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Weighted multiplicative decision function for distributed routing in transport logistics

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Abstract In transport logistics, routing is usually done by a central instance that is solving the optimization problem of finding the best solution to cover the current set of orders with the current set of vehicles under constraints such as punctuality, vehicle utilization etc. Approaches have been suggested recently which change this paradigm towards a distributed approach with autonomous entities deciding on their own. Autonomous entities denote, in this case, the vehicles as well as the goods. When each of the entities makes its own route decisions, it has to consider multiple parameters, which are partially static (e.g. distances) and partially dynamic. An example for a dynamic parameter is the knowledge about vehicle availability that goods need for their decisions. The work presented here is based on the information exchange concept DLRP (Distributed Logistic Routing Protocol), which has been proposed before. Within that framework, the concept of weighted multiplicative combination of context values into a decision function is now introduced for the route decisions made by autonomous entities.

1 Introduction

Routing in transport logistics is nowadays usually handled as a constrained optimization problem. This optimization problem is solved with the help of heuristic methods such as genetic algorithms, tabu search and others. If the optimization problem is dynamic in nature, e.g. because not all transport orders are known in advance, solutions to it are repeatedly calculated as time progresses, either in fixed time intervals (rolling horizon planning) or on demand. If the level of dynamics is high, these approaches are limited in their reactivity: Due to the time that is required to determine a new global solution, there is a limitation to the frequency of replanning. Here, a distributed approach that does local modifications to the original plan can have advantages.

This is where the paradigm of "Autonomous Cooperating Logistic Processes" [1] is targeted at. Within this paradigm, intelligence and decision-making capability is moved from the central dispatcher towards the individual actors in the logistic process, i.e. the vehicles and even the goods. That means they become autonomous in their decisions, and they have to cooperate in order to achieve their goals.

As a framework for the interaction of autonomous logistic entities, the "Distributed Logistic Routing Protocol" (DLRP) has been proposed.

The paper is structured as follows: Section 2 introduces the interaction of the entities using the DLRP. The multiplicative parameter aggregation function is presented in section 3, and results of simulations using this function with DLRP are shown and discussed in section 4. The paper ends with conclusions and an outlook to future work in section 5.

2 The DLRP

The Distributed Logistic Routing Protocol (DLRP) ([2], [3]) is based on the assumption that the vehicles and the goods in a logistic network are equipped with devices capable of computing and communicating. Thereby, they are able to interact and decide autonomously.

In contrast to classical routing problems such as the Vehicle Routing Problem (VRP) or the Travelling Salesman Problem (TSP), the scenarios where the DLRP is applied are restricted in the connections that are existing between locations (vertices) in the logistic network, i.e. scenarios are not only defined by a set of vertices, but by a graph connecting those. In reality, the vertices may be logistic distribution centers, and the edges the main motorway connections between them.

Vehicles and goods determine their routes by using a route discovery messaging that is similar to source routing methods in ad-hoc communication networks: When a vehicle or a goods item needs a route, it sends out a route request to the nearest vertex, which forwards this request to the neighbor vertices, which in turn do the same. Before forwarding an incoming route request, the vertex adds current context information to the request, including knowledge about other vehicles and goods that have announced to travel on the same route. So by the time the route request reaches the destination vertex, it has collected information about the complete route that it has travelled. Based on the information collected in the route request, the destination vertex sends a reply to the vehicle or good, which then can make a decision. After having made a decision, the chosen route is announced to all vertices that are involved in this route.

Consequently, the vertices play an important role in the DLRP: They act as information brokers. Vehicles and goods announce their intended routes to the vertices, where other vehicles and goods can access them to retrieve information which is relevant for their future planning. This facilitates the mutual interdependence of vehicle and goods routes. For more details about the DLRP, refer to [2] and [3].

The DLRP has shown to be able to achieve competitive results compared to Tabu Search in adapted vehicle routing problems [4].

3 The decision function

In [4], the route decisions were based on the shortest path in case of the goods' decisions, and on vehicle utilization in case of the vehicles' decisions. No time constraints or other decision criteria are used there. This is a largely simplified decision strategy. In reality, there are usually multiple criteria that have to be considered to achieve decisions which lead to a good logistic performance.

If multiple criteria are of interest, these criteria have to be combined in a decision system that leads to a unique decision. Several ways of combining are possible, for example sequential use of criteria, fuzzy logic, additive or multiplicative combination. A sequential use of criteria has the disadvantage that the sequence leads to a fixed prioritization of those parameters that are first used in the sequence. Fuzzy logic usually results in a set of fuzzy levels, and to avoid indifferent cases (multiple alternatives on the same fuzzy level) as much as possible, a high granularity of fuzzy levels and a large set of corresponding fuzzy rules are required. An additive or multiplicative combination of criteria does not prioritize criteria, nor does it have a limited granularity of output values. This makes it favorable to use such a way of combining the criteria.

Assuming that each of the criteria should be able to make a route impossible if its value is inacceptable, a multiplicative aggregation is the more practical option. In an aggregation of different criteria, the value ranges of those criteria are usually different. Therefore, they have to be mapped to a common range to avoid that one criterion dominates the decision.

Based on the constraints and assuming k criteria, the function

$$U_j = \prod_{i=1}^{k} \left(f_{s,i}(c_{i,j}) \right)^{w_i} \tag{1}$$

is defined as the Multi-Criteria Context Decision (MCCD) function for the decision alternative j. In this function, $c_{i,j}$ represents the value of criterion i for alternative j, $f_{s,i}$ is a function that scales the criterion values to a common range and w_i is a weight to adjust the importance of the criterion for the decision. A scaling function instead of a simple scaling factor is used because the criteria may have significantly different characteristics. Especially if the value range of a criterion is unbounded at the lower end, the upper end or both, a scaling factor is not sufficient to map the criterion into a bounded range. The scaling function as well as the weight is specific for the respective criterion. The target value range that the criteria are mapped to by the scaling functions is the interval [0, 1], with 1 being the best and 0 being the worst value.

3.1 Decision criteria

This generalized decision function is now applied to the specifics of the distributed routing in logistics. For vehicle routing, three criteria are taken into account:

- The revenue the vehicle is expecting, which is based on the goods' offers and the transport costs per km. Revenue per km is used here because they are a better representation of economical efficiency than absolute revenue values. The revenue values can be positive or negative (the latter is the case if the transport costs are higher than the price the goods offer). Negative revenues, however, mean that it is not useful for the vehicle to travel on this route. Therefore, the scaling function has to map negative values to 0. For positive revenues, the scaled value has to approach 1 for increasing revenue. A scaling based on the Error Function (erf) was applied for the positive revenue here.
- The ecological impact. Efficient utilization of a vehicle's cargo space reduces the pollution per tkm. As the ecological impact can consist of various effects, and not all of them are well measurable or even well understood, only the carbon dioxide output is considered here, as this can be easily calculated if the vehicles' fuel consumption is known. Low carbon dioxide output is preferred, while high output should be avoided. Here, a scaling function based on the Error Function Complement (erfc) is used. This function has the center of its slope at the targeted carbon dioxide maximum.
- The reliability. Based on historic data collected during previous transports on a route, it can be estimated whether the expected revenue can really be achieved. This reliability is a probability, and as such, its values are already in the target interval, so no further scaling is required.

For goods routing, there are three criteria as well:

- The route costs. These costs depend on the offers the goods make towards the vehicles, storage costs, transshipment costs and delay fines. The goods' offers are supposed to depend on the available budget and on the urgency. As the costs have a lower limit (0) and an upper limit (the budget), and this range can be scaled to the [0, 1] interval by using a linear scaling.

- The risk of damage. Each transshipment operation implies a risk that the goods may be damaged. Additionally, there is a damage risk related to the transport itself. It is assumed that there is a maximum acceptable risk that should under no circumstances be exceeded. Therefore, the scaling function is set to 0 for all risk values above the maximum acceptable risk. Between “no risk” and the maximum, a linear scaling is used that maps “no risk” to 1 and the maximum acceptable risk to 0.
- The risk of being delayed. This risk may be deduced from knowledge about how long it takes in average to travel on a specific route. This knowledge is based on feedback from previous transports. Based on the historic travel time statistics and the time that is still left for an in-time delivery, a probability of being delayed is calculated. The scaling function that is applied here has to map a low delay risk to 1 and a definite delay to a low, but nonzero value. It has to be nonzero because otherwise, goods that are already certain to be delayed on any route would not get a route any more.

4 Simulations

For simulative evaluation, a scenario was used that is based on a topology that has been first introduced in [5]. This topology represents 18 cities in Germany and major highway connections between them (see figure 1).

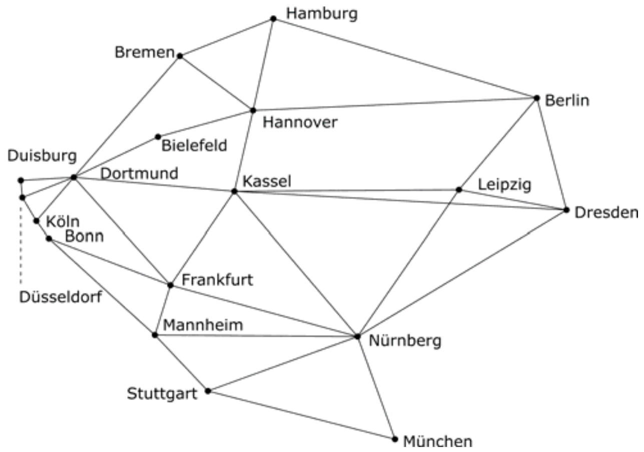

Fig. 1. Logistic scenario topology [5]

25000 goods are to be transported in this scenario. They are not all known from the beginning, but are generated during runtime at a rate of 23 goods per time unit. Each possible source-destination pair is present among the goods. 12 vehicles with a capacity of 12 goods each and a maximum speed of 100 km per time unit are present in the scenario. The delivery time window is 25 time units for each piece of good (the goods may be delivered anytime between 0 and 25 time units after entering the scenario).

The following results were obtained in simulations where all criteria are equally weighted with a weight of 1. Here, the average vehicle utilization is 0.7827. Figure 2 shows that after a transient phase in the beginning of the simulation, the utilization varies around this average value.

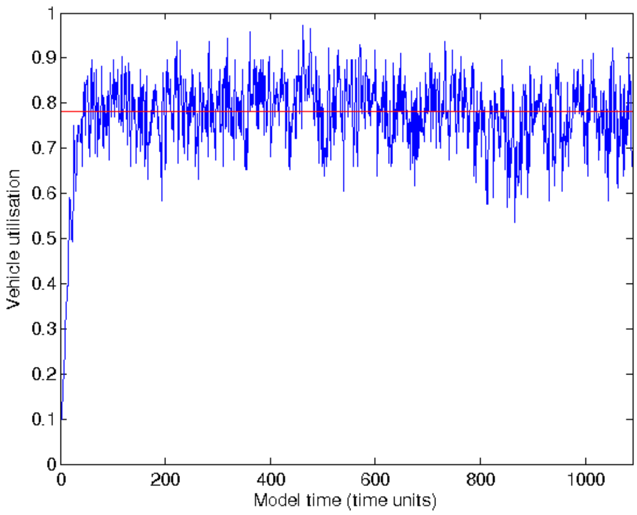

Fig. 2. Vehicle utilization

The performance with respect to the goods' deliveries is best represented by the delivery delays. The cumulative distribution of the goods' delivery delays can be seen in figure 3. In this figure, the delays are displayed with respect to the goods' due times, i.e. the delivery is late if the delay is greater than 0, otherwise it is on time.

The figure shows that around 70% of the deliveries are on time in this configuration. Note that no optimizations of criteria weights are done here yet. To improve the timeliness, weight variations were done for the criteria influencing the goods' route decisions. There are two criteria that are related to the timeliness: The delay risk and the costs.

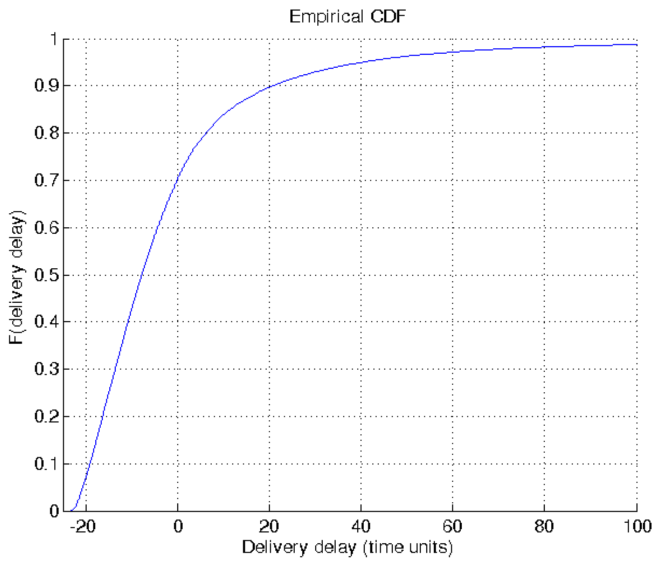

Fig. 3. CDF of the delivery delay

Figure 4 shows the CDFs for different weights on the delay risk criterion, while all other criteria are weighted with 1.

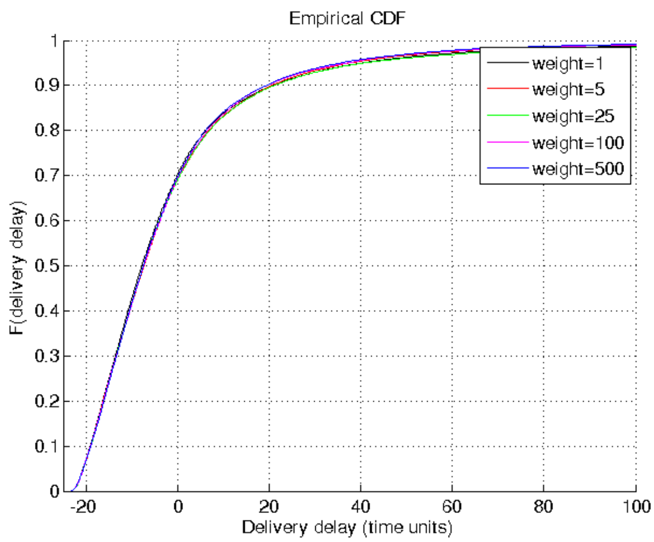

Fig. 4. CDFs of the delivery delay with different weights for the delay risk

As it can be seen from the figure, varying the weight for the delay risk does not show much influence on the logistic performance. While this discovery seems surprising, it can be explained because the risk only covers the question if, and not how much the delivery will be delayed. The cost, on the other hand, increases with longer delays due to higher storage costs and delay fines. Therefore, changing the weight of the costs in the decision can be more suitable to improve the timeliness. Figure 5 proves this.

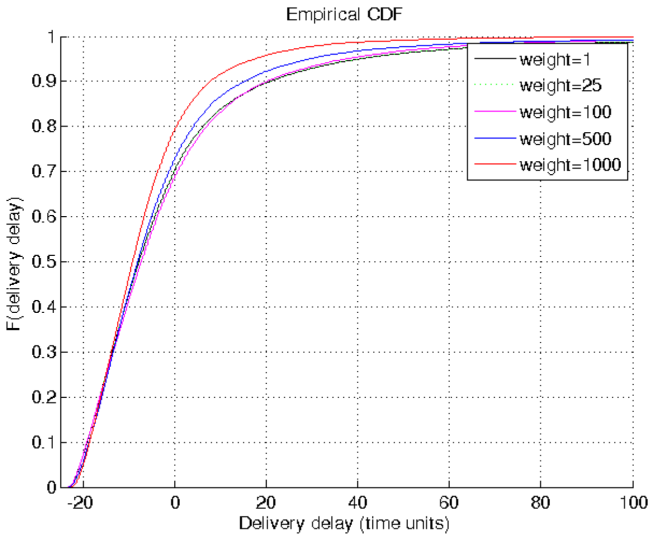

Fig. 5. CDFs of the delivery delay with different weights for the cost criterion

By tuning the cost weight, the percentage of timely deliveries can improved, as shown in the figure. With a very high weight, the percentage approaches 80 %. However, the average vehicle capacity utilization is reduced to 0.6988. This means that the vehicles take the goods on more direct paths, and the load consolidation potential is lower. A side-effect is that to ensure the timely delivery of more goods in total, some other goods are not transported at all. These goods would require costly individual transports.

To position the proposed route decision function in comparison to other routing approaches, the results achieved here were placed into the comparison chart which was introduced in [6]. Figure 6 shows this.

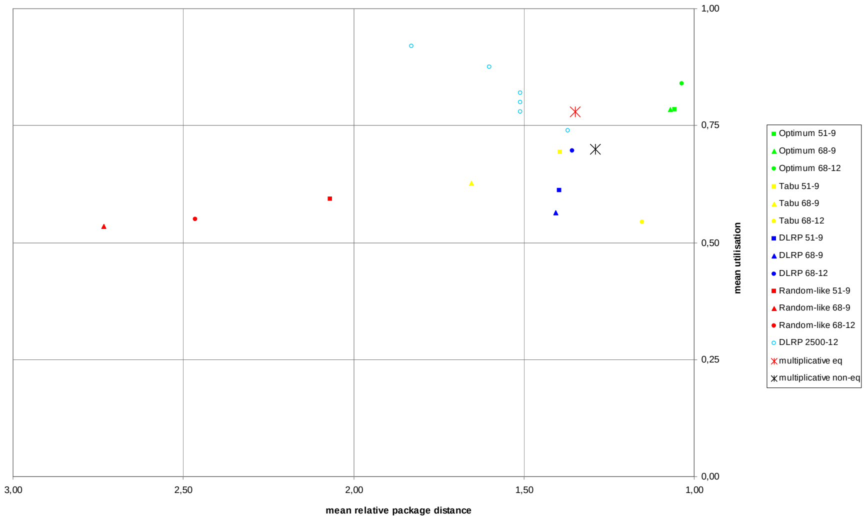

Fig. 6. Positioning of the MCCD decision approach (red star and black star) in the comparison chart introduced in [6]

It can be seen from the figure that the proposed decision function leads to good results compared with the other methods investigated in [6]. The red star represents the decision function with equally weighted criteria; the black star represents it with a weight of 1000 on the cost criterion.

5 Conclusions and Outlook

A multi-criteria decision function for autonomous routing with DLRP has been introduced in this paper. Simulation results have shown that the decision function performs well in comparison to other approaches and can be further improved by a fine-tuning of weights. Further research will include adaptive tuning of weights during runtime, and investigations on topologies of different scales.

Acknowledgments

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