LS/ATN: Reporting on a Successful Agent-Based Solution for Transport Logistics Optimization

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Abstract

A considerable volume of research exists concerning the domain of automatic planning and scheduling, but many real-world scheduling problems, and especially that of transportation logistics, remain difficult to solve. In particular, this domain demands schedule-solving for every vehicle in a transportation fleet where pick-up and delivery of customer orders is distributed across multiple geographic locations, while satisfying time-window constraints on pickup and delivery per location.

This paper presents a successful commercial-grade solution to this problem called Living Systems Adaptive Transportation Networks (LS/ATN), which has been proven through real-world deployment to reduce transportation costs through the optimization of route solving for both small and large fleets. LS/ATN is a novel agent-based resource management and decision system designed to address this highly dynamic and complex domain in commercial settings. We show how LS/ATN employs agent cooperation algorithms to derive truck schedules that optimize the use of available resources leading to significant cost savings. The solution is designed to support, rather than replace, the day-to-day activities of human dispatchers.

1 Introduction

The global transportation logistics sector is growing and consolidating day by day. European operators are joining forces with one another and with counterparts around the world. This growth only leads to exacerbating what is already a complex problem to solve: how to efficiently integrate distributed dispatching centers to bring about the means to strategically plan network operations using route optimization.

Any solution must account for the considerable volume of communication and remote coordination necessary to detect any opportunities of combining transportation between regional dispatching centers. More precisely, delays and coordination costs can significantly impact the chance to optimize resource consumption (i.e., deployed vehicles, number of dispatching centers) and finally fulfil all orders as expected. For instance, the average utilization of vehicles in a truck charter business is fairly low (as low as 55% [1]), partially because order consolidation between regions are missed. Furthermore, while a number of existing computational solutions allow the automatic creation of the dispatching plans, they typically do not, or only marginally, support the case of plan deviations resulting from unexpected, or previously unknown events. Naturally this problem grows by factors as companies expand their operations and integrate with others while constantly dealing with shrinking margins and substantial cost pressures. In response, this paper reports on a major step toward solving these problems through a new software agent-based application, the Living Systems Adaptive Transportation Networks (LS/ATN) [1] solution that has now been successfully deployed by two major transportation logistics companies, with third now underway. The latter of these installations will mean that the software will be in use across 17 countries, dealing with more than 15,000 trucks and 40,000 orders each day[2]. This will probably be the largest commercial deployment of agent technology in the world.

The LS/ATN solution is the result of several years of investment into learning how to harness the flexible and adaptive nature of software agent technology in application to the core scheduling optimization problems in the transportation logistics domain. As an intelligent transport optimization system, LS/ATN is able to dynamically adapt transport plans and scheduling according to possi-

[1]For further information please go to http://www.whitestein.com/pages/solutions/logistics/ls_atn.html
[2]Approximate numbers.

ble deviations and unforeseen events. This is achieved by solving the classic operations research dynamic multiple Pickup and Delivery Problem With Time Windows problem (mPDPTW) [4, 7, 8, 9], which is described briefly in Section 2. Several agent-based approaches have been proposed to deal with this kind of dynamic optimization problem, e.g. [3, 6].

The most recent success story of LS/ATN is an installation with ABX Logistics, who with a staff of around 10,000 in 30 countries, represent one of the world's leading transport and logistics service providers. Each day ABX dispatchers manage several hundreds of orders and several hundreds of trucks within the German full truck load and part truck load sector. A careful analysis of ABX's flow of goods detected significant potential for optimization that would lead to reduced driven-empty kilometers and thereby overall costs. Other stated requirements for the solution were (1) full visibility for all users, (2) exploitation of the potential for global optimization, (3) simplification and standardization of the dispatching and settlement processes, (4) immediate reaction to events such as order changes, order cancelations or other plan deviations and (5) generation of up-to-date business figures (KPIs) to ensure the highest quality of service.

After convincing ABX that software agents were a technically sound approach to achieving good results, the LS/ATN solution was installed with substantial impact. The LS/ATN system is now running successfully for several months. LS/ATN software agents support the dispatchers by performing optimization tasks following a bottom-up approach in first searching for local optima and then, in a second step, enlarging the search space to seek approaching more the global optimum. Results reported to date indicate that LS/ATN has delivered an estimated 30% improvement in process efficiency (see 1) for ABX resulting in a significant reduction of transportation costs.

The paper is organized as follows: Section 2 covers the mPDPTW problem domain and related work, Section 3 describes the LS/ATN system architecture and optimization approaches, Section 4 reports and discusses the empirical results obtained by solving a real world optimization problem and finally, in Section 5 we conclude the paper.

2 The mPDPTW Problem Domain

Our research concerns the *multiple Pick up and Delivery Problem With Time Windows (mPDPTW)* and is motivated by its application to the transport logistics domain. The mPDPTW problem consists of computing the optimal set of routes for a fleet of vehicles in order to satisfy a collection of transportation orders while satisfying the time windows at client locations. Each order includes a pickup and a delivery location, and time windows associated with each service location within which the order has to be picked up or delivered. Vehicles are located in various initial positions (there is no central depot) and must be dispatched and routed so that each request is picked up at its origin before being delivered to its destination. The goal of the mPDPTW is to provide feasible schedules, which satisfy the time window constraints, for each vehicle in order to deliver to a set of customers with known demands on minimum-cost vehicle routes.

While a significant amount of research exists in the domain of planning and scheduling, the problems of vehicle routing and order scheduling are far from adequately solved in practice. This is due to the fact that in research studies many parameters or customer requests are ignored. Moreover, although there exist efficient algorithms for solving static scheduling problems where all the data about the client orders is known in advance, in practice one has to deal with dynamic scheduling, where client orders or changes in already requested orders might arrive in the system at any time. Distributed aspects of planning and scheduling problems are hard to define in a generic manner since they often depend on the application domain.

Today, several industries including transportation logistics are faced with constantly spreading world-wide trading and goods flow. This global context requires distribution and high flexibility in the transportation scheduling system, which can be achieved through the application of multi-agent systems, as demonstrated by other approaches such as [3, 6]. The specific needs of the transportation domain computation can classified as follows:

- *Distribution*: When system capabilities are set apart into independent units/agents they may be intrinsically distributed over a large network of computers.

- *Task decomposition*: Transportation applications are especially suitable for the application of techniques such as task decomposition, where the schedule for each vehicle is computed by a single agent.

- *Decentralized scheduling*: Computation and system control are distributed among the agents. Each agent can be designed to act independently by computing a part of the schedule without needing knowledge,or reasoning, about the global process of the whole system.

- *Cooperation* among the agents: In order to achieve a better global solution, the agents must cooperate by exchanging client orders between one other and adjusting their schedules accordingly with the goal of minimizing the overall cost.

Based on our practical experience with transportation scheduling in medium and large-size logistics companies, we can testify to the suitability of these techniques to real-world problems.

Apart from the advantages given by the use of a multi-agent architecture for solving the mPDPTW problem, in real-life applications we need to handle also the dynamic aspects of this problem. For solving a mPDPTW problem dynamically, we distribute it among multiple interacting agents in order to (1) achieve scalability of performance with growing sizes of problem instances; (2) directly reflect the distributed nature of transportation networks/organizations and decision making centers; (3) facilitate the handling of local deviations without the need to propagate local changes and recompute the whole solution, and (4) increase robustness (avoiding single point-of-failure).

Several agent-based systems have been proposed in order to distribute the computation. The most radical one is to represent each vehicle by an agent [3, 6]. Solution generation is done by sequential insertion of orders handled by a contract-net interaction protocol (see, [3]). Optimization can be achieved by triggering order transfers between trucks whenever this improves the objective function. In such a fully distributed architecture, vehicle agents with a changed route start an optimization process in parallel to the other active vehicle agents. The main advantage of such an approach is in its fine granularity and high scalability, while its main disadvantage stems from a considerable overhead in computation time and resource usage. The overhead in computation time is mostly due to more expensive agent communications when compared to a fully centralized solution, while the overhead in resource usage depends on the memory and processing footprint of an agent.

3 The LS/ATN Approach

An agent-oriented approach to transport optimization system is proposed. First we present how LS/ATN is integrated into the main dispatching process followed by the agent-based architecture and optimization of the system.

3.1 LS/ATN Process Integration

In Figure 1, we show the integration of LS/ATN into the main dispatching process and how it interacts with the transportation environment.

Client orders are received by the LS/ATN system through communication with the Transportation Management System (TMS) Order Entry functionality. The client data is processed by the *Dispatching Support* module of the LS/ATN system. Routes are computed based on agent cooperation as described in Figure 3, and improved by agent-based optimization algorithms, see Section 3.3. The plan obtained from this collaborative processing is then reported

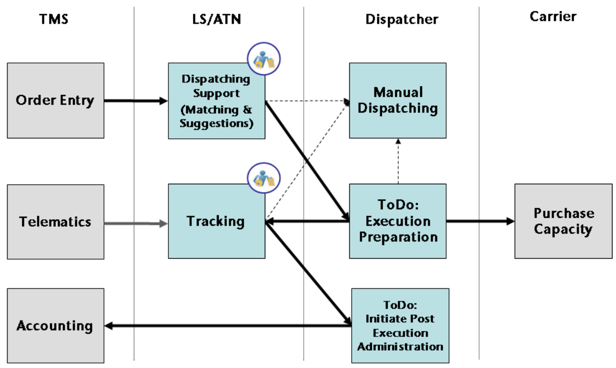

Figure 1. Main process of LS/ATN.

to the Dispatcher for execution, and optionally for manual dispatching. The final routes accepted for execution and potentially adapted with manual dispatching are ordered for execution to a carrier and reported to the *Tracking* module of the LS/ATN system. The tracking module supports tracking and event handling for orders and trucks during the execution phase of the transport. Once this is finished it sends the routes back to the Dispatcher for post execution administrative operations. The final decisions regarding costs are reported to the *Accounting* module of the TMS system.

3.2 LS/ATN Agent System Architecture

In Figure2, we present the main architecture of our transport logistics system. The agents used within the system can roughly be divided into two groupes: communication agents allowing to interface to external modules like the clients, geo-coding information systems [3], transport management systems, telematics systems and other external systems and we have optimization agents described in the next section. The agent-based architecture is very flexible and thus, highly extendable. It allows easily for the introduction of new agents occurring as a result of customer needs or system evolution.

3.3 LS/ATN Agent-Based Optimization

The agent design chosen for optimization directly reflects the way logistics companies actively manage the complexity of this domain. The global business is divided into regional businesses which are usually dispatched in distributed dispatching centers. This distribution is represented by

[3] We are using a PTV servers for geographical services, see: http://www.english.ptv.de/cgibin/logistics/log_emarket.pl

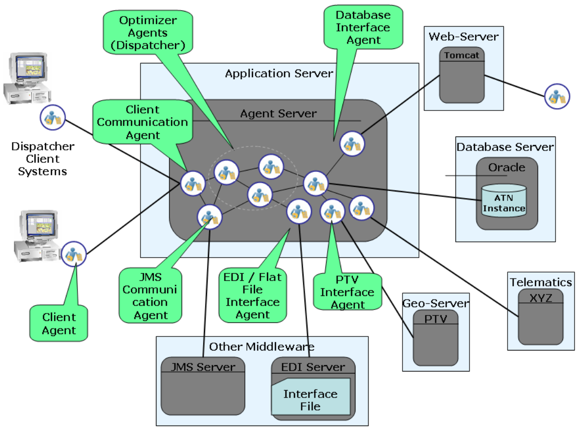

Figure 2. LS/ATN system architecture.

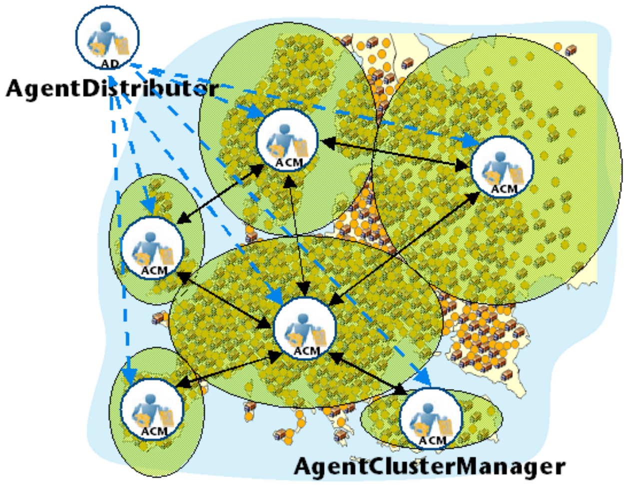

Figure 3. A summarized view of a cluster-based agent design.

agents communicating to each other. In the following we describe how automatic route planning is handled by our system based on agent collaboration, step 2 in Figure 1.

3.3.1 Agent Cooperation for Routes Solving

The transportation business is usually divided into regions/clusters. Transportation requests arriving at a cluster are first tentatively allocated and possibly optimized within that cluster. If the order′s pickup or delivery location is in a different cluster, the other cluster is also informed and asked to handle the request if it can do so in a cheaper way. In our agent-based framework, distinct software agents represent different regional clusters. All vehicles starting in the region of an agent are managed by a local AgentClusterManager. Incoming transport requests are distributed by a centralized AgentDistributor according to their pickup location (see Figure3). Clusters may also be configured to be managed dynamically containing all trucks that have routes passing the cluster allowing the clusters to overlap.

The main advantage of this latter design stems from its direct mapping to todays transport business organization and its good scalability. The computational overhead incurred by such a multi-agent based solution is also much lower than that occurring in a fully distributed solution. Nevertheless, besides degradation of the solution quality when compared to a fully centralized approach, the main disadvantage (also with respect to the fully distributed option) is that optimization within a cluster and among clusters has to be handled slightly differently.

3.3.2 Optimization Algorithms

The optimization process incrementally reflects the dynamics of the underlying mPDPTW settings. Whenever a new transport request is made available to the system, the current delivery plan is updated. This is done in a two-phase approach: First, a new valid solution is generated including the new transportation request. Then, the obtained solution is improved by negotiation between the agents to transfers orders in case this reduces the overall costs.

The algorithm used for assigning an order to a truck is a sequential insertion of orders [5]. All available trucks under control of the AgentClusterManager are checked to see if they are able to transport the order and what additional costs are incurred. The order is finally assigned to the truck with the least additional costs.

Sequential insertion with requests for quotes to all trucks potentially produces suboptimal solutions. See for instance the example given in Figure 4. Order 1 is the first to arrive in the system and is assigned to truck 1's route. Order 2 is also optimally assigned to truck 1's route since that produces least additional costs (and kilometres). When order 3 arrives truck 1 is fully loaded, therefore a new truck 2 is used for order 3 and later for order 4.

In order to improve the solution a further optimization step is performed by cyclic transfers between trucks. A cyclic transfer is an exchange of orders between routes. Figure 5 shows how the suboptimal example in Figure 4 is improved by a transfer of order 2 from route 1 to 2 while order 4 is transferred from route 2 to 1.

The optimization procedure must determine which transfers should be triggered. The AgentClusterManager therefore starts a negotiation process with the truck that was most recently changed. That truck is initiating transfer requests to all other trucks under control of AgentClusterManager. From all the requests the most significant cost-saving transfer is performed. This changes the routes of both trucks

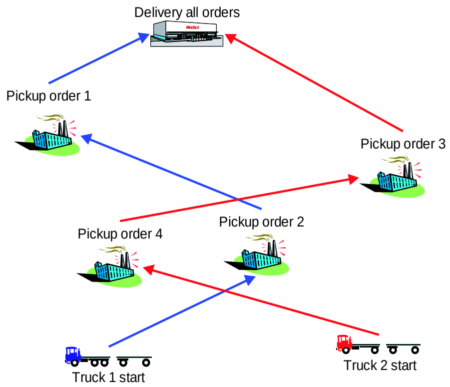

Figure 4. Example of a suboptimal solution given by the insertion algorithm for 4 orders.

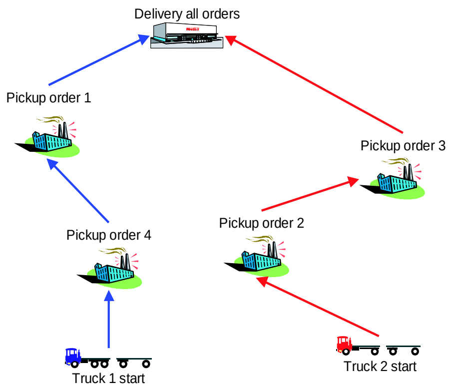

Figure 5. Optimal solution, for the example given in Figure 4, after an order transfer.

involved. This hill climbing process is then continued with all changed routes until no more cost-saving exchanges can be achieved.

4 Discussion and Results

There are various aspects which are requested for optimization in a transport logistic system and considered in LS/ATN: transportation cost, solution quality, process cost, more flexibility for dispatchers and cost transparency. We discuss how these parameters are treated by our system for a major European logistics company. We also report how the results are improved by automatic optimization provided by our system in comparison with manual dispatching used by the transport logistic companies today. Because of space limitations we present our results only relative to the first two parameters aforementioned. The given dataset contains roughly 3500 real-business transportation requests.

Evaluation Parameter 1	Saving (agent-based)
overall cost	11.7%
driven kilometers	4.2%
deployed vehicles	25.5%

Table 1. Savings achieved by the agent-based approach when compared to manual dispatching.

The major goal of logistics companies is reduction in transportation costs. This can be achieved by higher utilization of transportation capacity. This results in a reduced number of driven kilometers and less trucks needed. Table 1 summarizes the comparison of these major results gained by comparing the solution of manual dispatching with processing the same orders on ATN. A total of 11.7% cost savings was achieved, where 4.2% of the cost savings stem from an equal reduction in driven kilometers. An additional important achievement is that the number of vehicles used is 25.5% lower compared to the manual solution. The cost savings would even be higher if fixed costs for the vehicles were feasible, which is not the case in the charter business, but possibly in other transportation settings.

Our agent-based optimization system guarantees a higher service level in terms of results quality. The high solution quality corresponds to a reduced number of violated constraints. Our system allows for fine tuning of the desired level of service quality. Figure 6 presents various results obtained by our system relative to the solution proposed by manual dispatching. The first proposed solution (ATN1) provides a reduction of 8.33 % in driven kilometers at the same service level with no more than 25% of violated constraints with more than 6h pickup or delivery delay. Moreover, this solution provides also a reduction of 8% in terms of kilometers driven with empty trucks. The second solution (ATN2) proposes a reduction in driven kilometers of 0.78% relatively to the manual dispatching solutions, while providing a significant higher service level: only 2.5% of violated constraints with more than 6h delay. The third solution (ATN3) proposes an increase of only 1.66% in terms of driven kilometers, while meeting all the constraints.

Through the use of the automatic optimization a lower process cost is being achieved. This is due to automatic handling of plan deviations and evaluation of solution options in real-time. Moreover, through automation the communication costs in terms of dispatcher′s time and material is reduced. Better customer support can be guaranteed through fast, comprehensive and up-to-date information about order execution.

Automation also allows processing of a higher number of orders than with manual dispatching. This is an important issue as the size of data to be managed is increasingly grow-

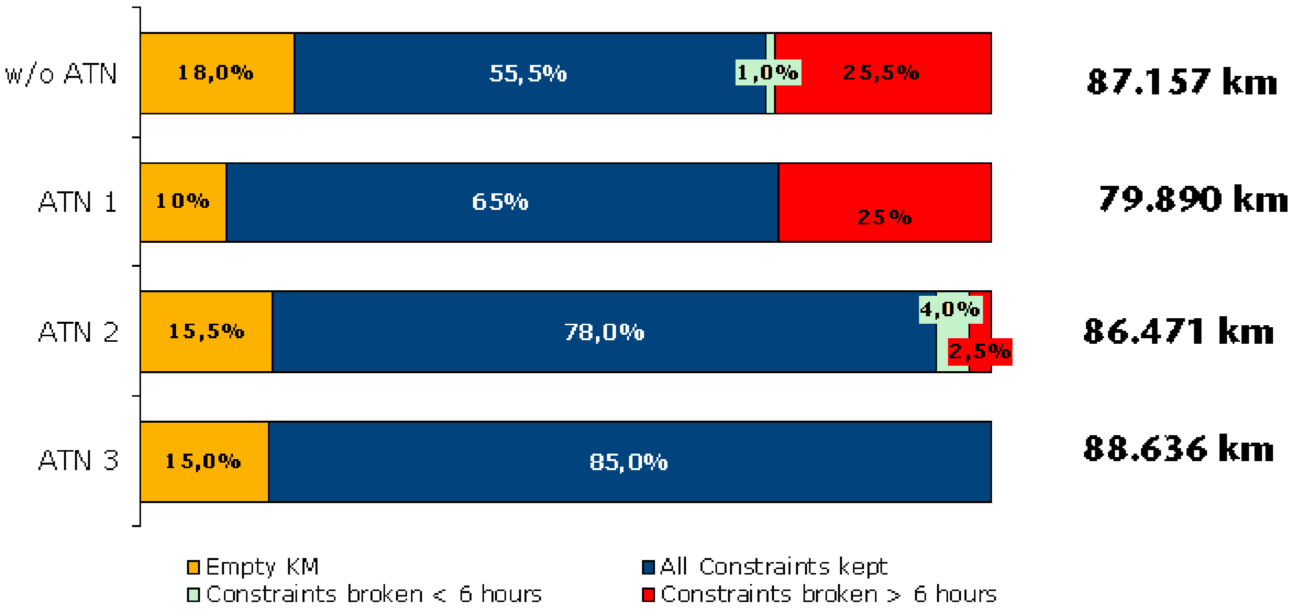

Figure 6. A summarized view of a cluster-based agent design.

ing. Other advantages of using LS/ATN are: cost transparency and seamless integration with TMS and telematics.

5 Conclusions

Interest in distributed agent-based decision systems for dynamic, unpredictable and distributed application domains such as transport logistics is increasing significantly as human dispatchers begin to be overwhelmed by the amount of data needed to be handled. We present LS/ATN as a solution to this problem that has been proven in use by a growing number of major transport companies. The design of LS/ATN as a software agent application is motivated largely by the high responsiveness of autonomous agents as entities that can react locally to changes in complex environments. Moreover, the agent-oriented paradigm for software engineering provides a strong basis for the construction of large, complex systems, in which components can be naturally distributed across a network of heterogenous computers, without demanding a complete analysis of their interactions.

Our solution, LS/ATN, is a commercial system for computing the truck schedules in transportation logistic applications. We are using multi-agent technologies as the platform underlying our system and we are experimenting with various techniques for schedule solving. Our production system is now successfully used by ABX logistics and several other medium to large-sized transport logistics companies. While ABX has achieved a reduction of 11.7% in costs relative to the manual dispatchers solution, we typically guarantee a reduction of at least 4% to 6%. This improvement is significant for transport companies that have huge number of orders to manage and significant costs, but small profit margins.

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