

An Empirical Evaluation on the Suitability of Market-Based Mechanisms for Telematics Applications

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October 1998

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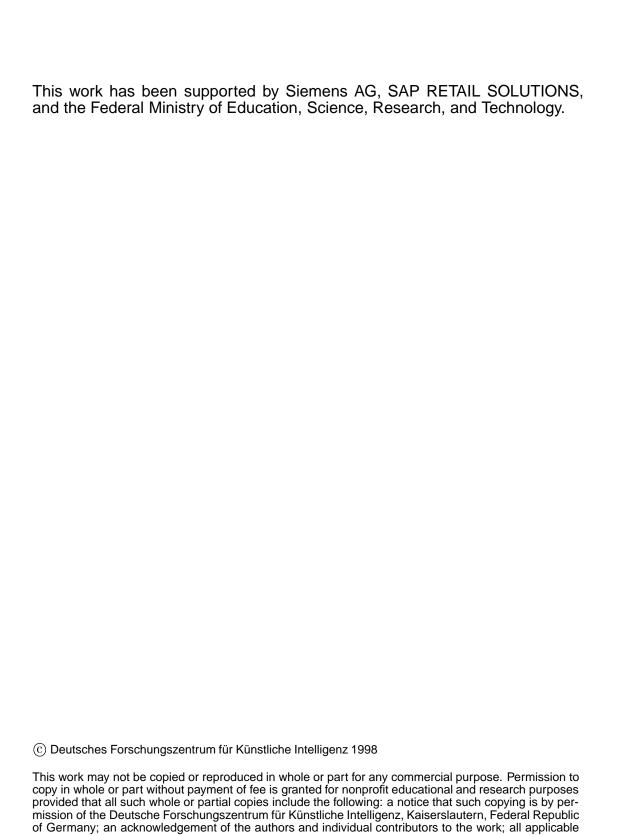
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DFKI-TM-98-02



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An Empirical Evaluation on the Suitability of Market-Based Mechanisms for Telematics Applications

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October 1998

Abstract

In this paper, we compare the suitability of several market-based allocation mechanisms, the *Vickrey auction*, the *matrix auction for multiple heterogeneous items* and the *simulated trading algorithm*, using the allocation of transportation tasks to a fleet of trucks as an example domain.

We distinguish three different organizational settings in which the set of vehicles, represented by autonomous agents, may be coordinated by the examined market-based mechanisms: in a cooperative setting, the truck agents are benevolent and try to reduce transportation cost on behalf of a central coordinator, i.e. an agent that represents the shipping company. In a competitive setting, the truck agents are self-interested and aim at optimizing their private surplus. In the hybrid setting a compromise between the conflicting goals, cost minimization and surplus maximization has to be found.

We analyze the communication complexity of the mechanisms on a theoretical basis. We empirically examine their scalability and tractability by comparing their processing time and allocative efficiency for order sets of different size. Thereby, the allocative efficiency of the mechanisms is measured in terms of cost, surplus, and number of trucks. The results are rated from the point of view of the different organizational settings.

1 Introduction

Auction-based market mechanisms are nowadays discussed for establishing virtual marketplaces in the growing area of e-commerce. For instance, these mechanisms can be applied for establishing networks of cooperating forwarding companies. In the highly competitive haulage business small and medium sized shipping firms that operate locally are often forced to form temporary inter-regional cooperative networks in order to bundle their resources and to establish competitive prices.

Since the partners in such a network are self-interested, i.e. they rate their own profit higher than the overall profit of the network, the network faces the *free-rider problem* that participants might try to take advantage of the group by betraying each other. Hence, a group of forwarders that try to optimize their own, local profit by lying about their true valuations risks to end up with a suboptimal global solution. Such an untruthful behavior decreases the competitive power of such a network and endangers its existence.

An approach to overcome this dilemma is the usage of truth revealing [Ma et al. 88] allocation mechanisms, i.e. mechanisms that are designed so that the best strategy for the bidders is to reveal their true preferences to the coordinator, a trusted individual within the network that coordinates the allocation process.

The most common truth revealing mechanism is the *Vickrey* auction [Vickrey 61] where the bidders submit one sealed bid for a single item which is granted to the highest bid for the price of the second highest bid. This principle, the *Vickrey principle*, enforces that neither bidding higher nor bidding lower then the true valuation is beneficial.

In their daily business, forwarders are faced with high dynamics and are often forced to manage multiple tasks in parallel. The *matrix auction* [Gomber et al. 98] allows to assign multiple tasks to a group of bidders in an truth-revealing fashion.

If the conditions in the network is less competitive, e.g. if the participating forwarders are subsidiaries of one company, the problem of selfishness is less dramatic. In this case mechanisms that allow global cost minimization can be applied. We examine the *simulated trading* algorithm [Bachem et al. 92] that simulates a dynamic market mechanism under central control. Nevertheless, in this setting the matrix- and Vickrey auctions are also applicable; hence, we compare them with the simulated trading procedure.

Besides these pure settings we have also to take into consideration that in reality there exist intermediate cases between competitive and cooperative settings, e.g. networks with strong internal commitments ensuring that local and global utilities can be distinguished only up to a certain extend. The usefulness of a mechanism depends on the degree of autonomy of the network's participants.

In this paper we analyze the communication complexity of the mechanisms which is the amount of information (in terms of sent messages) exchanged by the agents in dependence of the number of bidders and tasks. Furthermore, we empirically examine their scalability and tractability by comparing their processing time and allocative efficiency for order sets of different size. Thereby, the allocative efficiency of the mechanisms is measured in terms of cost, surplus, and number of trucks. The results are rated from the point of view of the different organizational settings.

We have implemented and evaluated the above mechanisms on the basis of the MAS-MARS scheduling system [Fischer et al. 96] for vehicle routing problems. The simulated trading procedure has already been incorporated in MAS-MARS as an optimization procedure for pre-existing solutions. For our purpose we extended the algorithm for the allocation of new tasks during an optimization process. Figure 1 is a screen shot of MAS-MARS executing a clustered benchmark.

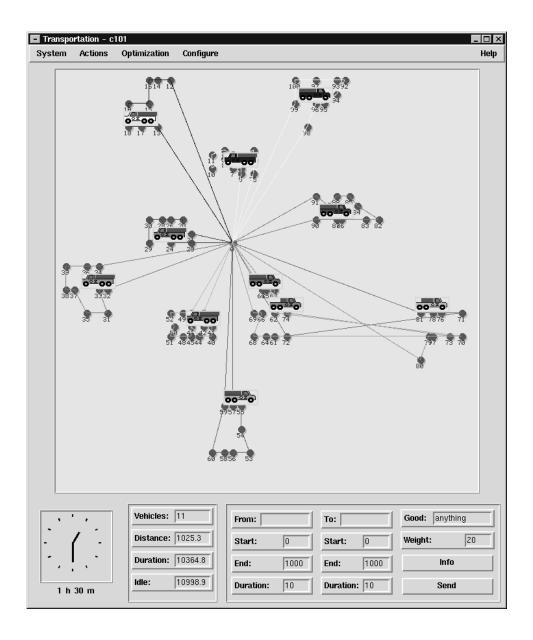


Figure 1: A MAS-MARS Screen Shot

For our evaluation we use the benchmarks generated by Solomon for the *vehicle routing problem with time windows* [Solomon 87]. The work presented in our paper focuses on a different issue from Fischer et al. [Fischer et al. 96] who examined the performance of simulated trading as an optimization procedure for a pre-existing allocation and were able to prove that the results obtained by simulated trading can compete with central OR techniques.

The paper is organized as follows: In the next section, we explain the allocation mechanisms underlying the protocols in use. In Section 3 the complexity of the allocation mechanisms is analyzed. In Section 4, we present the results of our test runs and compare the performance of the different allocation mechanisms for the different settings. Finally, we conclude and point to future work.

2 Market-Based Allocation Mechanisms

In this section, we briefly introduce the market-based mechanisms used in the evaluation. A detailed description can be found in [Fischer et al. 98].

The Vickrey auction and the matrix auction mechanisms base on the *Vickrey principle*, and hence, are *truth-revealing*: these market-based mechanisms force even self-interested bidders to truthfully reveal their valuations for the anounced items. Because of this revelation property, they are well-suited to generate cost-efficient allocations in competitive settings where the interacting forwarders are self-interested.

In contrast to these mechanisms, the simulated trading algorithm is not a pure allocation mechanism but combines the allocation of new items with the optimization of the existing allocation (which initially can be empty). Simulated trading is only suited for cooperative settings, in which complete information about the participants' valuations is available. Therefore, simulated trading is only applicable to the optimization of benevolent, truth-telling forwarders that do not hide private information.

2.1 Vickrey Auction

In the sealed-bid second-price or Vickrey auction (VA) every bidder submits a sealed bid for the item to be auctioned off to the auctioneer. In contrast to the sealed-bid first-price auction, in the Vickrey auction the bidder who submitted the best bid receives the item for the second highest bid made. This procedure achieves that a bidder whose bid exceeds his true valuation risks to be granted for this item at a price that exceeds the valuation as well. On the other hand, stating a bid lower than the true valuation might cause the rejection. In both cases a bidder cannot influence the price he has to pay.

Vickrey showed formally that in a sealed-bid second-price auction for symmetric risk-neutral bidders it is a dominant strategy to reveal their true cost or values [Vickrey 61]; i.e. truth-revealing strategies are not only equilibrium strategies but also dominant.

2.2 Matrix Auctions

Matrix auctions (MA) [Gomber et al. 98] are applicable for the simultaneous assignment of multiple items or tasks to bidders. The valuation of a set of items can differ significantly from the sum of the valuations of each single item. For instance, this may be the case if the items to be allocated reflect tasks¹. The auctioneer announces in a matrix-k-auction (MA-k) the k offered items to the bidders that, in turn, calculate their valuations for each potential combination of items (hence, the bidders have to compute $2^k - 1$ valuations) and report them to the auctioneer. From the transmitted bids or reported valuations of the bidders the auctioneer sets up a matrix where the cells represent the bids for each

¹Performing tasks is resource consuming and therefore may result in a loss of utility which can be reflected by a negative bid. Negative bids are explicitly allowed in a matrix auction. They are useful if a set of tasks *has* to be completely performed by a group of agents.

combination of items. Using that matrix, the auctioneer identifies the optimal allocation of all k items. The price for each assigned subset of items equals the second-highest bid in the matrix column for that set of items. This Vickrey pricing assures that the bidders reveal their true valuations because the bid as the revelation of a bidder's valuation for an item does determine if he gets awarded the item but does not influence the price he has to pay for it.

2.3 Simulated Trading

Simulated trading [Bachem et al. 92] is a randomized algorithm that realizes a market mechanism where the participating contractors optimize a task allocation by successively selling and buying tasks. Trading is done in several rounds, each of which consists of a number of decision cycles. In each cycle, the participants submit one offer to sell or buy a task. At the end of each round the stock manager, the central coordinating instance, matches the sell and buy offers of the contractors and informs them about the match. The stock manager tries to match the offers in such a way that the costs of the global solution decrease. This implements a kind of hill-climbing algorithm. Like in simulated annealing, a derivation that decreases from round to round can be specified: in early rounds the stock manager is willing to accept a worsening of the global solution which is helpful to leave local maxima in the solution space. Nevertheless, maxima that are left are saved, so that the best solution found up to this point in time can be returned if the algorithm terminates before a better solution is found. Hence, simulated trading is an interruptible anytime algorithm.

Originally, simulated trading was designed to improve an initial allocation. For our purpose we have extended the simulated trading algorithm such that an existing allocation is not required but can be generated during the trading process. To do so we have allowed the stock manager to state offers to sell tasks to the participants, and we have changed the matching procedure such that these offers are matched with priority, regardless that the costs of the solution increase.

3 Theoretical Analysis of the Mechanisms' Communication Complexity

In this section we investigate the communication complexities for agent-based implementations of the mechanisms described in Section 2, where the roles of the auctions' participants are taken by autonomous agents. We examine how the complexity of agent communication depends on the number n of agents and the number k of tasks to be allocated in the system.

Agent communication turns out to be a good performance indicator because in physically distributed domains, such as the transport domain, opening and using communication channels have shown to be very important limiting factors. As a measurement, we do not use the simple amount of communication acts but the overall number of communication primitives an act consists of. For the complexity analysis the decomposition of communication acts in primitives is sufficient, since

we regard that the amount of information, i.e. the number of transmitted bits, to be bounded.

Estimating computational complexity only, would be insufficient because the complexity of a computation an agent has to perform does not always have to effect the performance of another agent and the overall performance in a distributed system.

We now discuss communication complexity of the above introduced communication protocols *Vickrey auction*, *matrix auctions* and *simulated trading*. For the sake of independence of the underlying computational model we assume that agent communication is only possible in a point-to-point fashion. Hence, in this model, broadcast communication can only be realized by sequentially sending messages to communication partners. Assuming that the effort for sending messages equals the effort for receiving them, the possibility of broadcasting messages reduces the total effort for communication at most with the constant factor 2, since the effort for receiving broadcasts remains.

3.1 The Vickrey Auction

During a Vickrey auction the following communication acts are sent: a manager sends bid requests for a certain good or order to all bidders who reply with their bids. Then, the manager selects an appropriate partner, confirms the assignment of the order to this partner and sends rejects to all other bidders. Let n be the number of communicating agents. According to the point-to-point communication assumption, (n-1) requests (each of which consisting of one communication primitive) are made, followed by (n-1) bids, one confirmation and (n-2) rejects, all consisting of one communication primitive. Hence, the Vickrey auction has communication complexity of O(n) in terms of the number of participating agents.

3.2 The Matrix Auctions

In the matrix auction the auctioneer announces k items to n-1 agents $(O(k \cdot n))$. The bidders submit an offer for each of the 2^k-1 subsets of the item set, this corresponds to one communication act, consisting of 2^k-1 primitives $(O(2^k \cdot n))$. After computing the optimal allocation, the auctioneer needs (n-1) messages to inform the bidders about the final allocation (O(n)). This leads to an overall communication complexity of $O(2^k \cdot n)$. This result and the exponential computational complexity of the allocation procedure enforce small k. After fixing a sufficiently small k, a communication complexity of O(n) remains with a possibly high constant depending on k. As we will see in Section 4 k=3 is tractable even for large n while $k \geq 4$ is not tractable for n > 20.

3.3 Simulated Trading

A trading round within the simulated trading process (described in Section 2.3) consists of a fixed number of l decision levels. At each level, every contractor may announce a selling request or place a buying bid to the stock manager. The stock manager has to inform all contractors of received selling requests.

Again, let n be the number of agents participating in the negotiation. In the buying/selling announcement phase of each level, n-1 communication acts are performed. In the information phase, the stock manager has to send at most n-1 messages. Such a message may contain at most n-1 offers which are communication primitives. Hence, the complexity of one trading round is $O(l \cdot n^2)$. Since l is fixed in advance, and, hence, can be treated as constant, the communication complexity for simulated trading is $O(n^2)$.

The stock manager's task to process the trading graph (which is known to be NP-hard) does not influence communication complexity.

Summary From a theoretical point of view, all protocols have linear or at most squared complexity in terms of communication primitives. Speaking in practical terms, if only few agents take part in one of the market-based mechanisms described above, no communication bottlenecks arise which enables a good scalability of the mechanisms in terms of communication load.

However, if further processing is dependent on the final outcome of the negotiation, the measure of communication primitives is insufficient. For these reasons, we provide an empirical scalability evaluation of the mechanisms in the next section in which we examine the processing time and the overall allocative efficiency of the market-based mechanisms.

4 Empirical Evaluation

In this section, we analyze the performance of the matrix auctions (MA-k) where $k \in \{1, ..., 5\}$ orders are assigned simultaneously in comparison with the Vickrey auction and the simulated trading algorithm using the transportation domain as a testbed. Three major aspects are of concern:

- Tractability: is the algorithm suitable in terms of processing time? We have shown in the previous section that the complexity of the protocols in use is at the most squared in terms of number of communication primitives. However, the actual computing time is for some of the agents exponential. If other agents have to delay their actions until the task allocation process has been completed, processing time can be a critical issue for the usefulness of a mechanism.
- Efficiency: Which method leads to the most efficient results? Obviously, this issue depends on the chosen setting:
 - 1. A cooperative company: in this setting, the auctioneer agent represents the company and tries to minimize the overall **cost per order**. The forwarders represented by truck agents have no interest in optimizing their individual profits.
 - 2. A competitive situation, where the auctioneer does not optimize his or her profit and truck agents represent independent forwarders, e.g., drivers, working as free-lances and optimizing their **surplus per order**.

- 3. A scenario, where all, auctioneer and truck agents are rewarded. In such a case, the auctioneer tries to minimize the overall **payments per order** which is the sum of the costs and the forwarders' surplus, while the truck agents try to maximize their individual **surplus**.
- Number of trucks: Since the size of the truck fleet is an important cost factor for a shipping company, we investigate how many trucks are needed, using the different market-based mechanisms.

4.1 The Analyzed Problem Classes

For our evaluation we use the benchmarks, Solomon generated for the vehicle routing problem with time windows [Solomon 87]. Those data build up on a set of problems that Christofides et al. [Christofides et al. 79] developed for the vehicle routing problem without time constraints.

Solomon's benchmarks include six different data sets of transportation orders that have distinct characteristics concerning geometry, number of destinations, and time constraints. In particular, we distinguish between *clustered* (several groups of clients lie closely together) and non-clustered settings.

For our test runs we have averaged over three single problems². We have chosen to analyze the system outcomes for maximally clustered test data (test set = {c 101, c 102, c 103}) and completely non-clustered test data (test set = {r 101, r 102, r 103}). In contrast to the original setting where the subordinate trucks are initially located at a central depot, we have distributed the initial position of the trucks over the map, since we take also into account the setting where the trucks are independent forwarders.

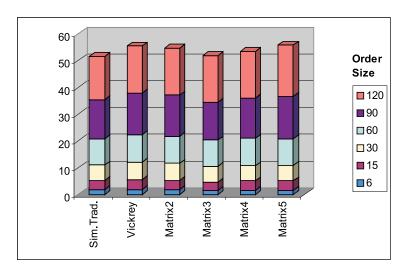


Figure 2: Number of granted trucks

Prior to the run of an experiment, the number of initial trucks in the system has to be specified. This number increases automatically if the tasks cannot be

²The use of only three problems was sufficient since tests with more problems showed that the variation of results were considerably small.

allocated to the trucks currently available. Starting with a large amount of trucks may be advantageous since their initial position is randomly distributed, leading to a rather high chance that the task to be announced is situated closely. On the other hand, the task allocation procedure takes more time for a large number of trucks. In our experiment, we have run every test twice: one time starting with two trucks initially and one time starting with the amount of trucks m needed in the test run started with 2 initial trucks (up to a maximum of 10 initial trucks). In order to examine scalability, we have run combinations of test sets for 6, 15, 30, 60, 90, and 120 orders³, leading to a total number of 422 test runs. The experiments have been performed using the MAS-MARS system which is implemented in Oz running on a 233 MHz Dual Pentium II PC with 256 MB RAM under Linux. The results of the experiments are listed in the apendix.

4.2 Results

Number of trucks The number of truck agent, being the base for our theoretical complexity analysis, depends on the size of the order set: It is increased dynamically whenever the present number of trucks is not sufficient for the planning of the task at hand.

As stated above, the number of used trucks can also influence the choice of the mechanism, since the truck fleet produces also maintenance costs a shipping company has to minimize. However, the use of different protocols leads to roughly the same number of trucks in action (Figure 2). MA-3 uses slightly less trucks than the other mechanisms.

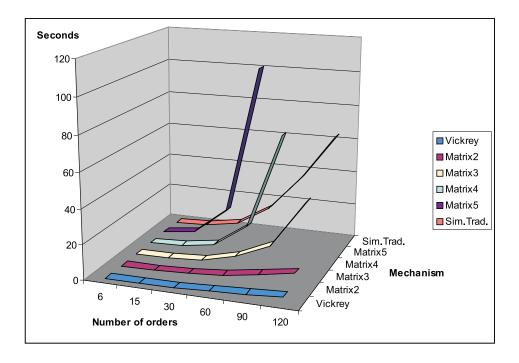


Figure 3: Run Time

³For the latter order set we enlarged Solomon's original benchmarks.

Tractability We have measured the run time of the various protocols for different number of orders. Here (and in the following) we average over quantities that are out of focus: For this examination, we have averaged over 12 results from clustered and non-clustered data sets, stemming from two or m initial trucks. Figure 3 shows the results, up to a maximum running time of 2 minutes. The figure does not contain all results from MA-4 and MA-5, since this would reduce the expressiveness of the figure. The Vickrey auction performs quite well, while the matrix auctions' running time is growing very fast with an increasing number of orders. (While the Vickrey mechanism could allocate 120 orders in 3.4 seconds, the test runs of MA-4 with 120 orders took about 15 minutes and MA-5 with 120 orders took more than 6 hours each.) Tractability is no longer fulfilled in such cases.

Performance differences between clustered and non-clustered data sets were significant only for MA-4 and MA-5 with high numbers of orders. In extreme cases, processing non-clustered orders took up to 50 times longer than clustered ones. Similarly, starting with two initial trucks only outperformed starting with m initial trucks at MA-4 and MA-5 with high numbers of orders in a significant fashion. In all other cases, no significant difference could be found.

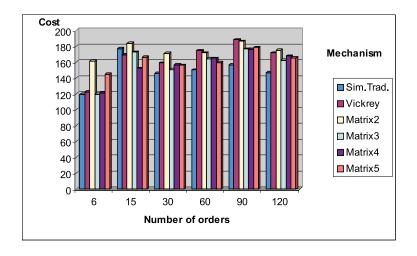
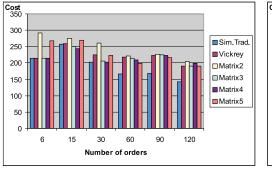


Figure 4: Overall cost per order



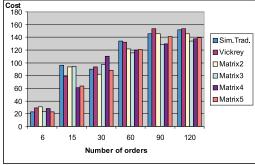


Figure 5: Overall cost per order for non-clustered and clustered settings

As the theoretical analysis has already indicated, the runtime of the MA-4 and MA-5 are intractable for large sets of orders while the others can be rated as tractable.

Efficiency for the cooperative setting As stated above, for such a setting, cost per order is the crucial issue. Figure 4 shows the overall results.

Generally speaking, all protocols show rather similar results. However, the simulated trading procedure is proved to be most efficient for large order sets where much optimization can be done. MA-3 and MA-4 perform slightly better than the remaining protocols. Hence, ST would be the protocol of choice for the auctioneer. Comparing the settings with 2 and m initial trucks, no major difference could be found; the m-truck setting performs slightly better.

Interesting though, is the discrepancy between clustered and non-clustered settings (Figure 5). Generally speaking, the costs for the performance of clustered task sets are lower than in the non-clustered setting, since trucks mostly act within one cluster. This effect vanishes for large order sets.

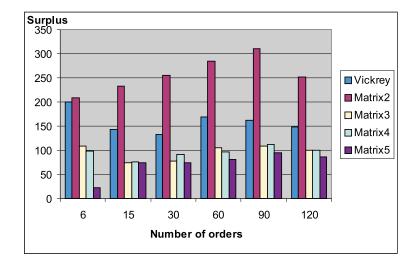


Figure 6: Overall surplus per order

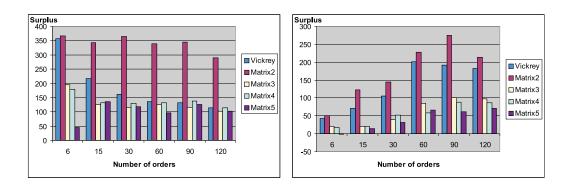


Figure 7: Overall surplus per order for non-clustered and clustered settings

In the case of clustered orders simulated trading looses its advantages over the matrix auctions, in such settings MA-3 and MA-4 outperform the other mechanisms mainly for tasks of 60 and more orders. This matches the intuition that it is cost efficient to allocate bundled tasks in clusters.

Efficiency for the competitive setting In a setting, where only trucks optimize their benefit, their individual surplus has to be compared (Figure 6). In this setting and in the hybrid one Simulated trading is not applicable because it requires cooperative agents.

MA-2 outperforms dominantly all other mechanisms, followed by the Vickrey auction. Figure 7 shows differences between non-clustered and clustered cases: for clustered cases, the Vickrey auction performs almost as well as MA-2, which is not the case in the non-clustered case. In general, surplus in the non-clustered case is roughly independent of the number of trucks, which again is not true for the clustered case.

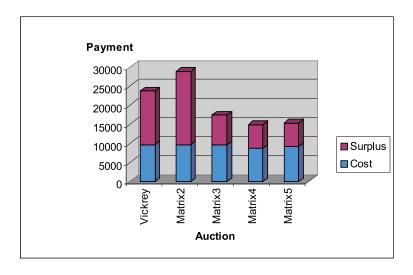


Figure 8: Payment for 60 orders

Efficiency for the hybrid setting In a setting where all, auctioneer and truck agents compete for profit, both surplus and cost have to be taken into account, since truck agents strive to maximize surplus, while the auctioneer tries to minimize the overall payments, i.e., the sum of cost and surplus. The goals of auctioneer and bidders conflict; hence, the protocol to be chosen then depends on the influence or power of the auction participants.

However, costs do not vary significantly, as Figure 8 shows for a representative example, where 60 orders were processed (starting with m=10 initial trucks). Hence, the expected surplus will determine the common choice (which is MA-4 in the case that the auctioneer is dominant and MA-2 if the truck agents are dominant).

5 Conclusion

In this paper, we have presented a theoretical complexity analysis of several market-based mechanisms for task allocation in terms of communication acts. The various mechanisms have been implemented and empirically evaluated in the domain of vehicle routing. For this purpose the mechanisms have been integrated into the MAS-MARS system for fleet scheduling, which offers convenient opportunities for testing their allocative efficiency.

ST, VA, MA-2, and MA-3 can be rated as scalable, while MA-5 and, for large order sets, MA-4 do not provide better results, but loose tractability, indicating that matrix auctions where six or even more items are traded in parallel are not expected to be particularly efficient.

In the cooperative setting the simulated trading procedure produces generally the best results with tractable effort. Nevertheless, MA-3 achieves acceptable results as well. The MA-2 procedure ensures a maximal payoff for the self-interested forwarders. In the hybrid setting the VA or various matrix auctions can be taken into consideration depending on the character of the compromise found between global and local interests.

Currently at DFKI a system for practical fleet scheduling is being developed in close cooperation with a transportation company [Bürckert et al. 98]. This system will be extended to enable collaboration between different companies within a cooperative network.

In future work, we will extend the MAS-MARS system with leveled commitment allocation procedures, to allow the truck agents to de-commit from previously made allocation decisions. Furthermore, we will investigate whether the presented results can be transferred to other application domains and how the proposed mechanisms can be used e.g. for the coordination of virtual marketplaces and the formation and operation of virtual enterprises.

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Apendix
Results of the Vickrey Auction

			2 init	ial truck	S		n initial trucks					
no.	order	run- no. sur- pay-						no.		sur-	pay-	
ord.	set	$_{ m time}$	tr.	cost	$_{ m plus}$	ments	$_{ m time}$	tr.	cost	$_{ m plus}$	ments	
6	r101	0.03	2	1577	1700	3277	0.03	2	1577	1700	3277	
	r102	0.04	2	1149	2368	3517	0.04	2	1149	2368	3517	
	r103	0.04	2	1149	2368	3517	0.04	2	1149	2368	3517	
	c101	0.03	2	140	290	430	0.03	2	140	290	430	
	c102	0.04	2	191	239	430	0.04	2	191	239	430	
	c103	0.04	2	191	239	430	0.04	2	191	239	430	
15	r101	0.1	6	5173	1805	6978	0.11	6	2270	3822	6092	
	r102	0.11	5	4526	3255	7781	0.11	5	3304	3810	7114	
	r103	0.1	5	4812	3390	8202	0.12	5	3304	3473	6777	
	c101	0.11	2	895	1028	1923	0.11	2	895	1028	1923	
	c102	0.07	2	1324	871	2195	0.07	2	1324	871	2195	
	c103	0.08	2	1324	1273	2597	0.08	2	1324	1273	2597	
30	r101	0.35	11	10395	2393	12788	0.51	9	4572	4699	9271	
	r102	0.35	9	8300	4439	12739	0.41	8	5266	5950	11216	
	r103	0.28	7	7372	5885	13257	0.45	7	4406	5716	10122	
	c101	0.19	3	1695	1028	2723	0.23	4	2080	4765	6845	
	c102	0.22	4	3619	2716	6335	0.33	9	3621	3316	6937	
	c103	0.18	3	2639	3300	5939	0.25	3	3247	3734	6981	
60	r101	1.38	17	16949	4085	21034	1.86	16	12533	9064	21597	
	r102	1.16	14	14844	9800	24644	1.43	14	12281	7256	19537	
	r103	1.22	12	13785	8661	22446	1.35	12	7819	9960	17779	
	c101	0.73	6	5352	2012	7364	0.98	7	8024	16721	24745	
	c102	0.64	7	8020	6321	14341	1.11	7	9368	20063	29431	
	c103	0.87	7	8624	6299	14923	0.97	6	8235	20935	29170	
90	r101	2.49	24	26585	5169	31754	3.16	24	19166	12042	31208	
	r102	2.3	20	23409	15598	39007	3.32	19	18727	10561	29288	
	r103	2	17	19465	13283	32748	2.68	18	13053	14964	28017	
	c101	1.14	10	10936	6615	17551	2.4	12	15044	22103	37147	
	c102	1.58	10	12779	13157	25936	2.14	11	14151	23160	37311	
	c103	1.13	10	14259	13733	27992	1.92	10	15762	24715	40477	
120	r101	4.22	27	29427	5821	35248	4.59	25	21409	13149	34558	
	r102	3.63	22	25812	16328	42140	4.37	21	21437	12142	33579	
	r103	3.53	21	22166	17735	39901	4.89	18	16590	17757	34347	
	c101	2.51	12	13623	10882	24505	2.98	14	18010	24690	42700	
	c102	2.22	12	15800	19234	35034	2.76	13	20106	29106	49212	
	c103	2.71	12	19163	19327	38490	2.8	13	23683	27845	51528	

Results of the MA-2 Auction

			2 init	ial truck	S		n initial trucks					
no.	order	run- no. sur- pay-					run-	no.		sur-	pay-	
ord.	set	$_{ m time}$	tr.	cost	$_{ m plus}$	$_{ m ments}$	$_{ m time}$	tr.	cost	$_{ m plus}$	ments	
6	r101	0.05	2	1753	2199	3952	0.05	2	1753	2199	3952	
	r102	0.05	2	1753	2199	3952	0.05	2	1753	2199	3952	
	r103	0.05	2	1753	2199	3952	0.05	2	1753	2199	3952	
	c101	0.05	2	180	300	480	0.05	2	180	300	480	
	c102	0.06	2	185	300	485	0.06	2	185	300	485	
	c103	0.07	2	185	300	485	0.07	2	185	300	485	
15	r101	0.28	6	5481	6030	11511	0.36	6	4406	5157	9563	
	r102	0.25	5	4937	5504	10441	0.42	4	3401	4929	8330	
	r103	0.2	3	3038	3636	6674	0.34	4	3401	5540	8941	
	c101	0.16	2	1404	1842	3246	0.16	2	1404	1842	3246	
	c102	0.13	2	1404	1842	3246	0.13	2	1404	1842	3246	
	c103	0.18	2	1404	1842	3246	0.18	2	1404	1842	3246	
30	r101	1.33	11	10589	12605	23194	1.5	10	6914	11390	18304	
	r102	1.35	11	10589	12605	23194	1.65	11	5664	9682	15346	
	r103	0.82	7	8109	9288	17397	1.01	7	5040	9999	15039	
	c101	0.51	3	1735	3221	4956	0.51	3	1762	4986	6748	
	c102	0.48	3	2204	3165	5369	0.64	4	3248	5490	8738	
	c103	0.42	3	2674	3798	6472	0.68	3	3197	5325	8522	
60	r101	3.88	17	15306	20548	35854	4.36	16	14400	25024	39424	
	r102	3.02	13	14606	21785	36391	3.18	13	11761	18040	29801	
	r103	2.47	10	13429	17276	30705	3.28	12	10250	19407	29657	
	c101	1.36	6	5392	8412	13804	1.65	6	5332	19886	25218	
	c102	1.5	7	7022	8516	15538	2.08	7	7497	15364	22861	
	c103	1.53	7	9515	13066	22581	2.23	7	9066	16991	26057	
90	r101	7.57	24	22149	31215	53364	8.62	23	21952	34915	56867	
	r102	6.95	21	23831	34404	58235	7.36	20	19288	30542	49830	
	r103	5.49	18	19325	26237	45562	6.58	18	15822	28943	44765	
	c101	3.2	10	10973	17427	28400	4.51	10	10528	32526	43054	
	c102	3.09	10	13260	15615	28875	4.69	11	13670	26712	40382	
	c103	3.15	10	15499	23642	39141	4.96	10	14861	32655	47516	
120	r101	13.7	24	25507	35998	61505				_	_	
	r102	15.7	24	25507	35998	61505	-	_	-	-	-	
	r103	9.75	20	22639	32212	54851	-	_	-	-	-	
	c101	4.43	12	13791	22200	35991	-	_	-	-	-	
	c102	4.9	13	18443	24438	42881	-	_	-	-	-	
	c103	5.48	12	20268	30238	50506	-	-	-	-	-	

Results of the MA-3 Auction

			2 initi	ial trucks	5		n initial trucks				
no.	order	run-								sur-	pay-
ord.	set	$_{ m time}$	tr.	cost	$_{ m plus}$	$_{ m ments}$	$_{ m time}$	tr.	cost	$_{ m plus}$	ments
6	r101	0.17	2	1577	1176	2753	0.17	2	1577	1176	2753
	r102	0.11	2	1149	1176	2325	0.11	2	1149	1176	2325
	r103	0.14	2	1149	1176	2325	0.14	2	1149	1176	2325
	c101	0.12	1	140	127	267	0.12	1	140	127	267
	c102	0.11	1	145	122	267	0.11	1	145	122	267
	c103	0.11	1	145	122	267	0.11	1	145	122	267
15	r101	0.77	6	4377	2037	6414	0.81	5	2987	1682	4669
	r102	0.54	4	3807	2117	5924	0.54	4	3816	2364	6180
	r103	0.52	4	3804	1466	5270	0.54	4	3813	1713	5526
	c101	0.27	2	1505	295	1800	0.27	2	1505	295	1800
	c102	0.39	2	1364	320	1684	0.39	2	1364	320	1684
	c103	0.3	2	1364	320	1684	0.3	2	1364	320	1684
30	r101	2.7	11	9222	4064	13286	3.31	9	5959	3096	9055
	r102	2.2	8	7996	2842	10838	2.08	7	4873	4377	9250
	r103	1.4	6	6414	3810	10224	1.67	6	2452	2761	5213
	c101	0.92	4	3362	932	4294	0.59	4	2860	1304	4164
	c102	0.73	3	2186	899	3085	0.66	4	2918	1552	4470
	c103	0.55	3	2897	725	3622	1.19	4	3216	1739	4955
60	r101	9.58	16	14244	7660	21904	8.84	15	13325	6565	19890
	r102	7.16	13	13982	7578	21560	9.79	13	11000	7709	18709
	r103	5.52	11	13407	8287	21694	10.06	11	11000	7709	18709
	c101	3.46	7	6882	932	7814	5.08	8	8659	8901	17560
	c102	2.82	6	5922	2648	8570	4.49	7	6936	8899	15835
	c103	3.16	6	6732	2336	9068	4.78	6	6511	6934	13445
90	r101	19.09	22	23043	10226	33269	11.67	11	20952	9626	30578
	r102	28.03	22	22842	10456	33298	30.66	22	20474	10898	31372
	r103	13.61	16	18139	10885	29024	21.38	17	15994	10771	26765
	c101	7.08	10	10207	1748	11955	11.33	11	12874	8786	21660
	c102	7.56	10	10233	4018	14251	12	10	10572	18410	28982
	c103	4.7	9	12793	4873	17666	12.15	9	12676	16432	29108
120	r101	67.84	25	26421	11067	37488	90.55	26	23637	10473	34110
	r102	76.24	24	25993	12308	38301	84.64	24	23392	13175	36567
	r103	37.76	18	20487	12961	33448	49.56	19	17612	13224	30836
	c101	12.12	12	12531	3959	16490	20.17	13	14957	11557	26514
	c102	11.95	12	16378	6917	23295	20.99	13	16091	22646	38737
	c103	11.25	11	18416	7535	25951	20.66	12	18152	17906	36058

Results of the MA-4 Auction

			2 initi	ial trucks	3		n initial trucks				
no.	order	run-	no.		sur-	pay-	run-	no.		sur-	pay-
ord.	set	$_{ m time}$	tr.	cost	$_{ m plus}$	ments	$_{ m time}$	tr.	cost	$_{ m plus}$	ments
6	r101	0.24	2	1577	970	2547	0.24	2	1577	970	2547
	r102	0.23	2	1149	1128	2277	0.23	2	1149	1128	2277
	r103	0.39	2	1149	1128	2277	0.39	2	1149	1128	2277
	c101	0.2	1	159	135	294	0.2	1	159	135	294
	c102	0.35	1	175	85	260	0.35	1	175	85	260
	c103	0.2	1	175	85	260	0.2	1	175	85	260
15	r101	1.81	6	4377	2974	7351	1.81	4	2918	1122	4040
	r102	1.11	4	3854	2035	5889	1.06	4	3454	1862	5316
	r103	0.9	4	3854	2035	5889	1.32	4	3454	1862	5316
	c101	0.34	3	108	312	420	1.08	3	1052	350	1402
	c102	0.82	3	1135	251	1386	0.921	3	1044	358	1402
	c103	0.83	3	1135	251	1386	1	3	1044	358	1402
30	r101	4.75	8	7066	3466	10532	6.54	7	4480	3685	8165
	r102	2.41	6	6793	4114	10907	4.99	7	6172	5361	11533
	r103	3.2	6	7659	3229	10888	4.96	6	4406	3599	8005
	c101	5.48	7	6172	5361	11533	7.25	6	2492	852	3344
	c102	1.94	4	2501	680	3181	2.29	4	2901	744	3645
	c103	1.72	3	2869	959	3828	2.31	3	2923	642	3565
60	r101	23.78	14	14794	8619	23413	3.28	15	10822	8431	19253
	r102	28.6	14	14351	8365	22716	57.96	15	10464	6140	16604
	r103	16.52	12	15820	7112	22932	33.32	11	9172	9016	18188
	c101	7.4	7	6808	2295	9103	14.34	8	7009	4225	11234
	c102	0.8	7	7011	2022	9033	14.61	7	7681	5442	13123
00	c103	6.79	6	7575	3693	11268	1.28	7	7217	3540	10757
90	r101	85.38	22	22996	14327	37323	114.4	23	19130	13140	32270
	r102 r103	82.11	19 18	21768 20876	15097 11660	$36865 \\ 32536$	$262.5 \\ 60.4$	$\frac{23}{15}$	19996 15234	$8492 \\ 11932$	$28488 \\ 27166$
	c101	$111.8 \\ 15.29$	10	10157	4672	14829	45.39	11	13234 12535	11932 11469	$\frac{27100}{24004}$
	c101	17.6	10	10137	$\frac{4072}{2501}$	13198	48.5	10	12035 12035	12039	$\frac{24004}{24074}$
	c102	16.86	10	14594	5704	$\frac{13198}{20298}$	5.62	10	12033 10082	12039 10817	20899
120	r101	974.3	$\frac{10}{25}$	26829	$\frac{5704}{15238}$	42067	1003	25	$\frac{10082}{21739}$	14046	35785
120	r101	410.4	23	20529 24523	15236 17337	42067	1063	$\frac{25}{25}$	$\frac{21739}{22795}$	14040 10975	33770
	r102	254.2	20	24323	14810	39113	10.49	$\frac{20}{20}$	$\frac{22795}{22639}$	9573	$\frac{33770}{32212}$
	c101	47.81	12	13409	6743	$\frac{39113}{20152}$	79.37	13	15150	13103	$\frac{32212}{28253}$
	c101	38.12	12	15409 15424	8569	23993	68.69	12	17868	14946	$\frac{23233}{32814}$
	c102	34.48	11	21449	7183	28632	82.43	$\frac{12}{12}$	15715	12113	$\frac{32814}{27828}$
	(100	94.40	11	41449	1109	20002	04.40	14	10110	14110	21020

Results of the MA-5 Auction

			2 initi	al trucks	3		n initial trucks				
no.	order	run- no. sur- pay-					run-	no.		sur-	pay-
ord.	set	time	tr.	cost	plus	ments	$_{ m time}$	tr.	cost	plus	ments
6	r101	0.64	2	1577	411	1988	0.64	2	1577	411	1988
	r102	0.68	2	1614	197	1811	0.68	2	1614	197	1811
	r103	0.73	2	1614	197	1811	0.73	2	1614	197	1811
	c101	0.43	2	140	1	138	0.43	2	140	1	138
	c102	0.69	1	140	1	128	0.69	1	140	1	128
	c103	0.75	1	140	1	128	0.75	1	140	1	128
15	r101	4.82	5	4639	1829	6468	6.23	6	3170	3232	6402
	r102	5.38	5	4403	2047	6450	0.66	4	3322	2087	5409
	r103	4.23	4	4715	1280	5995	3.96	4	3955	1781	5736
	c101	1.88	2	895	357	1252	1.88	2	895	357	1252
	c102	2.66	3	977	193	1170	2.66	3	977	193	1170
	c103	0.26	2	1006	66	1072	0.26	2	1006	66	1072
30	r101	26.14	11	9254	3073	12327	77.78	10	5280	4586	9866
	r102	13.77	8	8204	2800	11004	32.29	8	4686	4586	9272
	r103	10.37	6	8117	1539	9656	32.29	8	4686	4586	9272
	c101	3.65	3	1695	923	2618	4.24	3	2064	1010	3074
	c102	5.67	4	2906	1589	4495	4.94	3	2458	1392	3850
	c103	4.45	3	3465	70	3535	5.83	3	3339	622	3961
60	r101	14.52	15	13945	6394	20339	245.1	16	11999	7771	19770
	r102	96.6	13	13134	4427	17561	264	14	11518	7957	19475
	r103	97.59	13	13134	4427	17561	298.7	8	7834	3810	11644
	c101	20.92	7	6237	3039	9276	61.21	7	6558	6546	13104
	c102	33.58	7	6758	2023	8781	52.9	6	6991	6573	13564
	c103	22.2	6	7169	810	7979	44.9	7	9774	4581	14355
90	r101	928.8	24	22281	10417	32698	2002	23	18489	11321	29810
	r102	231.5	21	19558	12339	31897	2470	22	20729	13020	33749
	r103	552.4	17	20302	9588	29890	907.8	22	15380	11798	27178
	c101	58.75	10	10296	6669	16965	254.5	11	12111	11105	23216
	c102	68.65	9	13034	2228	15262	70.29	9	13034	2228	15262
	c103	91.84	11	12488	2350	14838	390.7	10	15273	8463	23736
120	r101	19402	26	24623	12013	36636	14516	25	21202	12582	33784
	r102	-	-	-	-	-	-	-	-	-	-
	r103	-	_	-	-	-	-	-	-	-	-
	c101	317.6	12	13201	7932	21133	525.4	13	15013	12436	27449
	c102	251.6	13	17655	5221	22876	513.7	13	18570	14021	32591
	c103	161.2	12	17063	2630	19693	775.3	13	18990	8839	27829

Results of the Simulated Trading

		2 init	ial trucks		n initial trucks			
no.	order	run-	no.		run-	no.		
orders	set	$_{ m time}$	${ m trucks}$	$\cos t$	$_{ m time}$	${ m trucks}$	$\cos t$	
6	r101	0.27	2	1577	0.27	2	1577	
	r102	0.2	2	1149	0.2	2	1149	
	r103	0.23	2	1149	0.23	2	1149	
	c101	0.2	2	140	0.2	2	140	
	c102	0.2	2	140	0.2	2	140	
	c103	0.28	2	140	0.28	2	140	
15	r101	1.04	5	4380	1.31	6	2973	
	r102	0.81	4	3960	0.91	4	3960	
	r103	0.84	4	3960	0.85	4	3960	
	c101	0.54	2	895	0.54	2	895	
	c102	0.6	2	1712	0.6	2	1712	
	c103	0.49	2	1712	0.49	2	1712	
30	r101	8	10	8573	6	10	4227	
	r102	5	8	7388	6	8	5318	
	r103	4	7	6562	4	7	4400	
	c101	3	3	1717	3	4	2592	
	c102	3	4	2597	3	3	3094	
	c103	3	3	3166	2	3	2970	
60	r101	28	14	12205	23	14	10650	
	r102	16	12	10594	18	13	9912	
	r103	14	10	9457	19	10	6946	
	c101	12	7	6121	14	8	7930	
	c102	9	8	8947	15	9	9530	
	c103	10	6	6523	11	7	9388	
90	r101	74	21	18085	88	22	16701	
	r102	52	18	14556	48	20	16538	
	r103	27	14	13537	31	15	11240	
	c101	17	10	10608	22	12	14094	
	c102	17	10	12483	21	11	16869	
	c103	21	9	11879	28	11	12857	
120	r101	115	22	20300	175	23	17540	
	r102	75	20	18644	97	21	17123	
	r103	58	16	15668	58	16	12726	
	c101	29	12	12931	36	14	16982	
	c102	29	13	19595	30	13	20519	
	c103	30	13	16434	30	13	23018	

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