Agents' Knowledge

Each agent a is required to perform a set of tasks T_a where each task $t_{i,j} = \langle a_{i,j}; l_{i,j}; w_{i,j} \rangle$ is defined by three attributes:

[1] Of course, even when considering all possible contract times for the customer and the supply side contract, the cost difference obtained by optimizing the new WJISP' is still a pessimistic estimate, since recontracting a subset of the existing contracts may lead to lower costs for WJISP'.

[2] Without this assumption we had to consider "waterfall effects" of on-time delivery failures leading to external effects imposed on subsequent tiers of the supply chain, thus prohibiting any local (unilateral or at most bilateral) cost calculus.

$a_{i,j} \in AGENTS$	the identifier of the agent that has to perform the task,
$l_{i,j} \in \mathbb{N}_+$	required execution time and
$w_{i,j} \in \mathbb{N}_+$	the price of outsourcing task $t_{i,j}$ without occupying the resource.

The following example (table I) shows three jobs j, which have to be executed by three agents. Additionally, $a_{i,j} = CN$ indicates that all jobs are delivered to an exogenous consumer, which is used to model the delivery time preferences.[3]

Each job is composed out of several tasks that have to be executed in a predefined order. This order is defined by i such that $t_{1,2}$ is the first task of job 2 and has to be executed by agent 3 (according to table I).

job	agent's position in task sequence			
	1	2	3	4
1	$a_{1,1} = 1$	$a_{2,1} = 2$	$a_{3,1} = 3$	$a_{4,1} = CN$
2	$a_{1,2} = 3$	$a_{2,2} = 1$	$a_{3,2} = CN$	
3	$a_{1,3} = 2$	$a_{2,3} = CN$		

TABLE I

TASK ASSIGNMENT TO AGENTS

Between each agent $a_{i,j}$ and its successor (regarding job j) the contract $c_{i,j} = \langle ctime_{i,j}; cprice_{i,j} \rangle$ defines their roles as supplier ($a_{i,j}$) and customer ($a_{i+1,j}$) according to a semi-manufactured product or service. Hereby $ctime_{i,j} \in TIME \subset \mathbb{N}$ is the discrete but possibly finite time horizon and $cprice_{i,j} \in \mathbb{R}$ is the contractual price denoting a real value.

C. Agents Internal Cost Minimization

To minimize its internal cost each agent a can choose the starting time $start_{i,j}$ of tasks $t_{i,j} \in T_a$ and if it prefers to execute the task by using its resource ($x_{i,j} = 0$) or not ($x_{i,j} = 1$). The utility function of the agent is defined as follows[4]:

$$U_a = \sum_{i,j | t_{i,j} \in T_a} (cprice_{i,j} - cprice_{i-1,j} - x_{i,j} \cdot w_{i,j}) \quad (1)$$

The following restrictions apply for each task $t_{i,j} \in T_a$:

$$ctime_{i-1,j} \leq start_{i,j}, \quad (2)$$

requires each task to start later than the supply contract time and

$$start_{i,j} + l_{i,j} \leq ctime_{i,j}, \quad (3)$$

[3]The willingness of the consumer agent to pay depends on the delivery date of the job. For each time unit earlier the delivery takes place our consumer is willing to pay 50 MU more. The initial delivery time is defined by a randomly generated starting schedule.

[4]To simplify the formula we define $cprice_{0,j}$ as the price for the creation of the raw material for job j and it is therefore fixed.

which requires each task to be finished before delivery contract time. Moreover, to ensure that the resource of an agent a is only utilized by one task at a time, for each pair $x_{i,j} = 0$ and $x_{i',j'} = 0$ with $x_{i,j}, x_{i',j'} \in T_a$ one of the following conditions has to be satisfied:

$$start_{i,j} + l_{i,j} \leq start_{i',j'} \vee start_{i',j'} + l_{i',j'} \leq start_{i,j} \quad (4)$$

This guarantees that either job j is finished before job j^* starts or vice versa. Based on these conditions each agent tries to minimize the total contract penalty by means of its scheduling activities. This is equivalent to maximizing the aggregated avoided penalty fees.

Because each agent solely has knowledge about its own contracts and resources a benevolent global planning agent has to be endowed with this knowledge. Either an incentive compatible mechanism for the revelation of this information or a bilateral negotiation protocol is required, achieving a good approximation of a globally utility maximizing contract situation.

Our approach models the latter one. The release times of the WJISP model correspond with the times fixed in the supply contracts, the due dates with the times of the delivery contracts.

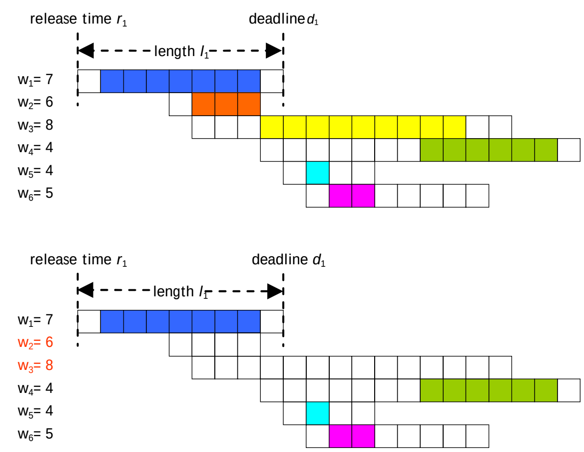

Fig. 1. Agents internal cost optimization for the WJISP (including optimal solution).

Figure 1 shows a potential situation of an agent a with 6 tasks and consequently 6 delivery and up to 6 supply contracts. The internal optimization problem of each agent is identical to the WJISP. The release times r_j of the WJISP model correspond with the times fixed in the supply contracts $c_{i-1,j}$ with $t_{i,j} \in T_a$, the due dates d_j with the times of the delivery contracts $c_{i,j}$. In our example the duration of the tasks $l_{i,j}$ is depicted by the amount of colored blocks. Task 1 (blue) has a duration of 2 time units (TU) less than the time available between the supply of the raw material and the delivery of the product. Thus the agent can schedule the job at three different starting times or alternatively buy it from an external source (paying $w_{i,1} = 7$ money units). The corresponding prices for external procurement are shown left to the figure. According to these weights one optimal solution to the problem is shown at the lower part of figure 1, incurring a cost of 6+8=14 MU.

D. Agents Schedule Optimizer

For the agent's internal optimization each task $t_{i,j}$ of an agent is represented in its optimizer by the duration of the task l_j^{ex} (which is $l_{i,j}$ in the global context) and its center point $p_j^{ex} = start_{i,j} + l_j^{ex}/2$. The timeslot in which the task has to be executed is also given by the length of the interval $l_j^{in} = ctime_{i,j} - ctime_{i-1,j}$ and its center point $p_j^{in} = ctime_{i-1,j} + l_j^{in}/2$. The optimizer has to identify the cost minimal combination of $x_{i,j} \in \{0;1\}$ (or x_j^* in the context of the local optimization) and p_j^{ex} according to the restrictions:

$$\left|p_j^{in} - p_j^{ex}\right| \leq \frac{1}{2} \cdot \left|l_j^{in} - l_j^{ex}\right| \quad \forall j | \exists i : a_{i,j} = a \qquad (5)$$

For the agent's internal optimization we relaxed restriction 5 and decreased the perceived utility depending on the degree of the restrictions' violation. By using this kind of penalty cost we implemented a model simulating a repulsive force for conflicting tasks. Figure 2 illustrates the model and the cost incurring edges of this model. The dashed edges (red) show the conflicting tasks for the example in figure 1.

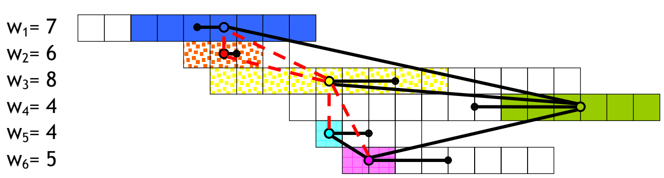

Fig. 2. Embedded spring model for the internal task optimization.

To search for the optimum to the above outlined optimization problem we applied Cooperative Simulated Annealing (COSA), a hybrid search method combining the basic principles of two major paradigms of heuristic search:

- Simulated Annealing (developed in analogy to thermodynamics) and
- Genetic Algorithms (developed in analogy to the theory of biological evolution).

COSA inherits the idea of population and information exchange from GA but replaces the usual crossover by so-called cooperative transitions. Like in standard SA these transitions are restricted a local neighborhood relation although they do not get selected according to a uniform distribution from all possible neighbors but rather according to a biased distribution, inducing a "gravity force" depending on the current position of other solutions within the population. The acceptance probability for these transition is controlled by the Metropolis criterion like in standard SA, depending on the virtual temperature and the difference in the solutions' objective function values (for more details see [44] and [45]).

E. Agents cooperative contract optimization

As mentioned above the payoff function of the consumer is higher for earlier deliveries. Consequently, an optimization of the schedule increases the payments that can be distributed among the agents. Therefore the question arises, how the agents can coordinate their schedules to maximize their profits. As a tool of coordination the agents calculate time-dependent prices. Figure 3 shows the contractual relationships between the example agent and its two suppliers (agents 1 and 2).

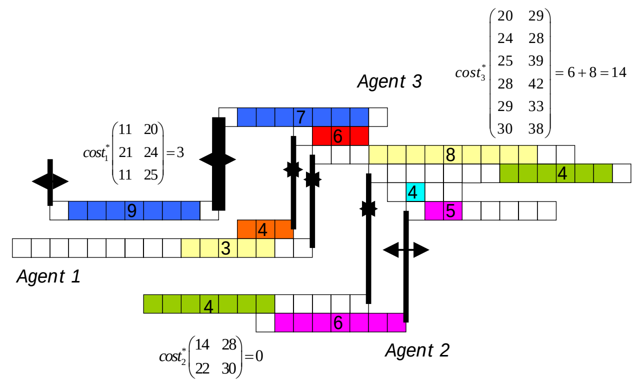

Fig. 3. Multi-agent WJISP for cooperative contract optimization.

For every given plan these functions reflect the opportunity cost or benefit incurred or gained by a specific agent from moving the contract time (defining release time at the supply side and due date at the customer side). Since widening of an interval always leads to a relaxed WJISP this new WJISP always has the same or lower cost while narrowing the interval generates a WJISP with the same or higher cost.

Consider for example agent 3 in figure 4: Recontracting the release time of job 1 (blue) from $t = 20$ to $t = 23$ or even later would render scheduling of this task impossible. On the other hand the resources freed by this would allow for scheduling of the second task in the optimal solution leading to total cost of 15 instead of 14 MU, i.e. a cost increase by 1 MU. Relaxing the contract to $t = 18$ or earlier would allow for scheduling both, the first and the second task thus yielding an additional profit of 6. For agent 1 a contract time of 17 or earlier renders job 1 (blue) impossible but in turn allow for scheduling the third task (yellow) causing a total cost increase by 6 MU. When relaxing the deadline to (at least) 21 however, all tasks can be scheduled by agent 1 (starting with the third one).

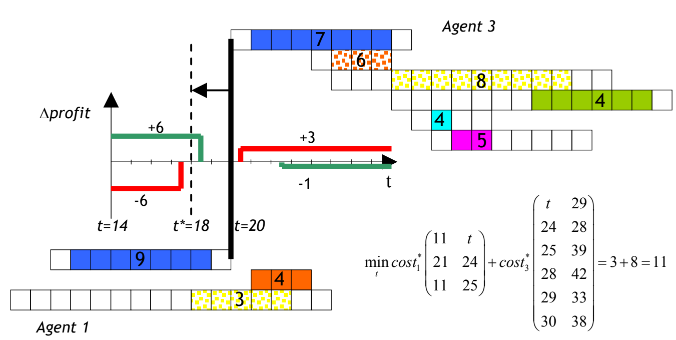

Fig. 4. Time dependent prices of the multi-agent WJISP.

Assuming both agents had agreed on a price x for $t =$

20 adding the respective cost deltas indicated in figure 4 would define time-dependent price functions representing the agents' opportunity cost or benefits. By communicating this function to the partner, each agent could calculate an optimal recontracting step. In our case agreeing on $t = 18$ would lead to a total surplus of 6 MU that could be shared by the two agents.

When calculating the price functions showing the optimal contract time for this task, we have to assume all other contracts to be kept constant. This in turn means, the recontracting operation for task 1 now leads to outdated price functions for all other tasks of agent 1 and agent 3, i.e. updating would be required to determine whether their contracting time is still optimal.

Of course, this raises the question whether it is really efficient to have the agent calculate the price functions for all points in time before communicating them, especially when the whole system of interdependent negotiations is still far from any equilibrium.

As an alternative we therefore considered a "memory-free" alternative randomly choosing a time offset[5] and then proposing this shift to the contracting party, making both agents estimate the implications of just this specific change (by solving their respectively modified WJISPs). Although this comes with the disadvantage of not finding the bilaterally optimal contract time for a given contact in one search step, it drastically reduces the number of WJISPs to be solved by each agent.

Since the WJISP is an NP-hard problem, it cannot be efficiently solved to global optimality, meaning that all calculated cost differences are estimates. To obtain them, the two agents' COSA processes solving the respective WJISPs are continued adapting the prior population of solutions to the modified problem instance by applying 2000 additional search steps to the population.

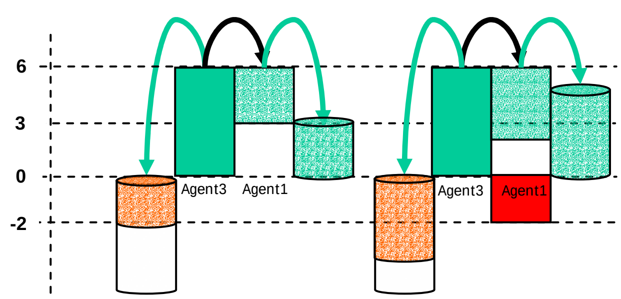

Fig. 5. Truthful agents using the account mechanism implemented in trusted annealing.

If the agents agree on a new delivery time (e.g. $t = 18$ in our scenario) and one agent profits more from the new delivery time than the other agent's additional cost, the total profit should be shared equally. In the example agent 3 makes a side payment of 3 MU to agent 1, leading to a situation where both agents profit from the change of the delivery contract.

Caused by the complexity of the global scheduling problem relying purely on improvement steps will not lead to schedules comparable to the optimal solution. Therefore we introduce a mechanism that gradually accepts delivery times making both agents worse of to find globally superior solutions[6]. Similar to the agents' internal optimization we used a SA like approach such that the agents accept transactions depending on the virtual temperature and the amount of monetary loss.

Unfortunately it would be very easy for an agent to increase its income by pretending to have higher costs (figure 5, right side). To avoid exploitation our agents use a memory, which stores the aggregated side payments. How the agents use this memory is detailed in the following section.

F. *Avoiding exploitation*

Agents who try to maximize their profits at the expense of other agents systematically underestimate their profits or overestimate the costs of a new delivery time. Caused by the willingness of the consumer to pay for earlier deliveries the agents should in general increase their income by agreeing to new delivery times. So in general each agent should limit its side payment to the other agent. Figure 6 illustrates how a trust limit restricts the transaction after a certain level of side payments is done. The trust accounting mechanism used in our model does not employ a composed reputation index using e.g. indirect reputation like most MAS reputation applications do. This is not necessary due to the equilibrium property of the system introduced by the SA negotiation process. Agents that permanently exploit the system get into competitive disadvantage by having no granted trust in further negotiations processes. In the long run the system dynamic of trusted annealing is comparable to an SA based calculation of a FP-equilibrium, while using randomized myopic strategies.

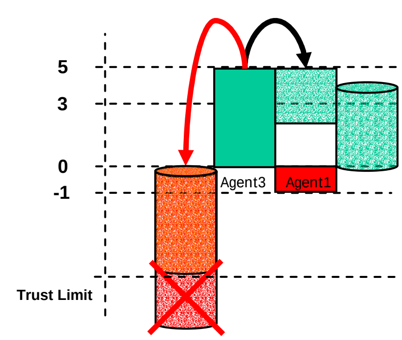

Fig. 6. Trust accounting for a truthful agent vs. a defecting agent.

IV. Results

For the evaluation of the decentralized economic scheduling protocols outlined above, we use the well known Fisher & Thompson 6x6 JSSP problem [13]. In the adaption of the

[5]The offset is calculated using a Gaussian distribution over integer values. It turned out that in most situations small small steps are more efficient but in few situation large steps help to get out of (some) local optima.

[6]The globally solution could here be measured by the external utility function of the consumer agent without taking the contract prices into account

F&J 6x6 JSSP to our setting, each shop is represented by an economic agent trying to maximize its profits. Furthermore, the outsourcing price of a task is set to 50 MU per TU of required processing time.

A. Selfish strategy

Figure 7 illustrates the total welfare surplus obtained by 50000 selfish renegotiation trials, defined as the total cost of the (heuristic) solution of the final WJISPs compared to the total cost of the agents' initial WJISPs' solution. We ran 150 simulations, yielding the individual sequences of dots (left chart), whereas the black line shows the average improvement over all simulation runs up to a given number of negotiations. The right chart shows the final distribution after 50000 negotiation trials. Implied by the selfishness of the protocol no agent will ever accept any proposal making him worse off compared to the current schedule, so there is no downside risk of any decrease in welfare, neither on a social scale nor for any individual agent. However, as the income distribution of figure 8 shows, the distribution of benefits from negotiation is significantly skewed towards later tiers of the supply chain, leaving almost no benefits for agent 0 and agent 1.

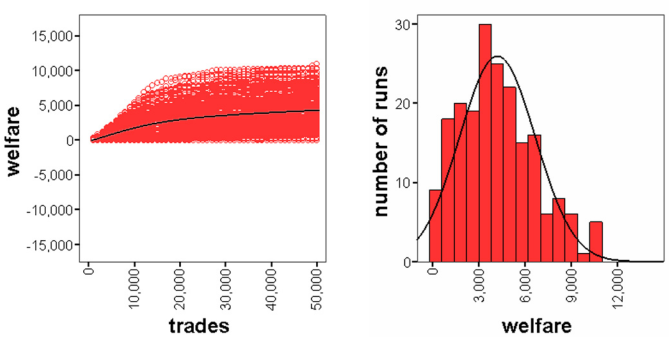

Fig. 7. Welfare distribution for randomized negotiation applying the selfish strategy.

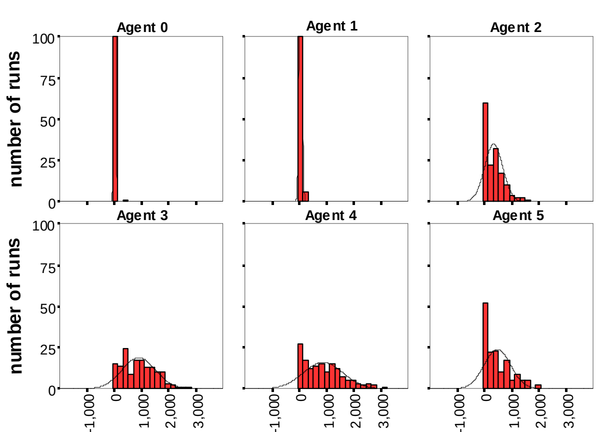

Fig. 8. Income distribution of the single agents applying the selfish strategy.

As we see from figure 9 an altruistic strategy (with an SA-based acceptance criterion for negative transitions) applied by all agents (no defecting agent) leads to worse results for the initial negotiation steps, but this temporary loss is compensated by a significant increase in total welfare after 20000 renegotiations, almost doubling the expected benefits of the selfish strategy.

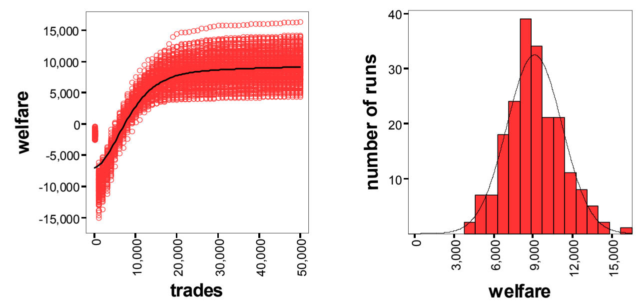

Fig. 9. Welfare distribution for randomized negotiation applying the altruistic strategy.

Unfortunately, the introduced altruism is extremely prone to exploitation as figure 10 illustrates: While the defecting agent generates extraordinary profits the other agents may be worse off in the end compared to their initial plans. Most of their side payments finally end up at agent 4, not returning anything to them.

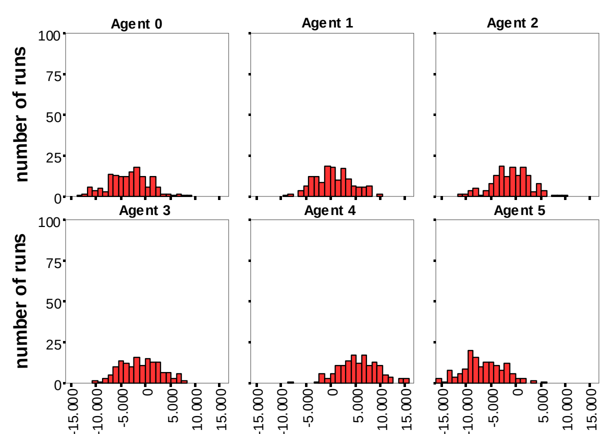

Fig. 10. Income distribution of the agents applying the altruistic strategy but agent 4 defecting (exaggerating by 20 %).

B. Parameterization

One drawback of our protocol could be a high sensitivity to the additional parameters introduced by the simulated annealing approach or the interleaving of contract renegotiation (cooperative action) and the agents' internal optimization of the WJISPs defined by these contracts. But although there is an impact on solution quality standard methods for parametrization work quite well. Figure 11 shows the typical impact of initial temperature and cooling rate exhibiting a standard pattern: cooling too fast or too low a starting temperature will rather emulate the selfish strategy while cooling too slow or too high an initial temperature will yield contracts which are not even locally optimal.

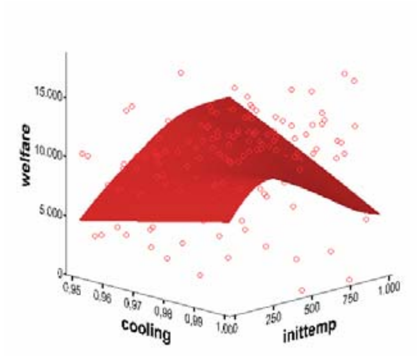

Fig. 11. Impact of initial temperature and annealing rate on agents welfare.

The same holds for the number of internal search steps trying to adapt the solution to the old WJISP to the new version after a recontracting step. Too few a number will generate "noisy" estimates of a recontracting step's cost impact on the two agents involved, increasing the number of false acceptance or rejection decisions. A high number reduces this error at the price of overall computational resources spent. Although there is a significant benefit of additional computational effort here (refer to figure 12), 250 steps per recontracting step already allow for adequate estimates of the cost difference and thus a low rate of erroneous acceptance or rejection.

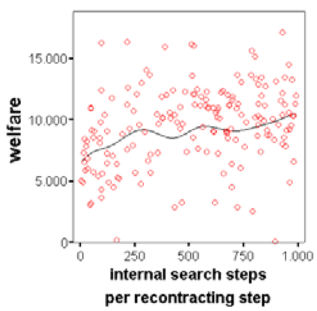

Fig. 12. Relation of global solution quality (welfare) and number of internal search steps per contracting steps.

C. Trust accounts

As we can see from figure 13 (left) and 14 even very low trust accounts do not pose a significant obstacle to generating benefits for altruistic agents: After a few initial rejections the accounts accumulate credit from beneficial negotiation thus leading to a more and more altruistic behavior. For prevention of exploitation by a defecting agent it might well be advisable to use a low initial setting for trust accounts as figure 13 (right) illustrates: Too much initial goodwill allows the defecting agent to withdraw this goodwill.

As Figure 15 illustrates, trusted annealing safely prevents exploitation by defecting agents. However, the problem of a

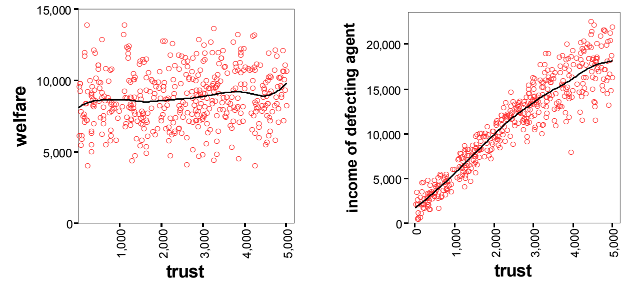

Fig. 13. Trust limits impact on global welfare loss caused by a defecting strategy of an agent.

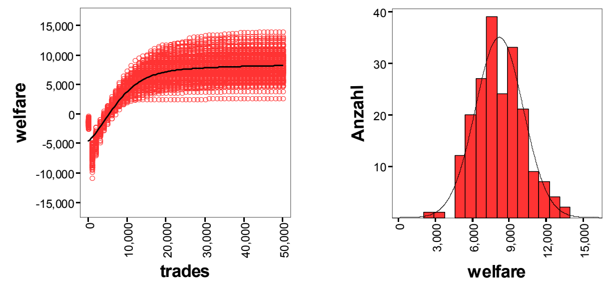

Fig. 14. Trusted Annealing: Result granting maximum credit 100.

strong bias in welfare distribution, as we have seen it in the selfish case, prevails: Agent 0 and agent 1 hardly participate in any gains. Although this is partially due to the fact, that they do not have a supply side to renegotiate with (but only customers), it nevertheless rises the question if it is possible to implement any "distributional fairness" criterion by a purely decentralized protocol or whether this requires communication to a central intermediary.

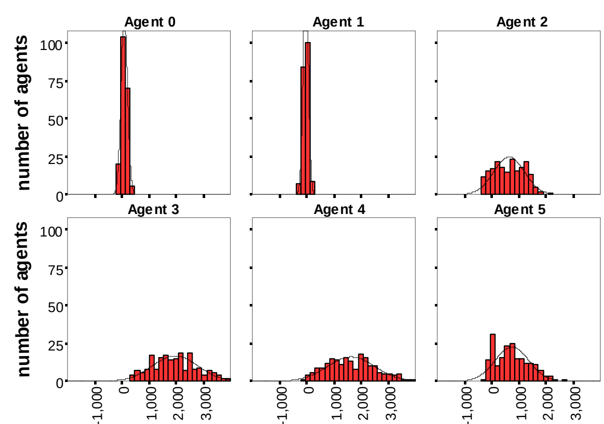

Fig. 15. Income distribution of the single agents applying Trusted Annealing granting maximum credit 100.

V. Conclusion and Further Research

Due to the growing number of applications of MAS in the production planning domain, decentralized scheduling mechanisms are of increasing interest especially in supply chain environments. A main problem while bringing optimizing software to work in real supply chains is the unwillingness of business participants to reveal sensitive information to a central planning institution. In the decentralized negotiation protocol presented here, agents are neither urged to reveal their internal planning state nor their exact utility function to other agents but nevertheless reach a solution of high quality.

We have shown how the quality of decentralized planning significantly improves when agents apply an altruistic simulated annealing protocol, temporarily allowing for decreases in solution quality (and profit) for the sake of escaping local contract optima which are far from a globally optimal solution. To limit this altruism's vulnerability to exploitation, trust accounts can be introduced, fortunately without sacrificing solution quality.

The downside of our approach is the high number of negotiation steps necessary to achieve good solutions. However, with ever decreasing cost of information and communication technology, we believe this will pose no major obstacle.

A number of future extensions could help to further improve the models solution quality or usability for real-world applications:

- Up to now our model assumes agents either to be truth-telling or defecting. An important extension could be the analysis of a trust discounting protocol, also allowing to protect against agents dynamically changing their behavior from altruistic to selfish in later stages of the negotiation process.
- Although the application of a simulated annealing renegotiation process defines a probability distribution over the agents' strategy space and the incorporation of trust accounts modifies this probability distribution based on the historic behavior of the other players, it is highly unlikely that this mixed-strategy and its evolution during the recontracting game is optimal in terms of a fictitious play analysis. Although our mechanism has been motivated by the idea of fictitious play, a rigid game theoretic analysis remains to be accomplished.
- As discussed while introducing the simplifying assumptions, the introduction of outsourcing service agents and multiple inputs to tasks are worthwhile extensions. The introduction of tasks simultaneously requiring multiple resources and more complex temporal restrictions as known from resource-constrained project scheduling should also be considered for future extensions.

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