CARGO TRANSPORTATION MODELS ANALYSIS USING MULTI-AGENT ADAPTIVE REAL-TIME TRUCK SCHEDULING SYSTEM

Oleg Granichin[1], Petr Skobelev[2], Alexander Lada [2], Igor Mayorov [2], Alexander Tsarev [2]
[1]*Saint Petersburg State University, Saint Petersburg, Russia*
[2]*Smart Solutions, Ltd, Samara, Russia*
Oleg_granichin@mail.ru, skobelev@smartsolutions-123.ru

Keywords: multi-agent systems, adaptive scheduling, trucks, cargo transportation, simulation, real-time, mobile resources.

Abstract: The use of multi-agent platform for real-time adaptive scheduling of trucks is considered. The schedule in such system is formed dynamically by balancing the interests of orders and resource agents. The system doesn't stop or restart to rebuild the plan of mobile resources in response to upcoming events but finds out conflicts and adaptively re-schedule demand-resource links in plans when required. Different organizational models of cargo transportation for truck companies having own fleet are analyzed based on simulation of statistically representative flows of orders. Models include the rigid ones, where trucks return back to their garage after each trip, and more flexible, where trucks wait for new orders at the unloading positions, where trucks can be late but pay a penalty for this, and finally where orders can be adaptively rescheduled 'on the fly' in real-time and the schedule of each truck can change individually during orders execution. Results of simulations of trucks profit depending on time period are presented for each model. These results show measurable benefits of using the multi-agent systems with real-time decision making - up to 40-60% comparing with rigid models. The profit dependencies on the number of trucks are also built and analyzed. The results show that using adaptive scheduling in real time it is possible to execute the same number of orders with less trucks (up to 20%).

1 INTRODUCTION

The problem of resource allocation, scheduling and optimization are usually solved taking well defined initial conditions, when all the orders and resources are given in advance and don't change in the process of scheduling. In these cases classical batch planning methods and tools can be used characterized by the time-consuming full or constrained combinatorial search or different types of heuristics still requiring a lot of computational power (Leung, 2004).

For solving complex problems of real time resource allocation, scheduling, optimization and controlling we apply multi-agent technology (Bonabeau, 2000, Wooldridge, 2002) allowing us to find acceptable solutions of problem by using adaptive scheduling of resources.

The adaptive scheduling approach we are working on is based on Demand-and-Resource Networks (DRN) of agents representing orders and resources (Vittikh, 2003, Skobelev, 2010). Agents can have conflicting interests, an ability to react to incoming events notifying about changes in orders and resources, find out conflicts in the schedule, make decisions and interact with each other in a way to resolve the conflicts and find trade-offs by negotiations. That allows us to find a 'well-balanced' solution acceptable for all the agents as well as for company as a whole.

Despite of the simplicity of the basic classes of agents and the logic of their competition and cooperation, which are described in more details in (Skobelev, 2011), the developed multi-agent technology allows us to solve complex resource allocation, scheduling and optimization problems in real time when the number of orders and resources is not given in advance and there is a high dynamics of occurring events (Basra, 2005, Himoff, 2006, Skobelev, 2010).

One of such problems is the cargo transportation scheduling in real time, when the time required for decision strongly affects efficiency of the transportation. In this paper we show that real-time decision making and adaptive scheduling provide significant advantages for cargo transportation.

The results of the research are important for the future developments of intelligent freight management systems and dispatching of any other mobile resources that are equipped with GPS sensors, have online connection with drivers via mobile phones and are able to operate in real time.

2 THE PROBLEM DEFINITION

Let's assume that we have a fleet of M trucks based in certain cities in a transportation network. The operation cost of each truck is given. Orders come into the system with the specified points of loading, points of unloading, loading start time, unloading finish time, order price and penalties for delays when a loading or unloading is done later than they should. Distances between points are also given and described by a matrix of distances.

The objective is to schedule the trucks in real time and determine transportation company profit depending on the scheduling strategy (model) and the number of trucks. Real-time scheduling means that at each particular moment only such orders are considered that have come before this moment. The optimization criterion of the task is the maximal total profit of all the trucks in company fleet.

The research is done for four different models of organization of transportation process including not-adaptive and adaptive models described below.

3 THE MODELS OF TRANSPORTATION PROCESS ORGANIZATION

The total profit of the fleet of trucks is calculated as a sum of profits of each truck:

$$P = \sum_i p_i . \tag{1}$$

The profit of one truck is:

$$p_i(t) = \sum_j \{(c_j - q_i)t_{ij} - q_i t'_{ij}\} \tag{2}$$

where sum includes all orders j executed by the truck i, c_j - price of order j per time unit, q_i – cost of the truck per time unit, t_{ij} - time of execution order j by truck i, t'_{ij} – empty run time for order j.

Below we consider four different models (strategies) of cargo transportation:

1) The 'Returning to base after an order execution';
2) The 'No return to base after an order execution';
3) The 'Delays with penalties';
4) The 'Adaptive scheduling with penalties'.

Model 1 – The 'Returning to base after an order execution' model. After each order execution the truck should return to the base point. Order is assigned to a truck that has a "window" in its schedule during the order time period. If the loading point of the order is a different city, then the truck should arrive there at the loading time. No reassignments of the trucks already assigned to the orders are allowed.

Model 2 – The 'No return to base after an order execution' model. After each order execution truck stays at the order destination point, without returning to base, and waits for a next order.

Model 3 – The 'Delays with penalties' model. Orders can be scheduled with delays of time of arrival at the loading point.

In this case profit with penalty calculation is:

$$p_i(t) = \sum_j \{(c_j - q_i)t_{ij} - q_i t'_{ij}\} + \sum_k \{(c_k - q_k)t_{ik} - q_i t'_{ik} - p_k t''_{ik}\} \tag{3}$$

where the sum by index j includes all orders that were executed just in time by the truck i, the sum by index k includes all orders that were executed with delays t''_{ik}, p_j – penalty of each delay per time unit.

Model 4 – The 'Adaptive scheduling with penalties' model. It is equal to the previous model, but it allows the truck reassignment when a profit from a new order is higher than a profit from the previous one. So then a new order comes, the reassignment starts and it reorganizes part of orders that are already assigned to resources, in order to find a more profitable solution.

4 OVERVIEW OF THE MULTI-AGENT SIMULATOR OF REAL-TIME SCHEDULING SYSTEM FOR CARGO TRANSPORTATION

A special multi-agent simulator (MAS) has been created for modeling of adaptive real time scheduling. This system provides functionality for simulation and experimenting with the flows of modeled orders, randomly generated or manually constructed. It works as follows. Every truck is associated with a truck agent, every order – with an order agent. The agents are able to send and receive messages in MAS-environment and take decisions according to their logic and current situation, which is de-fined by state of every agent. The unified spatio-temporal scale is defined to achieve visibility of results and unified logic: time is counted from the start of the modeling process, i.e. from the moment of the first order entry. The upper border of planning is determined by the planning horizon, calculated in days. The distances are brought to time scale by division of the distances by the average speed. By doing this, we can account for quality conditions and traffic capacity of roads (that's why longer road can result in shorter trip due to higher speed, it allows).

Current states of agents are changing and are measured when new orders come into the system and at the moments of start and finish of execution of each order. That's why the scale of N orders in general case consists of 3N points.

When a new order comes into the MAS-system, a request for its allocation is sent to all the truck agents. Then the agents analyze their current state, availability of 'time slots' in the future schedule, need for empty run to loading point, assess their possible profit and send answer to the order agent. 'Candidates' for re-scheduling (in case of increasing profit) are ordered of the prospective profit. Then the order agent chooses the truck that gives the maximal profit. The profit is calculated as a difference between the order revenue (price) and the order full cost. When order implies an empty run to loading point, its cost is also deducted from the revenue. That's why orders with high revenue, but long empty runs to loading points, can be ousted by orders with lower revenue, but without empty runs. In case of strategy (model), where penalties are applied, their influence on profit is analyzed. For penalty is proportional to time of delay, the orders with big delays will not be scheduled. Orders in the past (earlier than the current time) do not participate in the scheduling.

The process continues by processing of the events of order arrival, start and finish of order execution, simulating real-time order management.
In the process of research the above 4 models of cargo transportation were implemented and compared to show benefits of adaptive scheduling.

5 WORLD OF SIMULATIONS

Let's consider world of simulations and example of calculation of fleet profit in adaptive real time scheduling for one truck. Let's look at the example.

There are 4 cities (points) given, among which the distances are determined by the matrix (see Table 1) in days of trip. Time of trip doesn't necessarily correspond to the distance, because quality of roads may be different that affects the maximum speed of truck on the roads.

Table 1: Matrix of distances among cities.

	Point 1	**Point 2**	**Point 3**	**Point 4**
Point 1	0	1	1	2
Point 2	1	0	2	1
Point 3	1	2	0	1
Point 4	2	1	1	0

Table2: Parameters of orders.

Characteristics	**Order number**				
	1	**2**	**3**	**4**	**5**
Time of entry	1	3	5	6	7
Start time of execution	3	4	7	8	9
Finish time of execution	5	5	9	9	10
Where from	4	3	1	4	3
Where to	1	1	4	3	1

At the beginning of the trip the truck is located in the point 1.

At different times cargo transportation orders #1-5 to different points come into the system. Duration of execution of an order is 1-2 days. Scheduling horizon equals t = 10 days. The costs of orders are calculated equally using company tariff as c = 3 standard units (SU) / day, i.e. 2-days trip would have cost of 6 SU. Idle time of a truck leads to daily loss of qa=0.3 SU. Use 15-point type for the title, aligned to the center, linespace exactly at 17-point with a bold font style and all letters capitalized. No formulas or special characters of any form or language are allowed in the title.

Daily running cost in case of empty run of truck or order execution is q=1. Drivers are allowed to execute orders with delays, but every day of delay costs $pp = 0.6$ *SU*. Some orders are shifted to the right on the time axis because of this. The aim is to be able to schedule trips, as orders come in (the orders are not known in advance) and calculate profit.

Orders are marked with a number according to the place in the sequence of entry into the system and characterized by time of their entry (moment of entry t), moments of start and finish of order execution, duration (in days), point of loading and point of unloading (Table 2).

Figure 1 shows orders as rectangles, with the order number and the time of entry, divided by comma inside the rectangle, above each rectangle ’where from – where to‘ locations are described. The start and the finish of each rectangle correspond to the start and the finish of the order execution.

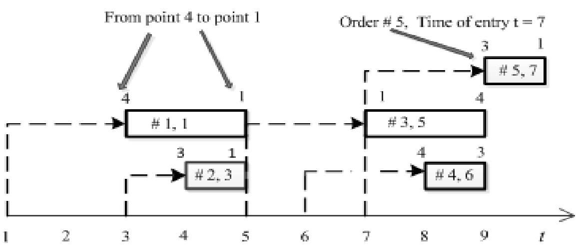

Figure 1: Diagram of orders entry and scheduling.

Let’s calculate the profit of truck# 1 in the Model #3, where penalties are applied. We will calculate the profit *v* at the moments of transition of the truck from one state to another. Let’s look at the step by step profit calculation.

Execution of order #1 will require to start at the moment *t*=1 from point #1 to point # 4 and will take 2 days till the moment *t*=3. At the moment *t*=3 the profit is *P*=-*q**2=-2. Let’s show the change of the profit *P* in real time (Figure 2).

The transportation of cargo from point 4 to the point 1 will take 2 days, and at t=5 the truck will arrive at the point 1 with the profit *p*=-2+(*c*-*q*)*2=-2+2*2=2.

Assume that the truck agent assesses options of further schedule and execution upon arrival to point 1 at time *t*=5. Its profit at point 4 is *v*=2. By this time order # 3 has been entered at the moment of time #3. There are two options to execute it:

- Order #2 is to be executed with delay;
- Order #2 is rejected, idle time cost is accepted, order #3 from the same point 1 is to be taken; for order # 2 can be executed with delay before execution of order #3, no further options will be taken into consideration. Let’s take a more precise look at 2 options.

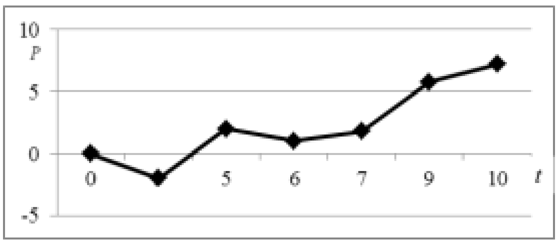

Figure 2: Profit of truck agent depending on time.

Truck needs to reach point 3, moving from point 1 (1 day trip), pick up the order and execute it, going from point 3 to point 1 (1 day). The increase of profit is *dp*=-1**q*+(*c*-*q*)*1=-1+2=1.

Penalty applied because of delay is -*pp**2=-2*0.6=-1.2. As a result the truck will be at the moment *t*=7 at the point 1 with the profit *P*=2+1-1.2=1.8. Execution of the order would seem to be unprofitable, but one should take into consideration that in case of cancellation of the order the truck would stay idle for 2 days, and the profit at the moment *t*=7 would be *P*=2-2*0.3=1.4.

That’s why the truck agent is interested in the execution of order #2 with delay, order #3, *t= 7…9* (from point 1 to point 4) - 2 days, profit is *P*=1.8+2*(*c*-*q*)=1.8+2*2=5.8, and the truck moves to point 4.

At the moment *t*=9 new order# 5 comes in at the point 3 with start time of execution *t*=9; empty run to its loading point is 1 day, what puts the order beyond the 10-days scheduling horizon limit. That’s why the truck agent rejects the order. There is an outdated order #4 from point 4 to point 3, its execution start time should be *t*=8. The truck agent assesses profit from possible shift of order by a day.

Execution of the order #4, empty run is not required, *dp*=(3-1)*1=2-*penalty* 0.6=1.4. If this order were rejected, the truck would stay idle for 1 day till the end of the scheduling horizon and then *dp*=-1*0.3=-0.3.. That’s why the truck agent accepts the order #4.

Outcome: orders #1 and 3 are executed without delay, order #2 – with allowed delay of 2 days and order #4 – with allowed delay of 1 day. Order #5 is rejected (Figure 3).

Total profit in 10 days is *P*=5.8+1.4=7.2.

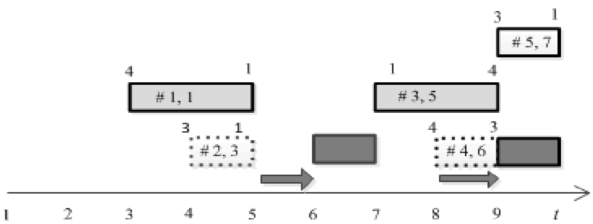

Figure 3: Diagram of execution of adaptive schedule by one truck.

The delayed orders on Figure 3 are shown with dark grey, when penalties are applied; light grey marks orders without delay; shifts in schedule are shown with wide arrows; shifted orders are shown with dotted borders; rejected order is white (not visible). White arrows stand for empty runs, light grey ones – executions of orders with delay; dark grey ones – executions of orders on time.

As a larger-scale example, task of scheduling of execution of 100 orders for 10 trucks has been studied (Figure 4). The Figure 4 shows incoming orders, where the length of a segment shows a preferred time of the order execution.

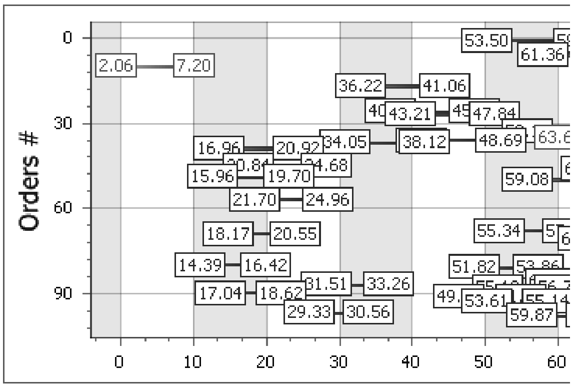

Figure 4: Allocation of input orders in time.

Orders were generated with equal distribution among cities (points) and by dates. Times of start of execution are also equally distributed, but all – within the time of entry and the end of the scheduling horizon. That's why the intensity of orders increases at the end of the time period of simulation. Trucks are based initially in one point – base. Orders are distributed equally among 18 points. Distances between points are from 1 to 6. The scheduling horizon is 100 days.

6 THE RESULTS OF THE EXPERIMENTS

Trucks schedules were created for orders based on the 4 used models of transportation. As an example of the result let's see the schedule (Gantt chart) of truck #0 in the Model 1 and Model 4 which are presented on Figure 5 and Figure 6.

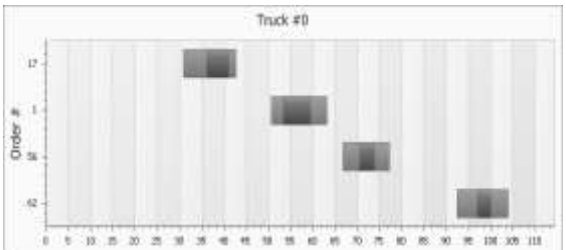

Figure 5: Truck schedule in the Model 1 with returning to base.

Horizontal axis of Figure 5 and Figure 6 shows time in days, vertical shows orders numbers. The executed orders are shown in a dark colour. Brighter rectangles before an order accord to a trucks running process in a loading point. Rectangles on the Figure 5 also show a truck that is returning to base point according the Model 1. Dark rectangle on Figure 6 shows an order that was executed with delay and penalty.

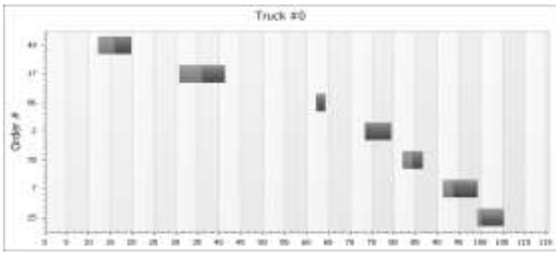

Figure 6: Truck schedule in the Model 4 with adaptive reschedule and penalties.

Graphs of dynamic profit per each truck depending on time was found. Figure 7 shows profit dynamics for the truck according to Model 1 –Model 4. It accords the truck schedules represented above by the Gantt chart diagrams.

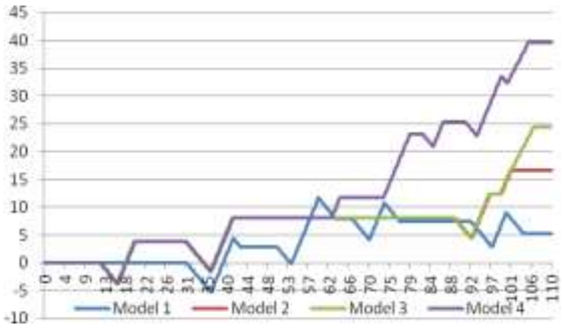

Figure 7: Dynamics of a profit for the truck depending on model of transportation.

Straight horizontal segments accord to a truck stop periods, segments with positive growth show a profit growth while an order was running, segments with negative growth show idle run costs of the truck to the loading point or to the base in the Model 1.

The summary profit for all vehicles in each of the 4 models of transport is the sum of profits in each truck. It's shown in Figure 8.

The designed MAS allows also to study the profit depending on trucks number for each flow of orders. For simplicity we don't consider standing costs of trucks. For the initial orders schedule (Figure 4) the trucks schedules and approximate profit were modeled according to Model 1 – Model 4.

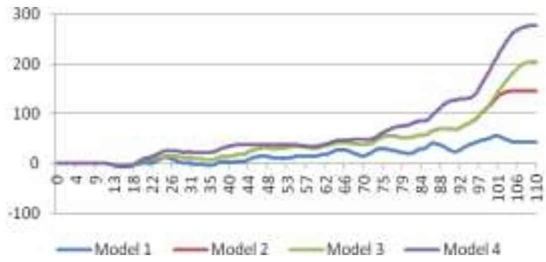

Figure 8: Dynamics of sum of trucks profit depending on transportation models.

The trucks amount was varied from 0 to 50 (Figure 9).

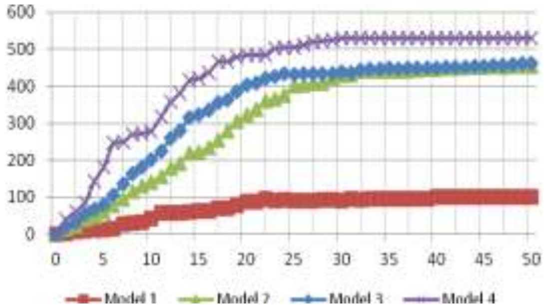

Figure 9: The dependence of the profit to the used trucks number in the different transportation models.

Each graph of total profit has two typical regions. The first region contains an almost linear increase profits with the number of trucks and the second is a 'saturation' region, for which the profit is almost constant and does not vary with the number of trucks. That is due to the fact that most of the new orders have been assigned to the trucks.

Saturation modes differ for the different models. The lowest profit value is in the Model 1 because less amount of orders are scheduled and additional expenses occur after returning to the base. The Model 3 far exceeds the Model 2 because it uses the same amount of trucks as in the Model 2 but more orders are scheduled. But in a satiation mode it gives almost no benefits vs. the Model 2, because when the trucks number is high enough there are very few orders that are executed with delays so The Model 2 and the Model 3 will be almost equal.

The Model 4 is the best one. It gives approximate 20% more profit then the Model 2 and the Model 3. It allows using less trucks during the plan execution.

The reason is the adaptive re-scheduling of orders in real time.

7 CONCLUSIONS

The paper studies benefits of multi-agent system for real time adaptive truck allocation, scheduling and optimization in long-distance transportations of cargos.

It was shown that multi-agent technology allows to create significantly more profitable schedules (up to 40-60% compared with rigid models) and save a number of trucks (up to 20%) for the same amount of orders. The results of the research can be used for improving management of any type of mobile resources.

REFERENCES

Leung , Y-T., 2004. *Handbook of Scheduling: Algorithms, Models and Performance Analysis*. Chapman & Hall. London.

Bonabeau, E., Theraulaz, G., 2000. Swarm Smarts. What computers are learning from them? *Scientific American*, vol. 282, no. 3, pp. 54-61.

Wooldridge, M., 2002. *An Introduction to Multi-Agent Systems*. JohnWiley & Sons. London, 2nd edition.

Vittikh, V., Skobelev, P., 2003. Multi-Agent Models for Designing Demand-and-Resource Networks in Open Systems. *Automation and Remote Control*, vol. 64, no. 1, pp. 162-169.

Skobelev, P., 2010. Bio-Inspired Multi-Agent Technology for Industrial Applications. *Multi-Agent Systems – Modeling, Control, Programming, Simulations and Applications.* Faisal Alkhateeb, Eslam Al Maghayreh and Iyad Abu Doush (Ed.). InTech Publishers. Austria. 28 p.

Skobelev, P., 2011. Multi-agent technology for real time resource allocation, scheduling, optimization and controlling in industrial applications. In *HoloMAS 2011, 5th International Confrence on Industrial Applications of Holonic and Multi-Agent Systems.* Springer. Berlin. pp. 1-14.

Basra, R., Lü, K., Rzevski, G., Skobelev, P., 2005. Resolving Scheduling Issues of the London Underground Using a Multi-Agent System. In *Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science)*, 3593. pp. 188-196.

Himoff, J., Rzevski, G., Skobelev, P., 2006. Magenta Technology: Multi-Agent Logistics i-Scheduler for Road Transportation. In *AAMAS 2006, 5th International Conference on Autonomous Agents and Multi Agent Systems.* Japan.

Skobelev, P., 2010. Multi-Agent Technologies for Industrial Applications: Towards 20 years Anniversary of Samara Scientific School of Multi-Agent Systems. *Mechatronics, Automation, Control*, no. 12, pp. 33-46.

Published: Proceedings of the 5th International Conference on Agents and Artificial Intelligence (ICAART'2013), February 15-18, 2013, Barcelona, Spain. – SciTePress, Portugal, 2013, Vol. 2. – pp. 244-249. ISBN 978-989-8565-39-6.

DOI 10.5220/0004225502440249