Performance of Self-Organizing Logistics: a Practical Comparison between Centralized and Decentralized Logistics

Ruben Fransen, Lola Sprenger, Wan-Jui Lee and Jaco van Meijeren
TNO Sustainable Transport and Logistics, The Hague, The Netherlands
Corresponding author: ruben.fransen@tno.nl

Abstract: *In the vision of Physical Internet there is no central authority that regulates decision making and asset use, the decision making is decentralized to make logistics self-organizing. A theoretical downside of decentralization is reduction of system performance due to lack of system overview leading to sub-optimal decisions. This research shows that the system performance is not significantly reduced when making decentralized decisions in a trucking network on small problem instances. Furthermore, the theoretical advantages of decentralized control compared to centralized are evaluated with the practical implementation.*

Keywords: *Autonomous transport, Centralized control, Container logistics, Self-organizing logistics (SOL), Supply chain management*

Conference Topic(s): *Autonomous systems and logistics operations (robotic process automation, autonomous transport/drones/AGVs/swarms) business models & use cases; logistics and supply networks.*

Physical Internet Roadmap *(Link): Select the most relevant area for your paper:* ☐ *PI Nodes,* ☐ *PI Networks,* ☒ *System of Logistics Networks,* ☐ *Access and Adoption,* ☐ *Governance.*

1 Central and decentral control structures in logistics

The advancements in digitalization and automation within transportation and logistics are creating new opportunities for organizing supply chains. Real-time connectivity and improved data sharing allow for innovative decision-making methods that can alter the control structure of logistics operations. More (autonomous) data-driven decision-making can be applied in various control structures, including centralized coordination (control tower approach) and decentralized coordination (self-organizing approach). These advancements lead to new opportunities for transport companies to improve methods of scheduling assets in daily practice, reducing inefficiencies in their operations and reducing costs and energy or fuel use. The question at hand is which methods of governing fleets of vehicles and optimizing transport scheduling are most suited to real world transport problems and most effective in decision support in transport operations.

Centralized control structures, known as the control tower approach, involve one party collecting and analyzing data to make optimal operational decisions that are communicated to parties in the logistics chain. This approach has the potential to optimize performance at the system level, placing the interests of the chain above individual interests, and standardizing communication through one system. On the other hand, a decentralized control structure is characterized by each unit in the logistics chain making independent decisions (self-organization) based on local intelligence and autonomy, with the goal of achieving more flexible operations or allowing for prompt rescheduling. Next to increased autonomy, there can also be an advantage in data governance, as autonomy on vehicle level enables a situation where specific vehicle and driver data does not need to be shared and only communication on which orders to transport is required. Physical Internet is a concept that aims to create a global logistics network that is more efficient, flexible, resilient, and sustainable by integrating these two approaches.

This work focusses on specific on one decentral and one central approach, where most likely a hybrid form with collaboration between centralized and decentralized logistics is necessary to get to a functioning Physical Internet. A hybrid form allows for the efficient use of resources, improved flexibility, and increased resilience and sustainability in the logistics network (Quak et al., 2018) and as such, a hybrid approach could combine the advantages of both control methods. An example of a hybrid approach is developed by Phillipson (2015).

To allow for effective decision-making and coordination across the Physical Internet, it is important to create proper control structures for the problem at hand. In the study Hopman et al. (2022), a framework was developed to examine the trade-offs and conditions that are most appropriate for different control structures, from centralized to decentralized. Their research suggests a hybrid approach to enhance the collaboration between centralized and decentralized logistics. This paper focusses on the extremes and not on a hybrid approach by comparing decentral with central scheduling. In this study, we researched a real-life logistics problem of order scheduling, which resembles a combination of job shop scheduling and vehicle routing with time-window constraints. The theoretical benefits and drawbacks of both centralized and decentralized approaches are examined by practical experiments to discover and close the gap between theory and practice as discussed in section 4. The three experiment data sets are real world data originating from a Dutch transport company. One of the main activities of this company is transporting deep sea containers by truck to and from multimodal terminals in the hinterland.

Key contributions of this study are:

1. The Talking Trucks problem (Pingen et al., 2022) is formulated with Mixed Integer Linear Programming to include the geographical component which was missing in the centralized Linear Programming control structure in the previous study (Karunakaran, 2020).
2. The solution of the exact, central method is compared with the solution from the decentral approach to evaluate the gap in optimality.

Firstly in this paper, the background on comparing central and decentral control in transport planning problems and the specific case study is described. This is followed by a description of the approach of comparing control methods and the Mixed Integer Linear Program (MILP) formulation of the central planning problem. The problem has been solved for 3 instances. Section 4 describes the comparison to previous decentralized solutions from Pingen et al. (2022). Section 5 wraps up on the comparison of central and decentral scheduling methods.

2 Background of self-organizing trucks

In previous research by Pingen et al. (2022) on self-organizing trucks, decentralized planning results were compared to the planning of a human planner, a random assignment of orders to trucks, a greedy assignment, a reinforcement learning model, and a modified centralized control to obtain a good understanding of the performance of decentralized control. However, the central control method in this previous study included a modification to the problem to increase scalability: it was assumed that all trucks always start and end at their depot in between orders. As a result, subsequent orders with a start location close to the last end location were not explicitly considered to be executed in that order. This step was taken to reduce the problem complexity, making it easier to solve the linear planning problem. However, in order to make a better and more equal comparison between the performance of centralized and decentralized control on the same problem, this study examines a centralized control approach that does take the geographical component into account.

2.1 Centralized versus decentralized control

To choose the appropriate control method, sufficient knowledge about the constraints of the application and how the different control methods align with these is crucial. A centralized control method, using exact methods, is likely to require more computational time to find a solution than a decentralized control method, as the scheduling problem is NP-hard and decentralizing the decision making is a way of batching the problem to smaller subproblems and reduces the required computational effort, as, for example, shown by Lalla-Ruiz and Voß (2016). Therefore, a decentralized control method is better suited for dynamic situations where quickly generating new plans after disturbances is crucial. However, a decentralized approach may not necessarily lead to an optimal solution. Pingen et al. (2022) briefly discuss the theoretical advantages and disadvantages of a centralized solution for the Talking Trucks problem. Differences include the scalability of problems that can be solved, dealing with heterogeneous agents with different preferences or limitations, and the quality of the solution.

Using heuristics, a centralized method can be sped up to reach a suboptimal solution; an example of this is dividing the problem into sub-problems to solve them in a limited time. This example can already be considered decentralization, but from a centralized perspective with global information. On the other hand, a possible disadvantage of the decentralized approach is that the obtained solutions may not be optimal, as decisions are based on a limited set of local information.

In a decentralized method, each agent has its own decision logic to optimize its decisions in the planning process, before communication and coordination with other agents takes place. In this logic, the individual preferences of an agent can be processed, and the logic can be different for each agent or uniform for all agents. As the agents do not necessarily share all information with each other, a decentralized control method can relatively easily lead to a local optimum for the system, and therefore not reach the global optimum. Depending on the problem and the intended objectives, different strategies and heuristics in the individual decision logic of the agents can have an effect on the speed of the planning process and the quality of the solutions. In this research, we further examine the quality of solutions of the previously developed decentralized method of Talking Trucks, by comparing it with the outcomes of the central control approach in this research. The aim is to better understand the differences between central and decentralized methods.

3 Comparing self-organizing with exact central truck planning

To gain insight in the optimality gap between the decentralized talking trucks solutions and the optimal solution for the provided variant of the Vehicle Routing Problem with Time Windows (VRPTW) we have formulated an MILP for this problem and used exact methods to get to an optimal solution. The problem formulation can be found in section 3.1. We have used the SCIP-solver (Bestuzheva et al., 2021) to get to the optimal solution. Formulating and implementing the exact problem from a central planning perspective provided us with insight into what is needed to develop such an approach for a real world trucking company. Given this insight from implementation and additionally the analysis of results from experiments allowed us to compare the requirements and performance of central planning with self-organizing decentral planning. This comparison is provided in the second part of the results section.

3.1 Talking Trucks problem formulation

In this section, the mixed integer linear programming (MILP) formulation for the Talking Trucks problem is provided. The problem is to assign container transport orders to available trucks in the fleet. Container transport orders include picking up a deep sea container, which we for the scope of this paper consider to be a full truck load, driving a certain route to one or multiple stops. Stops can either be picking up a container (with or without trailer), live loading of a container or delivering a container. At pick-up, it can either be that the container is already loaded onto a trailer which the truck needs to couple, or that the truck needs to bring an empty trailer on which the container is loaded at arrival. Similarly, at delivery, the truck can end with or without an empty trailer. We call this the trailer state. To change trailer state between orders, we added so called “trailer state orders” in which a truck can (de)couple a trailer at a depot. We assume trailers are an infinite resource, they are always available and provide no planning constraints. The trailer state orders add travel time and distance to the schedule. The schedule is static and made one day ahead.

Orders can have routes of multiple stops. However, for planning constraints, only the location and trailer state of the first and last stop are relevant, as well as the total travel time in between the first and last stop of an order. Therefore, this formulation assumes “flattened” orders, where orders only contain information about the first and last stop. The travel time between stops is combined into travel time from the first to the last stop, and the order of stops cannot be changed. Initially, each stop has a specific time window defining the first possible arrival time and the deadline before which the container must arrive at each stop. This time window at each stop and driving time in between stops define a condensed time window at the first stop for the “flattened order”. A visualization of this process is shown in Figure 2.

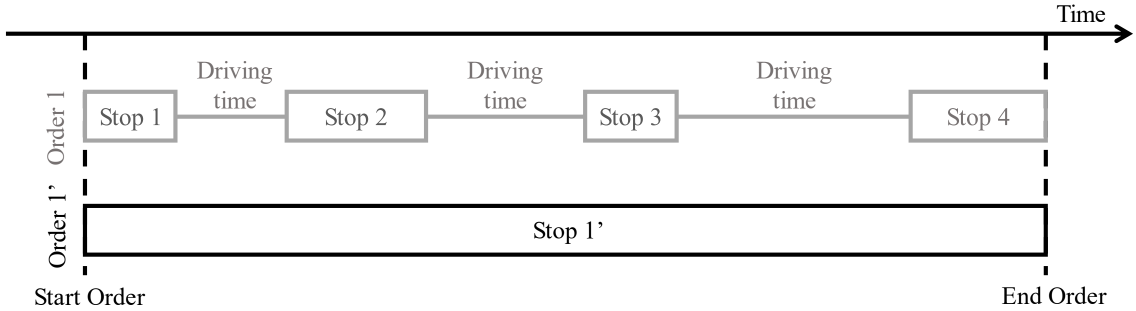

Figure 1 Schematic example of a “flattened” order. Order 1 is the original order and Order 1’ is the flattened order.

The orders need to be assigned to trucks. Hence, the problem definition includes a fleet of vehicles, where each vehicle has a start and end time of its shift and each vehicle starts and ends at a certain depot. All vehicles start without a trailer. The notation for this problem is given in Table 1. The combined decisions to be made are (a) which vehicle is going to transport which order (b) at which point in time.

Table 1: Notation for the Mixed Integer Linear Program

Notation	Description
$x_{i,j,k}$	vehicle k travels from order i to order j; **binary decision variable**

$\boldsymbol{s_{i,k}}$	arrival time of vehicle k at order i; **continuous decision variable**
$\boldsymbol{V}$	set of vehicles
$\boldsymbol{C}$	set of orders
$\boldsymbol{N}$	set of orders and depots
$\boldsymbol{d_k^s, d_k^e}$	start and end depot of vehicle k; $d_k^s, d_k^e \in N$
$\boldsymbol{o_i}$	total handling time of order i
$\boldsymbol{p_{i,j}}$	travel time from order i to order j
$\boldsymbol{t_{i,j} = o_i + p_{i,j}}$	total time between the start of order i and the start of order j
$\boldsymbol{[a_i, b_i]}$	a_i is the earliest possible start time, and b_i is the latest possible end time of order i
$\boldsymbol{[e_k, f_k]}$	e_k is the start time of vehicle k, and f_k is the end time of vehicle k
$\boldsymbol{TS_i^{start}, TS_i^{end}}$	TS_i^{start} is the trailer state at the start, respectively end (TS_i^{end}), of order i

3.1.1 Optimization objective

In general, the Talking Trucks problem knows different objective functions, as the objective that best fits company goals can vary daily, given customer requirements and operational deviations. In this research, we want to compare our results with the results from Pingen et al. (2022), who have optimized with the goal to maximize the number of on-time deliveries and minimize the number of trucks used. In order to make the decentral decision making steer towards the system objective (from a company perspective), Pingen et al (2022) have translated the system objective into objectives for individual trucks. For this MILP, we have defined the following two objective functions to align with the company objective. Having multiple objectives makes the formulation proposed in this paper a multi-criteria problem, for which, in theory, a mixed, weighed, objective can be calibrated to obtain the best required result (Jozefowiez et al., 2008). In this research no extensive search to best fit multiple criteria has been done. The the effects of two different objectives, providing two different scenarios, have been analyzed.

The objective of the first scenario is to minimize the arrival time at the end of day depot, such that the working time of the drivers left at the end of the day is maximized. This can be seen as slack in the schedule to account for delays and disruptions. The second scenario has as objective to maximize occupancy (ratio of the effective driving time with load and the total available time of a truck) and in parallel minimize the total travel time, in other words: to minimize the driving time between orders, without load. Both scenarios aim to schedule all trucks as efficiently as possible by maximizing asset usage, which is in line with the company goals. Being on time is provided as hard constraint as described in the next section.

Objective per scenario:

1. Minimize arrival time at the end of service, depot:
$$\min \sum_{k \in V} s_{d_k^e,k}$$
2. Maximize truck occupancy and minimize travel time:
$$\max \sum_{k \in V} \frac{\sum_{i \in N} \sum_{j \in N} x_{i,j,k} \cdot o_i,}{f_k - e_k} - \sum_{k \in V} \sum_{i \in N} \sum_{j \in N} x_{i,j,k} \cdot p_{i,j}$$

3.1.2 Constraints

The constraints for the planning problem are given below. They all follow from the problem description as described before and are generic for a VRPTW. Note that the travel time constraint (5.) for the start time of subsequent order was initially not linear, but has been linearized using the big-M method (Dantzig, 1948).

1. Pick each order exactly once: $\sum_{k \in V} \sum_{j \in C} x_{i,j,k} = 1, \quad \forall i \in C$
2. Each vehicle starts at its start depot: $\sum_{j \in N} x_{d_k^s,j,k} = 1, \quad \forall k \in V$
3. Each vehicle ends at its end depot: $\sum_{i \in N} x_{i,d_k^e,k} = 1, \quad \forall k \in V$
4. Orders are sequential: $\sum_{i \in N} x_{i,h,k} - \sum_{j \in N} x_{h,j,k} = 0, \forall h \in C, \forall k \in V$
5. Linearized travel time constraint: $s_{i,k} + t_{i,j} - M(1 - x_{i,j,k}) \leq s_{j,k}, \quad \forall i,j \in N$ $\forall k \in V$
6. Account for time windows: $a_i \leq s_{i,k} \leq b_i, \quad \forall i \in N, \forall k \in V$
7. Account for working hours: $s_{i,k} + t_{i,d_k^e} - M(1 - x_{i,d_k^e,k}) \leq f_k,$ $e_k \leq s_{i,k} + M(1 - x_{d_k^s,i,k}) \quad \forall i \in N, \forall k \in V$
8. Trailer state constraint: $x_{i,j,k}(TS_i^{end} - TS_j^{start}) = 0, \; \forall i,j \in N, \forall k \in V$

Two scenarios, each with one of the two objective functions and these constraints, have been implemented and experimented on using three test cases. The results are presented in the next section.

4 Experiments

4.1 Numerical results

In this study, we have optimized the MILP of the Talking Trucks problem using the two previously mentioned variants of the objective function. The first objective function aims to minimize the total arrival time at the depot at the end of the day. This scenario is referred to as CENTR1. In addition, we have optimized the MILP with an objective function that combines the maximization of vehicle occupancy and minimization of travel time. This scenario is referred to as CENTR2. In the experiments, we will compare the results of optimizing these two objective functions with the results of the decentralized planning technique from Pingen et al. (2022), as well as the planning results of the human planner Van Berkel, as described in Pingen et al. (2022). Each planning technique – decentralized (DECENTR), human (HUMAN), and the central variants (CENTR1/CENTR2) – has been applied to three different days. Specifically, we have applied these techniques to plan a subset of the orders from Dutch logistics company Van Berkel on September 24th, October 1st, and October 8th, 2021 (experiment 1, 2, and 3, respectively). Experiment 1 has relatively short time windows for orders (15 minutes), while experiment 3 has relatively long time windows (up to 12 hours). Moreover, there are differences in truck properties between the different experiments; in experiments 1 and 2, the trucks are relatively homogeneous in terms of working hours, while they are more heterogeneous in experiment 3. The size of the analyzed problems is up to 10 trucks and up to 40 orders per instance. With these relatively small instances the SCIP-solver took around 3 minutes to find an optimal solution on a regular notebook (i7-8650U 1.90GHz) for scenario CENTR1, where the CENTR2 scenario finds solutions within around 5 minutes. This was on these small instances already significantly more than the matter of seconds the decentral approach required (Pingen et al., 2022).

Note in the results below that the human planner outperforms the exact method. This is due to the fact that this planner breaks some of the constraints to achieve a better solution, but does not abide by the rules of the problem which the algorithms have to adhere to. This human flexibility in adherence to the constraints can be observed in the negative waiting time in the Human planner scenario for experiment 2 in Table 3.

The most relevant outcomes are:

- In experiment 3, the driving time with and without load are equal for the decentral and central approaches, in other words, the decentral solution is equal to the optimal solution found in both exact central scenarios, see Table 2;
- In experiment 1, both exact central approaches found a solution with 32 km less driving time without load, which means a reduction of 9% of the total driven 373 kilometers in the decentral solution. In the second experiment, the exact central solutions are 5% lower in total km compared to the decentral solution, see Table 2;
- The distribution of waiting time before the first order (start of day), in between orders (middle of day) and at the end of day is quite different for the various solutions, see table 3. This depends on the timing of certain orders and this is influenced by the difference in objective functions.

Table 2: Total number of driven kilometers per experiment

	With load				*Without load*			
Exp.	DEC.	CEN.1	CEN.2	HUM.	DEC.	CEN.1	CEN.2	HUM.
1	280.45	280.45	280.45	263.27	93.82	61.68	61.68	110.64
2	910.18	910.18	910.18	900.76	389.31	326.83	324.52	432.30
3	873.61	873.61	873.61	858.01	93.63	93.63	93.63	93.63

The results show that CENTR1 and CENTR2 get to similar, but slightly deviating solutions. This is to be expected, given the same planning problem with objective functions that have a similar goal of maximizing asset use, and hard constraints such as delivering all orders on time. The number of driven kilometers with load is equal for all scenarios as the same transport orders have been executed. The interesting comparison is on the number of kilometers driven between transport orders, without load, where the exact method performs up to 30% better than the decentral approach in experiment 1.

Table 3: Average time of waiting per vehicle (in hours).

	Start of day				*During the day*			
Exp.	DEC.	CEN.1	CEN.2	HUM.	DEC.	CEN.1	CEN.2	HUM.
1	2.31	0.36	0.74	1.49	0.23	1.83	0.50	0.45
2	2.44	0.12	0.34	1.24	0.35	1.30	1.15	-0.20*
3	2.27	0.5	0.5	1.06	0.08	0.0	0.0	0.0

Exp.	*End of the day* DEC.	CEN.1	CEN.2	HUM.
1	7.37	6.91	7.78	7.17
2	2.37	4.13	4.09	4.40
3	3.62	4.58	4.58	3.68

Table 4: Problem size and computation time per scenario in minutes on a regular notebook (i7-8650U 1.90GHz). In comparison the human planner required 1 day of work.

Exp.	# orders	# trucks	DEC.	CEN.1	CEN.2
1	38	8	< 1	1	3
2	37	9	< 1	3	5
3	41	9	< 1	6	8

4.2 Central and decentral control in theory compared to practical experiments

Implementing, experimenting and analyzing the VRPTW with decentral and central based solution algorithms provides a base to evaluate advantages and disadvantages of the different approaches. There are four points to compare the central and decentral method on: solution time, scalability, distribution of the computation and distribution of the data.

The first point is the time it takes to find an optimal solution. For the exact central algorithm, this is the time it takes to find a globally optimal solution. For the decentral algorithm, this can also be a local optimum. In our experiments, we have seen that the decentral algorithm took less than 10 seconds to find an optimum, while the solution time for the central algorithm ranged from 2 to 15 minutes. In our current formulation, both methods are very fast compared to the human planner, who needs 6-8 hours to get a schedule.

With more decision variables, the exact method computation time scales exponentially due to the fact that the problem is NP-hard. The decentral method computation time scales linearly. This means that the bigger the problem, the bigger the gap in solution time between the decentral and exact method, in favor of the decentral solution method. The solution time is also influenced by the size of the solution space: the central solution method needs significantly less time in experiment 1 compared to experiment 2 and 3 (see Table 4). This is due to the tighter time windows in experiment 1, which lead to a smaller search space.

Another comparison for the different solution methods is the distribution of the computation of the schedule. In the exact method, computation is done on one machine, while the computation of the decentral method is distributed to the machines of each agent. This means that the computation demands of each machine is smaller in the decentral method, because the decentral method only explores the neighborhoods of each agent. The central method can search the entire solution space, which means that the computation demands can be heavier. The heavier demand in computation time by the central method is also observed in the experiments.

Lastly, the distribution of the data is different for the two methods. For the central method, the data is stored in one location in order for the algorithm to take everything into account. In the decentral solution method, a major part of the data is stored on agent-basis and not centrally. Especially the vehicle and driver specific data are only known to the vehicle and do not need to be shared with other entities. The information on the available transport orders is still provided to the trucks via a central information point, in this case the transport company. The resulting individual truck schedules can be shared to an overseeing entity such as the truck company, however, in theory, this is not necessary. The distribution of data is a relevant factor in developing real world truck scheduling methods. For companies the location and storage of the data can be a sensitive topic, because the transport data is commercial sensitive information for the transport company, but mainly for the concerning shippers. The latter is because production volumes and product launches are trade sensitive information. Transport companies therefore need to be careful in sharing transport data. The decentral approach provides a method of distributing data in a different manner than the central approach and provides opportunities for transport companies to collaborate in transport planning without giving complete insight in company data.

5 Conclusions and recommendations

5.1 Conclusions

The implemented MILP solved with the SCIP-solver leads to optimal solutions for the provided scenarios when given enough runtime. As expected, the solutions show equal and better results on the performance indicators compared to results from the same experiments with the decentral Talking Trucks approach. The main takeaway is that for these, rather small, experiments, the optimality gap between the decentral solution and optimal solution is small, but is present. These experiments already show that it depends on the specific experiment whether the decentral method approaches the exact method optimum. There is an exact match in results in experiment 3, but in experiment 1 the central method gets to a solution with 30 km less empty driven kilometers compared to the decentral scheduling solution, which is a 10% reduction in driven kilometers for this day.

Both the decentral approach and the exact central method are manners to create schedules for these small problem cases in a reasonable amount of time, especially compared to the time the human planner needs to schedule all orders. The decentral approach wins from the exact methods on computation time, especially when looking at bigger instances where the decentral approach scales linearly in computation speed compared to the exponential growing computation requirement of exact methods.

Next to scalability of the problem size, the decentral approach also has other organizational and implementational advantages compared to the exact central approach. Truck and truck driver information do not have to be shared with other entities, only preferences on available transport orders are shared and negotiated. This allows for new ways of collaborating and (self) organizing logistic structures.

5.2 Recommendations

Given the small experiment instances analyzed in this research, it would be interesting to extend the comparison to larger and more varying datasets, because the used experiments are relatively small. The main questions to verify on larger instances would be to compare scalability of exact methods compared to decentral approaches to be able to draw further conclusions on the instances for which exact methods are most relevant and in which situations decentral or hybrid forms are a better option.

In this research we have approached the static problem with a one day ahead scheduling, where in the logistic practice a real time rescheduling method, which really requires high computation speed, could benefit from a fast, decentral approach. Researching applicability and performance of decentral methods in such a setting requires attention.

Additionally, the logistic planning problems in practice have broader scopes than single company truck fleets. Looking into multimodal, or even synchromodal, planning problems and especially situations of multi-fleet or multi-company problems could provide insight in advantages and benefits of the decentral planning approach and get logistic systems closer to the Physical Internet. This would contribute to the goal of making our transport systems more efficient and sustainable.

References

- Bestuzheva, K., M. Besançon, W.-K. Chen, A. Chmiela, T. Donkiewicz, J. van Doornmalen, L. Eifler, O. Gaul, G. Gamrath, A. Gleixner, L. Gottwald, C. Graczyk, K. Halbig, A. Hoen, C. Hojny, R. van der Hulst, T. Koch, M. Lübbecke, S. J. Maher, F. Matter, E. Mühmer, B. Müller, M. E. Pfetsch, D. Rehfeldt, S. Schlein, F. Schlösser, F. Serrano, Y. Shinano, B. Sofranac, M. Turner, S. Vigerske, F. Wegscheider, P. Wellner, D. Weninger, J. Witzig. (2021): The SCIP Optimization Suite 8.0. ZIB-Report 21-41.
- Dantzig, G.B. (1948): Programming in a Linear Structure. Comptroller, United Air Force, Washington, D.C.
- Hopman, M., R. Fransen, J. van Meijeren, I. Zubin. (2022) : *A Framework on Centralised to Decentralised Logistics Control Structures Applied in Two Case Studies*. In: de Armas, J., Ramalhinho, H., Voß, S. (eds) Computational Logistics. ICCL 2022. Lecture Notes in Computer Science, vol 13557, Springer, 369–381.
- Jozefowiez, N., F. Semet, E.G. Talbi, (2008): Multi-objective vehicle routing problems, European journal of Operational Research, 189 (2). 293-309.
- Karunakaran, J. (2020): *Optimal Fleet Assignment in Inland Container Logistics*. Master's thesis, Eindhoven University of Technology.
- Lalla-Ruiz, E., S. Voß, (2016): POPMUSIC as a matheuristic for the berth allocation problem. Ann Math Artif Intell 76, 173–189.
- Phillipson, F. (2015): *Creating Timetables in Case for Disturbances in Simulation of Railroad Traffic*. TNO.
- Pingen, G.L.P., C.R. van Ommeren, C.J. van Leeuwen, R.W. Fransen, T. Elfrink, Y.C. de Vries, J. Karunakaran, E. Demirovic, N. Yorke-Smith, (2022): *Talking Trucks: Decentralized Collaborative Multi-Agent Order Scheduling for Self-Organizing Logistics*. Proceedings of the International Conference on Automated Planning and Scheduling, 32(1): 480–489.
- Quak, H., E. van Kempen, W.M.M. Hopman, (2018) : *Moving Towards Practical Implementation of Self-Organizing Logistics - Making Small Steps in Realizing the PI Vision by Raising Awareness*. IPIC 2018 - 5th International Physical Internet Conference.