Intelligent and Sustainable Transportation through Multi-Objective Model for the Logistic Route-Order Dispatching System

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ABSTRACT

Solution of multi-objective optimization in the logistics sector have become an integral important part of the Intelligent Transportation System (ITS). In this work we focus on the intelligent and sustainable transportation processes through the design of the multi-objective model for the logistic route-order dispatching system. We consider transportation costs, emissions, order importance and risks for failures, for the logistic route-order dispatching system. We present an Integer Linear Programming (ILP) optimization model and apply state-of-the-art techniques as a part of SCIP framework to solve *pilot problem instances* and evaluate the performance of the model. We obtain results of solving the model on a single monolithic Google Cloud Compute (GCP) to estimate the time complexity of the solving process in relation to the various problem sizes. The results from the experiments show low complexity of the problems of various sizes. Therefore scalability of the model looks promising for the applicability in various industry-related scenarios and computing environments. In particular, using hybrid-cloud systems and state-of-the-art optimization frameworks such as IBM CPLEX or Gurobi.

CCS CONCEPTS

• **Computer systems organization**; • **Applied computing** → **Transportation**;

KEYWORDS

Logistics, Sustainable Transportation, Multi-Objective Optimization, Dispatching Systems

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1 INTRODUCTION

In the last few years, the world has gone through a series of global crises with direct impact on the government systems, people's lifestyles, and habits. The world economy turned the entire supply chain system upside down and challenged governments in various national systems. In the wake of the global COVID 19 pandemic, the urgency of efficient and rapid transport systems has taken on a new dimension in its importance, given the heterogeneous and complex border closures and demand for medical products at the time. The global availability and diversity of products, as in terms of the vital medical products, visualized a necessary condition of reliable and efficient transport systems. Sustainability and efficiency became the most contemporary prioritized problems of contemporary logistic networks.

Consequently, governments all over the world were struggling to secure supplies for their respective national health care systems. In addition to that, United Nations (UN) 2030 Agenda[1] for Sustainable Development provided a shared blueprint for peace and prosperity for people and the planet, now and into the future. At its heart are the 17 Sustainable Development Goals (SDGs), which are an urgent call for action by all countries - developed and developing - in a global partnership.

In this work we focus on addressing some SDGs by improving intelligent and sustainable transportation processes through the design of the multi-objective model for the logistic route-order dispatching system. Our model assumes a quasi-static ITS environment, operating on the level of *route-order abstraction layer*. In addition to that, we consider order's and route's delivery-related

[1]https://sdgs.un.org/2030agenda.

dynamic properties such as costs, reliability, and CO_2 emissions not to vary during the planning period. Moreover, problems that affect the optimal allocation in any way after the optimization process was started (e.g., activation/deactivation of routes) are assumed to be minor or non-existent in the reasonable timing horizon. Considering this information we can see the importance of ILP adjustable models and therefore emphasize the need for research into such models. The allocation problem presented in this paper is NP-hard and thus bounded within moderate dimensions sizing within the pilot study with SCIP framework [14].

We start with a literature review in Section 2, we present environment and optimization models in Sections 3 and 4. In Section 5, we present the experimental setup and numerical results. Finally, we conclude with a reflection and future work in Section 6.

2 LITERATURE REVIEW

2.1 Systems Design Models

The literature on system design models for freight transportation and ITS is quite extensive [37, 38]. Many issues are often addressed by evaluating topologies of the corresponding network models for tactical or operational planning of transportation activities. When formal models are proposed, they generally take the form of discrete allocation and scheduling formulations to address issues related to the location of consolidation or hub terminals and the routing of demand from its origin to its destination terminals. Furthermore, routing of the route-order flows determines the direct connections between origins, destinations, and consolidation terminals. When these connections must be explicitly decided *(e.g., the allocation of "local" terminals to major classification facilities)*, a combined location-network-design formulation is often used. All formulations aim to capture the potential economies of scale associated with the consolidation of freight. Extensive literature on location and network design models and solutions is available: Mirchandani and Francis [28], Daskin [10], Drezner [12], Labbé et al. [22], Labbé and Louveaux [21], Crainic and Laporte [9], Drezner and Hamacher [13], and Daskin and Owen [11] review location issues and literature, while Magnanti and Wong [25], Minoux [27], Nemhauser and Wolsey [40], Salkin and Mathur [30], Ahuja et al. [24] and Crainic [7] survey the network design field. Further, within previous research in Kashansky et al. [18], transport systems are prescribed as multi-scale complex systems [1, 17]. For these complex systems, we proposed an optimized approach to monitoring data collection in transportation systems [16]. Later, Validi et al. [36] demonstrated a dynamic multi-scale *control system architecture*, enabling distributed multi-scale monitoring and analysis, that is designed to assure reliable operation of the transport network, improved transportation costs and lower CO2 emissions.

2.2 Automated Optimization and Decision Making

The optimal management of the multi-scale distributed resources is one of the central problems for the previous decades and the current economy. Logistics and transportation context is traditionally addressed via the VRP-based[2] [23], CFLP-based[3][6], ELS-based[4] [29], RCPSP-based[5] [4, 19, 20] and GAP-based[6][5] formulations, subject to various additional resource constraints in the context of the contemporary ERP/MRP [29] systems. This problem plays a prominent role in the fields of physical resource distribution, logistics in intelligent transportation systems in general. Determining the optimal solution to all these formulations is NP-hard [8, 35], limiting the scales of optimally solvable problems using conventional techniques of mathematical programming and software like SCIP [14] and CPLEX [3]. In recent years, there has been a growing trend towards developing tractable solutions through structural decomposition. This approach aims to create computational structures that are more manageable and numerically efficient. Traditionally, a common optimization method involves solving a centralized MIP instance [32] over a planning horizon using various techniques such as direct primal-dual methods [14], heuristic algorithms, or metaheuristics. However, when dealing with large-scale systems [1], the centralized optimization approach becomes impractical due to the exponential increase in complexity. This leads to significant computational and communication overheads, especially in data-intensive scenarios [34]. To address this challenge, hybrid schemes [1] have been proposed to handle large-scale problems effectively [37]. These schemes are capable of breaking down complex problems into several smaller sub-problems, making them more tractable. One interesting aspect that remains to be explored is the establishment of static and dynamic relationships between these controllers and groups of controllable agents [37]. This issue was partially examined in a previous study of Kashansky et al. [15]. Our approach however, does not require complex decomposition techniques and is expected to enable *nearly optimal (Table 1 2.80% Inital Gap)* allocations in moderate-scale ITS environments. Nevertheless, large scale experiments were studied in Yuji et al. [32] in the context of SCIP framework performance evaluation over general MIPLIB benchmark sets in the parallel environment.

3 ENVIRONMENT MODEL AND USE-CASE SCENARIO

Environment model for transportation [8, 38] systems derives from the interplay between production and consumption systems with significant distances that often separate them. Production facilities require transportation services to move raw materials and composite products, in order to meet customer demands. To visualize the process more closely, the complex transportation systems carry the goods from source to destination, while monitoring systems transfer the data from the different subsystems of the whole corresponding ITS architecture: from the vehicle to the data centers, where the artificial intelligence further processes the data and makes fast performance decisions.

Shippers, which may be the producers of goods or some intermediary company (e.g., brokers) and demand efficient transportation. *Carriers* supply transportation services to meet demand. Among

[2]Vehicle Routing Problem
[3]Capacited Facility Location Problem
[4]Economic Lot Sizing
[5]Resource-Constrained Project Scheduling Problem
[6]Generalized Assignment Problem

others, railroads, maritime shipping lines, trucking companies, and postal services, as well as seaports and other intermodal platforms, under the premise of what form of services they provide [9] can be understood as carriers in those transportation systems. In fact, after development of the general architectural concept for multi-scale *control system architecture* by Validi et al. [36], there was a lack of the adequate optimization model operating on the level of *route-order abstraction layer*. It was a *particular motivation* for this model, given set of the recommendations in Wang et al. [37].

3.1 Transportation Model

3.1.1 Transportation Order Pool. We consider a set O of n orders *without precedence relations*:

$$O = \{O_i \mid 1 \leq i \leq n\}. \tag{1}$$

Each order instance $O_i \in O$ characterized by desired delivery due date $\mathcal{T}_i^*$ and relative importance factor σ_i.

3.1.2 Transportation Route Model. We consider a set R of m heterogeneous routes *without precedence relations*:

$$R = \left\{R_j \mid 1 \leq j \leq m\right\}. \tag{2}$$

Each route instance $R_i \in R$ characterized by activation cost c_j, and order capacity B_j^*.

3.1.3 Transportation Matrices. Let $\widetilde{Q}_k$ be the k^{th} *transportation matrix* that contains the corresponding values $\forall (i,j) \in O \times R$:

$$\widetilde{Q}_k = \begin{array}{c c} & \begin{array}{ccc} R_1 & \cdots & R_j \end{array} \\ \begin{array}{c} O_1 \\ \vdots \\ O_i \end{array} & \begin{bmatrix} q_{k1,1} & \cdots & q_{k1,j} \\ \vdots & \ddots & \vdots \\ q_{ki,1} & \cdots & q_{ki,j} \end{bmatrix} \end{array} \tag{3}$$

Let the values of the k^{th} *transportation matrix* correspond to:

(1) Route-order pair completion times $q_{1ij} \in \mathcal{R}$;
(2) Route-order pair costs $q_{2ij} \in \mathcal{R}$;
(3) Route-order pair availability binary matrix $q_{3ij} \in \{0,1\}$;
(4) Route-order pair CO_2-impacts $q_{4ij} \in \mathcal{R}$;
(5) Route-order pair failure rates $q_{5ij} \in \mathcal{R}$;

The provided information defines a transportation problem on the level of route-order abstraction layer. The orders are characterized by their delivery due dates and relative importance factors, while the routes are characterized by their activation costs and order capacities. The transportation matrices contain various values for the route-order pairs, including completion times, costs, availability, CO2 impacts, and failure rates.

4 OPTIMIZATION MODEL

In this section, we present a formal multi-objective model and a set of definitions essential for our work.

4.0.1 Matching and Activation Variables. We define the *matching* of O orders with R routes as a binary variable:

$$x : O \times R \longrightarrow \{0,1\},$$

where $x_{ij} = 1$ indicates the assignment of the order O_i with the route R_j and $x_{ij} = 0$ indicates the contrary. Further:

$$y : R \longrightarrow \{0,1\},$$

where $y_j = 1$ indicates activation of the route R_j and $y_j = 0$ indicates the contrary.

4.0.2 Total Transportation Costs. We define the *total transportation cost* $\mathcal{B}(x)$ of a matching O orders with R routes as:

$$\mathcal{B}(x) = \sum_{i=1}^{n} \sum_{j=1}^{m} q_{2ij} \cdot x_{ij} + \sum_{j=1}^{m} c_j \cdot y_j, \tag{4}$$

where c_j is the activation cost for route $R_j \in R$.

4.0.3 CO_2 Costs. We define the *CO_2 costs* $CO(x)$ as:

$$CO(x) = \sum_{i=1}^{n} \sum_{j=1}^{m} q_{4ij} \cdot x_{ij}, \tag{5}$$

4.0.4 Importance. We define the *importance* $\mathcal{I}(x)$ as:

$$\mathcal{I}(x) = \sum_{i=1}^{n} \sum_{j=1}^{m} \sigma_i \cdot x_{ij} \tag{6}$$

4.0.5 Risks Mitigation. We define the maximum fault probability as:

$$r^* = \max_{i,j}\{q_{5ij} \cdot x_{ij}\} \quad \forall (i,j) \in O \times R. \tag{7}$$

By minimizing the maximum fault probability r^* we make sure that the corresponding risks are mitigated.

4.0.6 Route Capacity Constraints. We define the *Route Capacity constraints* $\forall R_j \in R$ as:

$$\sum_i x_{ij} \leq B_j^* \cdot y_j \quad \forall 1 \leq j \leq m \tag{8}$$

4.0.7 Deadline Constraints. The execution of the orders must complete before a *deadline* $\mathcal{T}_i^*$ on each route $R_j \in R$, $\forall O_i \in O$:

$$q_{1ij} \cdot x_{ij} \leq \mathcal{T}_i^*, \quad \forall \; (i,j) \in O \times R. \tag{9}$$

4.0.8 Order-Route Availability Constraints. Every order $O_i \in O$ can be available for route $R_j \in R$ or not:

$$x_{ij} \in \begin{cases} \{0,1\} & where \; q_{3ij} = 1 \; \forall (i,j) \in O \times R \\ \{0\} & where \; q_{3ij} = 0 \; \forall (i,j) \in O \times R \end{cases} \tag{10}$$

4.0.9 Non-redundant Placement Constraints. Every order $O_i \in O$ should match particular route $R_i \in R$ (no duplicates):

$$\sum_{j=1}^{m} x_{ij} \leq 1, \quad \forall 1 \leq i \leq n \tag{11}$$

Total sum for each order $O_i \in O$ over all routes $R_j \in R$ restricted to be less or equal to 1, meaning that each order O_i is assigned to only one route R_j and there can also be unassigned orders O_i.

4.1 Construction of the Objective Function

Further, to transform the multiple objective optimization problem into a single objective model, we chose factors for each objective and transformed all into minimization objectives by changing the sign. The factors α, β, γ and δ are individually assigned according to the importance of each objective and sum up to a total of 1, weighting each single objective to a fraction of total optimization function. We define the problem, where the constraints are equivalent to the equations: **(12b) ≐ Eq.8**, **(12c) ≐ Eq.9**, **(12d) ≐ Eq.11** and **(12e) ≐ Eq.10**, as:

$$\min_{x,r^*} \quad \alpha \cdot \mathcal{B}(x) + \beta \cdot r^* + \gamma \cdot CO(x) - \delta \cdot \mathcal{I}(x) \tag{12a}$$

$$\text{s.t:} \quad \sum_i x_{ij} \leq B_j^* \cdot y_j, \quad \forall j = 1, \ldots, m \tag{12b}$$

$$q_{1ij} \cdot x_{ij} \leq \mathcal{T}_i^*, \quad \forall \begin{array}{l} i = 1, \ldots, n \\ j = 1, \ldots, m \end{array} \tag{12c}$$

$$\sum_{j=1}^{m} x_{ij} \leq 1, \quad \forall i = 1, \ldots, n \tag{12d}$$

$$x_{ij} = \begin{cases} \{0, 1\} & where\ q_{3ij} = 1 \\ \{0\} & where\ q_{3ij} = 0 \end{cases}, \quad \forall \quad \begin{array}{l} i = 1, \ldots, n \\ j = 1, \ldots, m \end{array} \tag{12e}$$

$$y_j \in \{0, 1\} \quad \forall j = 1, \ldots, m \tag{12f}$$

When transforming multiple objectives in such a way, it is important to also normalize all the objective variables first. In case of $\mathcal{B}(x)$ and $CO(x)$, we normalized with the maximum value from the cost matrix $\widetilde{Q}_2$ and for $\mathcal{I}(x)$, we normalized with the importance σ. This yields a single objective model in the mixed sense of CFLP [6] and GAP-based[5] formulations. That approach provides optimum in weak-Pareto sense [26, 39] for all objectives according to the chosen factors and can easily be adjusted to prioritize certain objectives more by modifying their corresponding scalarization factors.

5 PRELIMINARY EVALUATION

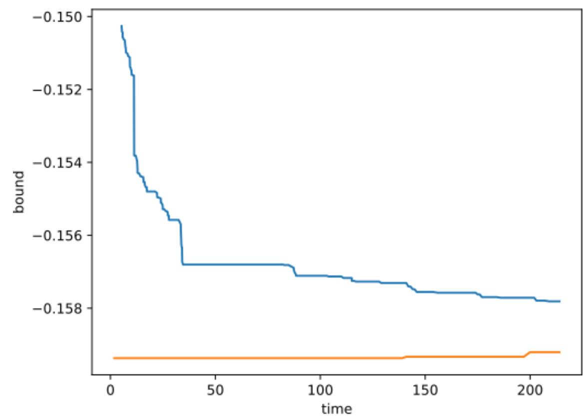
Our experimental setup is based on an instantiated computational cluster using Google Cloud Services (GCP). Further testing of the model (Table 1 and Figs. 2, 1a and 1b) was run on a *n1-standard-1* GCP VM with a setup of scipoptsuite-8.0.3 [7] and an image of the Debian-10 image family.

5.1 Preliminary Experimental Data

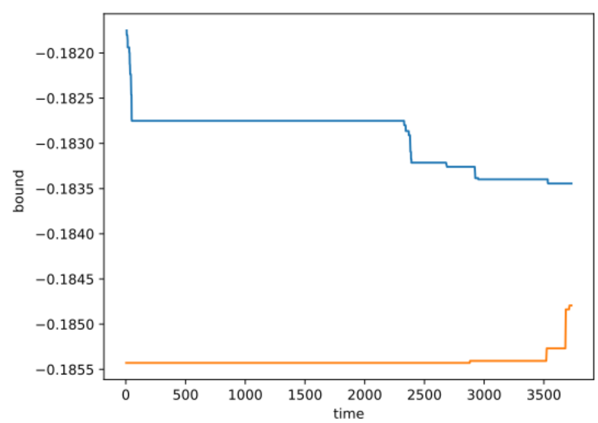
For our preliminary evaluation, we have considered the case with *maximum uncertainty*. In particular, we generated random vectors and matrices of the appropriate sizes as input for the generation of the linear program. We used the build-in library *random* in Python 3.9.7 to generate *uniformly distributed* values and *class A* [15] for the GAP-type constraints. The problem sizes we chose were $m = 50$ for the routes and $n = \{50, 100, ..., 950, 1000\}$ orders. The amount of routes was fixed to simulate a realistic scenario where routes are typically static over longer periods than the order counts and orders were chosen from 50 to 1000 to investigate the scalability of the model for various problem sizes.

5.2 Preliminary Numerical Results

The solving process of an instance with 50 routes and 250 orders provided the plot in Fig. 1a, where we can see the evolution of the upper and lower bound over time during the solving process. Initially we can see many larger improvements for the upper bound, while the lower bound only gradually moves closer to the upper bound until the optimal solution is found. In Fig. 1b for 50 routes and 700 orders we see similar results, but here we can see that



(a) 50 routes and 250 orders.



(b) 50 routes and 700 orders.

Figure 1: Upper bound (blue) and lower bound (orange) plotted over time in seconds. Solved on GCP instance with SCIP 8.0.3.

the upper bound was not improved over a longer time period and eventually when some better bound were found the solving process concluded soon after as well.

Table 1 illustrates the solving progress of a problem instance with $n = m = 50$ with the *counter emphasis* settings for SCIP on a single machine. LP heuristics find a primal solution after 0.2 s to restrict the search neighborhood. More heuristics improve the primal solution after 0.4 s seven times. After 0.2 s of computation, when the first primal bound was set, the gap between primal and dual bound started out at only 2.82%. A low initial duality gap here is very important, because the search space grows rapidly for this problem.

Finding a good primal-dual bound early keeps the search space small and therefore results in much faster solving time for the problem. In this table we see that after 1 s the B&B-tree spans 2000

[7] https://www.scipopt.org.

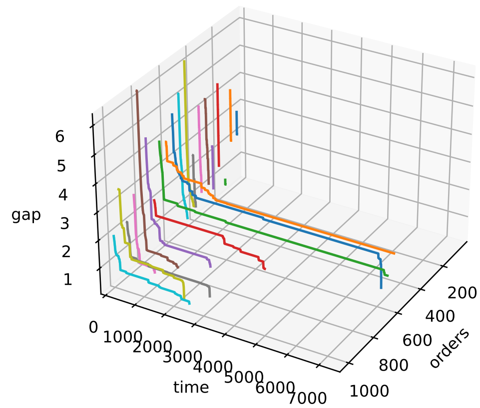


Figure 2: Duality gap *(primal-dual)* in percentages between upper and lower bounds over time during problem solving using SCIP for the presented problem with fixed 50 routes and orders ranging from 50 to 1000 with a step size of 50.

nodes. Looking at the size of the problem over time during the solving process, we see that only three constraints and no variables are reduced after the presolving step at 0.3 s.

From the makespan of all problems displayed in Fig. 2, we depict that the problem time complexity for different orders scales mostly linear with some outliers. Assuming that increasing the amount of routes as well as the amount of orders will result in quadratic complexity, we can conclude that overall the problem has high time complexity and cannot easily be scaled up on a single node.

By using multiple nodes in SCIP and the UG framework [31], we can distribute the solving process over multiple computing nodes and increase the scalability of the problem. The process involves splitting up the problem workload and distributing it to all available nodes. During the pre-solving phase, the algorithm aims to fix variables and detect redundancy of certain constraints. The result is a typically smaller pre-solved instance from the SCIP environment, distributed to all available worker processes, and embedded into each (local) SCIP worker environment. This is the only completely transferred instance that enables transferring differences between a sub-problem and the pre-solved problem later. This approach allows utilizing unused resources within particular partitions by preserving locality and local load balancing.

Load balancing highly depends on the primal and dual bounds updated during the solving process. As the primal bound is the value of the best-found solution so far, the workers send any improved solution to the master, distributing the updated primal bound to all workers. If a worker receives an improved primal bound, it immediately applies bounding and prunes all nodes in its search tree that cannot contain any better solution.

6 CONCLUSION AND FUTURE WORK

In this work we have focused on the intelligent and sustainable transportation processes through the design of the multi-objective model for the logistic route-order dispatching system. Our model considered a static ITS environment, operating on the level of *route-order abstraction layer*. We have explored the concept of using SCIP as framework [14] and found that framework efficiently solves the problem on moderate problem dimensions. Smaller problem sizes with 50 routes and up to 250 orders can be solved optimally quite quickly. For problem sizes of 50 routes and up to 1000 orders we get *small relative gaps efficiently*, so with some compromises on precision these problem sizes can be solved efficiently. This factor allows application of our approach to the wide variety of ITS dimension scenarios, using conventional commercial optimization MINLP frameworks like IBM CPLEX [3] and general purpose cloud computing systems like Amazon AWS and Google Cloud.

For larger problem sizes we consider possible distributed B&B frameworks [31] which can improve the scalability of the optimization system substantially. Several parallelization schemes can deal with large-scale MIPs beyond architectural capabilities by dividing a complex problem into several less-complex sub-problems. Future work will include experimentation with UG [31] - generic framework to parallelize branch-and-bound based solvers in a distributed or shared memory computing environment. The ParaSCIP extension developed using UG consists of a set of base classes to instantiate parallel branch-and-bound based solvers.

6.1 Further integration of the Model with State-of-Art ITS Data Frameworks

We plan to map the current transportation network and analyze, using collected data and the degree of co-modality on national and regional levels in Austria. The vehicles equipped with On-Board Diagnostic (OBD) dongles collect data related to fuel consumption, acceleration, and deceleration patterns, for forming different analysis models. The analysis of the collected data concerning cost and other measures for sustainable transport enables the comparison of transportation modes, such as air, rail, and waterways. The results of this analysis will bring important suggestions for efficient simulations.

6.2 Integration of the Model with Connected and Automated Transport Modeling in SUMO

Further, we plan to model connected and automated technologies like platooning, aiming at reducing fuel consumption and CO_2 emissions using the open-source Simulation of Urban Mobility (SUMO) simulation package [2]. To better depict, analyze and implement the platooning of vehicles, we will integrate the Veins open source vehicular network simulation framework [33] for vehicular communication, which relies on the OMNeT++ [8] discrete event simulator. The integration of Veins, OMNeT++ and SUMO simulators enables autonomous vehicles to cooperate using wireless communication and exchange position, speed, and acceleration data.

[8] https://omnetpp.org/.

Table 1: Solving process after presolving stage for the optimization of the linear integer program, based on the model presented in this paper, with 50 routes and 50 orders. The problem was solved on a single n1-standard-1 GCP VM with a setup of scipoptsuite-8.0.3 and debian-10 image.

time	*node*	*left*	*LP iter*	*LP it/n*	*mem/heur*	*mdpt*	*vars*	*cons*	*rows*	*cuts*	*sepa*	*confs*	*strbr*	*dualbound*	*primalbound*	*gap*	*compl.*
0.2s	1	0	995	-	17M	0	500	556	556	0	0	0	0	-7.624578e-02	–	Inf	unknown
0.2s	1	2	995	-	17M	0	500	556	556	0	1	0	0	-7.624578e-02	–	Inf	unknown
* 0.2s	34	22	1152	4.8	LP	33	500	556	556	0	1	0	0	-7.624578e-02	-7.415655e-02	2.82%	unknown
* 0.2s	48	28	1186	4.1	LP	33	500	556	556	0	1	0	0	-7.624578e-02	-7.416917e-02	2.80%	unknown
0.2s	100	36	1341	3.5	18M	42	500	556	556	0	1	0	0	-7.624578e-02	-7.416917e-02	2.80%	unknown
0.3s	200	24	1559	2.8	18M	43	500	556	556	0	0	0	0	-7.624578e-02	-7.416917e-02	2.80%	unknown
* 0.3s	204	1	1563	2.8	LP	43	500	556	556	0	1	0	0	-7.624578e-02	-7.422442e-02	2.72%	23.85%
* 0.3s	227	1	1695	3.1	LP	43	500	554	556	0	1	0	0	-7.624578e-02	-7.425330e-02	2.68%	37.60%
* 0.3s	300	20	1921	3.1	LP	43	500	553	556	0	1	0	0	-7.624578e-02	-7.428375e-02	2.64%	39.04%
* 0.4s	360	14	2019	2.9	LP	43	500	553	556	0	1	0	0	-7.624578e-02	-7.428740e-02	2.64%	53.88%
* 0.4s	369	12	2035	2.8	LP	43	500	553	556	0	1	0	0	-7.624578e-02	-7.473270e-02	2.02%	54.81%
0.4s	400	17	2102	2.8	18M	43	500	553	556	0	1	0	0	-7.624578e-02	-7.473270e-02	2.02%	56.41%
0.4s	500	15	2296	2.6	18M	43	500	553	556	0	1	0	0	-7.624578e-02	-7.473270e-02	2.02%	56.41%
* 0.4s	577	16	2436	2.5	LP	43	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	56.94%
0.4s	600	11	2470	2.5	18M	43	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	57.45%
0.5s	700	9	2673	2.4	18M	43	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	57.93%
0.5s	800	9	2890	2.4	18M	43	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	57.93%
0.5s	900	11	3103	2.3	18M	43	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.06%
0.6s	1000	9	3272	2.3	18M	43	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.21%
*1.0s	2200	9	5643	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.38%
1.1s	2300	9	5832	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.39%
1.1s	2400	9	6024	2.1	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.39%
1.1s	2500	7	6234	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.41%
1.2s	2600	9	6432	2.1	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.59%
1.2s	2700	11	6600	2.1	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.59%
1.2s	2800	9	6771	2.1	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.59%
1.3s	2900	9	6976	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.59%
1.3s	3000	13	7170	2.1	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.59%
1.3s	3100	7	7346	2.0	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.59%
1.4s	3200	11	7545	2.0	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.60%
1.4s	3300	7	7719	2.0	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.60%
1.4s	3400	9	7924	2.0	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.60%
1.5s	3500	9	8118	2.0	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.60%
1.5s	3600	7	8350	2.0	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.60%
1.5s	3700	7	8562	2.0	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.60%
1.6s	3800	5	8768	2.0	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.60%
1.6s	3900	9	9005	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.60%
1.7s	4000	5	9230	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.60%
1.7s	4100	9	9426	2.1	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.67%
1.8s	4200	9	9592	2.0	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.67%
1.8s	4300	9	9851	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.67%
1.8s	4400	7	10096	2.1	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.67%
1.9s	4500	5	10325	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.67%
1.9s	4600	5	10579	2.1	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.67%
1.9s	4700	11	10793	2.1	18M	51	500	553	556	0	1	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.67%
2.0s	4800	13	10990	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.67%
2.0s	4900	11	11183	2.1	18M	51	500	553	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	58.67%
*3.0s	7400	3	16823	2.1	18M	51	500	549	556	0	0	0	0	-7.624578e-02	-7.476253e-02	1.98%	77.90%

7 DATA AVAILABILITY

All data supporting findings are available from the authors upon request.

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