Cooperative Routing with Heterogeneous Vehicles

Extended Abstract

Keisuke Otaki, Satoshi Koide, Ayano Okoso, Tomoki Nishi
Toyota Central R&D Labs., Inc.
Nagakute, Aichi
{otaki,koide,okoso,nishi}@mosk.tytlabs.co.jp

ABSTRACT

Cooperation among different vehicles is a promising application for Mobility as a Service (MaaS). A primary problem is optimizing the vehicle routes. In this paper, we propose a new concept, named *delegation*, where heterogeneous vehicles cooperate to reduce the total travel cost. Our study models a case in logistics, where a large truck for long-distance delivery carries small self-driving cargoes for the last mile delivery, and the travel cost of the small ones is discounted. We define an optimization problem enabling delegation, propose its integer programming (IP) instance, and discuss our concept through numerical experiments using a modern IP solver.

CCS CONCEPTS

• **Computing methodologies** → *Planning and scheduling*;

KEYWORDS

Cooperative routing; Heterogeneous vehicles; Integer programming

ACM Reference Format:

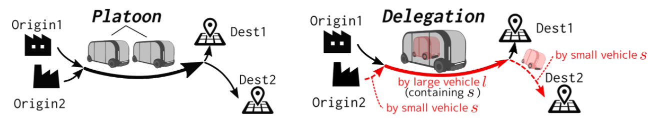
Keisuke Otaki, Satoshi Koide, Ayano Okoso, Tomoki Nishi. 2019. Cooperative Routing with Heterogeneous Vehicles. In *Proc. of the 18th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2019), Montreal, Canada, May 13–17, 2019,* IFAAMAS, 3 pages.

1 INTRODUCTION

To cope with transportation-related social problem (e.g., traffic jams), we need to optimize the way we use our transportation systems. Services provided by autonomous vehicles in MaaS (Mobility as a Service) have the potential to solve the problem, where we need to optimize both the routes that vehicles take and the locations that are used for cooperation (e.g., transfers between vehicles or cross-docking in logistics). In ride-sharing applications, the optimization is critical to reducing the total service costs [1, 2, 4, 7].

Sharing transportation has attracted considerable attention when optimizing vehicle routes [3, 6, 8, 9]. Let us begin our discussion using Fig. 1 that illustrates operation of trucks. Traveling *accompanied by sharing transportation* is an approach to planning the trucks' routes, where operators can *reduce* travel costs. They move trucks as a *platoon* as shown in Fig. 1a, because forming platoons decreases the air resistance on the vehicles. The value of this discount has been validated both theoretically and experimentally [3, 6], where the problem is formalized as *vehicle platooning problem* (VPP).

Proc. of the 18th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2019), N. Agmon, M. E. Taylor, E. Elkind, M. Veloso (eds.), May 13–17, 2019, Montreal, Canada.



(a) Traveling as a platoon **(b) *Delegation* by stacking**

Figure 1: Concept comparisons

We develop a new framework beyond platooning, where heterogeneous types of vehicles cooperate. A new concept, which we have termed *delegation*, defines the way to evaluate the travel costs by *cooperation between heterogeneous vehicles*. With delegation, we can model a case illustrated in Fig. 1b; For a small and large vehicle s and l, l can travel by stacking s as a *cargo*, and the travel cost of s is *delgated to* l. In our proposed model, we optimize both the vehicle routes and assignments among heterogeneous vehicles while the VPP cannot distinguish types of vehicles due to its formulation.

2 PROPOSED CONCEPT

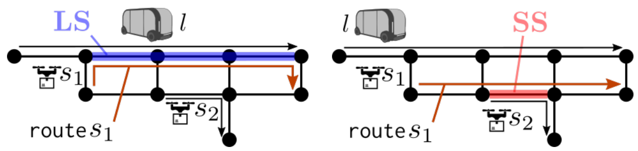
2.1 Notations

For a natural number $n \in \mathbb{N}^+$, $[n] = \{1, 2, \cdots, n\}$. Let $G = (V, E, w)$ be an underlying weighted directed graph with the set V of vertices, the set $E \subseteq V \times V$ of edges, where an edge (u, v) corresponds to the move from u to v, and the weight function $w : E \to \mathbb{R}$, which indicates the travel costs on G. For two vertices $u, v \in V$, the set of all paths connecting u and v is denoted by $\Pi(u, v)$ and a shortest path between them is represented by $\pi(u, v) \in \Pi(u, v)$.

We introduce two vehicle types: *large* and *small*, assuming that both vehicles have the ability to move, and *several small vehicles can be carried by the large vehicle* as shown in Fig. 1b. To distinguish between vehicles, we often identify a large vehicle by l and a small vehicle by s. We let N_L (or N_S) be the number of large (or small) vehicles. We assume that each vehicle has its transportation *request*. A request is a pair of vertices $r = (o, d) \in V \times V$. A path p *satisfies* the request $r = (o, d)$ if and only if $p \in \Pi(o, d)$.

2.2 Cooperation among heterogeneous vehicles

Following the vehicle types defined in Section 2.1, we consider four types of possible cooperation among large and small vehicles, labeled **SS**, **SL**, **LS**, and **LL**. We name the cooperation among heterogeneous vehicles *delegation*, which results in the travel cost reduction for heterogeneous vehicles. We explain the effects arisen from the heterogeneousness using Fig. 2. Here we can optimize the route of s_1. We would select the **LS** reduction to carry s_1 in l with its good as in Fig. 2a for the request when the platoon **SS** with s_2 illustrated in Fig. 2b is less effective than the effect of **LS**. Although



(a) LS cooperation **(b) SS cooperation**

Figure 2: Cooperation with heterogeneous vehicles

we have four possible combination, we here focus on the **LS** effect to model truck-UAV cooperation, which is named 2MP^3.

Problem 1 (2MP^3). *Given sets $\mathcal{R}_S = \{r_1^{(S)}, \cdots, r_{N_S}^{(S)}\}$ and $\mathcal{R}_L = \{r_1^{(L)}, \cdots, r_{N_L}^{(L)}\}$ of requests for small and large vehicles, $2MP^3$ involves computing $\mathcal{P}_T = \{P_i \mid i \in [N_T], P_i \in \Pi(o_i^{(T)}, d_i^{(T)})\}$ for $T \in \{S, L\}$, and $\mu = \{(s, l, u, v) \mid s \in [N_S], l \in [N_L], u, v \in V\}$ that minimizes*

$$c^{(\text{del})}(\mathcal{P}) = \textstyle\sum_{(u,v)\in E} w((u,v)) \sum_{T_1 \in \{L,S\}} g_{u,v}^{(\text{del}),T_1}, \text{ where}$$

$$g_{u,v}^{(\text{del}),T_1} = \#(\text{leading } T_1 \text{ vehicle at } (u,v))$$

$$+ \textstyle\sum_{T_2 \in \{L,S\}} \eta^{(T_1 T_2)} \#(T_2 \text{ vehicle delegating to } T_1 \text{ at } (u,v)) \tag{1}$$

by setting $\eta^{(SL)} = \infty, \eta^{(LS)} = 0, \eta^{(SS)} = \eta^{(LL)} = 1$, under the constraint of the number of small vehicles whose costs are delegated to a large l is less than or equal to $Q_l^{(LS)}$.

Note that the term $g_{u,v}^{(\text{del}),T_1}$ is a generalization of the way used in VPP. For 2MP^3, we need to optimize simultaneously the binary variables $f^{(L)}$ and $f^{(S)}$ related to the routes (e.g., $f_{u,v,l}^{(L)} = 1$ means the large vehicle l travels on (u,v)), and the assignment μ. To reduce the total travel cost, the objective is set to

$$\min_{f^{(L)}, f^{(S)}, \mu} \textstyle\sum_{(u,v)\in E} w((u,v)) g_{u,v}^{(\text{del}),L}, \tag{2}$$

and the following constraints are introduced for 2MP^3; For $s \in [N_S], l \in [N_L], T \in \{S, L\}, (u,v) \in E$, and the subscript $i \in [N_L]$ when $T = L$ and $i \in [N_S]$ when $T = S$,

$$g_{u,v}^{(\text{del}),L} = \textstyle\sum_{l\in[N_L]} f_{u,v,l}^{(L)} + \sum_{s\in[N_S]} \phi_{u,v}^s, \tag{3}$$

$$\phi_{u,v}^s = \textstyle\prod_{l\in[N_L]} (1 - \mu_{u,v}^{s,l}) \times f_{u,v,s}^{(S)}, \tag{4}$$

$$2\mu_{u,v}^{s,l} \le f_{u,v,s}^{(S)} + f_{u,v,l}^{(L)}, \tag{5}$$

$$\textstyle\sum_{l\in[N_L]} \mu_{u,v}^{s,l} \le 1, \sum_{s\in[N_S]} \mu_{u,v}^{s,l} \le Q_l^{(LS)} \tag{6}$$

$$\textstyle\sum_v f_{u,v,i}^{(T)} - \sum_v f_{v,u,i}^{(T)} = \begin{cases} 1 & \text{if } u = o_i^{(T)} \\ -1 & \text{if } u = d_i^{(T)} \\ 0 & \text{o/w} \end{cases}, \tag{7}$$

$$f_{u,v,l}^{(L)}, f_{u,v,s}^{(S)}, \mu_{u,v}^{s,l} \in \{0, 1\} \tag{8}$$

Note that Constraint (3) defines the evaluated flow on (u,v) from Eq. (1). Constraint (4) represents a small vehicle s traveling alone if and only if no assignments are given from s to $l \in [N_L]$ at $(u,v) \in E$. Constraint (5) indicates that $\mu_{u,v}^{s,l}$ can be 1 if and only if both l and s travels (u,v). Constraint (6) represents the exclusiveness for assignment and the capacity constraint. Constraint (7) means that all requests are satisfied. Constraint (8) defines variables.

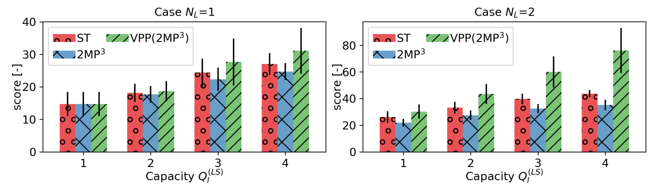


Figure 3: Comparing costs by ST, 2MP^3, and VPP(2MP^3).

3 COMPUTATIONAL EXPERIMENTS

We evaluated our IP instance on synthetic graphs. In the experiments, we used labels $(N_L, Q_l^{(LS)})$; the label $(N_L, Q_l^{(LS)}) = (2, 3)$ means the number of large vehicles is two and the capacity of each large vehicle is three. For the label $(N_L, Q_l^{(LS)})$, we always prepare $N_L \times Q_l^{(LS)}$ small vehicles and generate $N_L + N_L \times Q_l^{(LS)}$ requests.

Settings and Results. For a 10×10 grid graph with noisy coordinates, we generated random requests. We then compare the travel costs of optimized solutions obtained by (1) shortest paths (labeled **ST**), (2) routes optimized by the 2MP^3 (labeled **2MP^3**), and (3) routes optimized by the VPP, where no travel costs are required if cooperate, and evaluated as routes by 2MP^3 (labeled **VPP(2MP^3)**). Note that (3) is prepared to validate the effect of introducing four cooperation combination and that of focusing on the **LS** effect in 2MP^3. For both (2) and (3), we use Gurobi to optimize the problems [5].

Figure 3 shows the obtained travel costs for labels $(N_L, Q_l^{(LS)}) \in [2] \times [4]$. They indicated that the PPP achieved smaller travel costs than shortest paths. We can interpret that the PPP could utilize the **LS** effect in optimization. In contrast, travel costs optimized by the VPP were *worse than the routes by the shortest paths*. This was because the VPP, which cannot distinguish vehicle types, tried to form the four cooperation combination.

Discussions. The above results showed that the heterogeneous cooperation could be beneficial to optimize the routes of heterogeneous vehicles. Although the VPP cannot distinguish the cooperation type, we can focus on optimizing the routes only with the **LS** effect in the 2MP^3. Evaluating the cooperation separately according to vehicle types is essential for heterogeneous vehicles as we explained in Sec. 2.2. Further, the reduction effect in VPP could be interpreted as the *homogeneous* cooperation (in **LL** or **SS** effects). We therefore conclude that the optimization based on heterogeneousness is an important baseline for cooperative routing.

4 CONCLUSION

We propose a new concept, named delegation, to model heterogeneous cooperation of vehicles. Our IP instance can deal with two types (large and small) of vehicles, where small vehicles could board in large vehicles and the travel costs get discounted. We validated our IP formulation through experiments. Delegation can be applied to MaaS applications for transportation and logistics.

Our future work include the development of more general framework that supports different types of cooperation among more than two vehicles. Further, developing distributed solvers is also an important problem for our researches.

REFERENCES

[1] Niels Agatz, Alan Erera, Martin Savelsbergh, and Wang Xign. 2012. Opimization for dynamic ride-sharing: A review. *European Journal of Operational Research* 223 (2012), 295–303.

[2] Javier Alonso-Mora, Samitha Samaranayake, Alex Wallar, Emilio Frazzoli, and Daniela Rus. 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. *Proceedings of the National Academy of Sciences* 114, 3 (jan 2017), 462–467. https://doi.org/10.1073/pnas.1611675114 arXiv:arXiv:1507.06011

[3] Christophe Bonnet and Hans Fritz. 2000. *Fuel consumption reduction in a platoon: Experimental results with two electronically coupled trucks at close spacing*. Technical Report. SAE Technical Paper.

[4] Masabumi Furuhata, Maged Dessouky, Fernando Ordóñez, Marc-Etienne Brunet, Xiaoqing Wang, and Sven Koenig. 2013. Ridesharing: The state-of-the-art and future directions. *Transportation Research Part B* 57 (2013), 28–46.

[5] Gurobi Optimization, LLC. 2018. Gurobi Optimizer Reference Manual. (2018). http://www.gurobi.com

[6] Erik Larsson, Gustav Sennton, and Jeffrey Larson. 2015. The vehicle platooning problem: Computational Complexity and Heuristics. *Transportation Research Part C: Emerging Technologies* 60 (2015), 258–277.

[7] Shuo Ma, Yu Zheng, and Ouri Wolfson. 2015. Real-Time City-Scale Taxi Ridesharing. *IEEE Transactions on Knowledge and Data Engineering* 27, 7 (2015), 1782–1795.

[8] Kazuki Takise, Yasuhito Asano, and Masatoshi Yoshikawa. 2016. Multi-user routing to single destination with confluence. In *Proc. of the 24th ACM SIGSPATIAL*. 72:1–72:4.

[9] Xinpeng Zhang, Yasuhito Asano, and Masatoshi Yoshikawa. 2016. Mutually Beneficial Confluent Routing. *IEEE Transactions on Knowledge and Data Engineering* 10 (2016), 2681–2696.