Improving upon package and food delivery by Semi-autonomous Tag-along Vehicles

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Abstract. This paper aims to improve current last mile distribution and package delivery by introducing basic concept of delivery using Semi-autonomous Tag-along Vehicles (SaTaVs) driven by their own agency and desires. SaTaVs are introduced as vehicles capable of traveling by following leading vehicle and thus reducing requirements for their autonomy while maintaining most of the advantages. Whole system is designed as maintaining long term equilibrium with agents goal in maximizing future investment.

Keywords: Vehicle routing problem, perishable food delivery, intelligent transportation, agent systems

1 Current state

Package and food delivery consists mainly of Vehicle Routing Problems (VRPs) which is NP-hard problem [1]. Distribution plan [2] is then set as plan of a fleet vehicles used to deliver (or pick-up) goods to (or from) customers with the other endpoint being warehouse. Additional complication arise when dealing with perishable goods this is usually refereed as Vehicle Routing Problem with Time Windows and Temporal Dependencies (VRPTWTD) and is comprehensively described by Hsu at al. [3]

When dealing with Point-to-Point (PtP) deliveries (like food deliveries from restaurants or delivering timely legal documents) the distribution throughout warehouses becomes impossible due to the inherent time delays. This could be solved by adaptation of methods like advanced Dial-A-Ride Paratransit (DARP) solution [4]. But in reality the cost of managing rides for food delivery exceeds the costs of self-owning of delivery vehicles and thus majority of food providers use their own delivery cars and systems of High Coverage Point-to-Point Transit (HCPPT) [5] are yet to arise. Change to this may be introduced by Shared Autonomous Vehicles (SAVs) as showed in recent studies [6][7] - one SAV can replace multiple conventional vehicles thus lowering prices of distribution. The cost benefit for packages is even greater then for person transportation due to higher potential capacity for packages. Using SAVs for package distribution could also improve Levin et al. 2017 model [8].

1.1 Last Mile Distribution

Last mile distribution represents last step in shipments when packages are delivered to end-customers of process. That usually means driving to customer address notifying him of arrival and waiting for him to sign the receive documents. Additionally when dealing with temperature sensitive cargo - the opening the cargo hold is important factor impacting inventory costs as noted in [3].

1.2 Point-to-Point deliveries

Distribution of prepared food from restaurants is usually handled as some version of VRPTWTD where restaurants either schedule food preparation according customer location and thus creating less predicable delivery times or running distribution one item at a time which inevitably increases the prices.

2 Semi-autonomous Tag-along Vehicles - SaTaV

Our solution to this problem is introducing concept of vehicles capable of following a car or motorbike - SaTaVs. Such vehicles would need properties of maximum speed around 50 km/h (or 30 mph) - most common city speed limit. These vehicles would also of course need GPS (or other positioning) unit to monitor their real-time position, wireless communications and means of tracking leading vehicle which would provide routing.

Other features of SaTaVs would also need to be ability to travel in formation and safely manage short distance reposition on their own. Lastly they should be able to provide customers with secured access to the cargo.

Such vehicles would bring the advantage for last mile distribution in form of reduced stop time of leading vehicle – SaTaVs would wait for their customers on their own while other packages are on their way to their customers. And for PtP deliveries they would present more immediate expedition if opportunity arises.

2.1 Package as agent

This basic premise lets us intuitively treat every package as its own agent. The agent then has desire to get to the target position and constraints in form of time and cost. Considering one SaTaV carrying one package desires need to be expanded by desire of being in particular city zone and costs of travel to sender and return from customer.

2.2 Desire zones

Every SaTaV has desire to be in the zone with lowest possible SaTaV population index i_p. For the most part this paper will present three types of zones dependent on SaTaVs population in current zone: **low** - zones where is less SaTaVs then there is expected to be demanded of: **fair** - number of SaTaVs should suffice

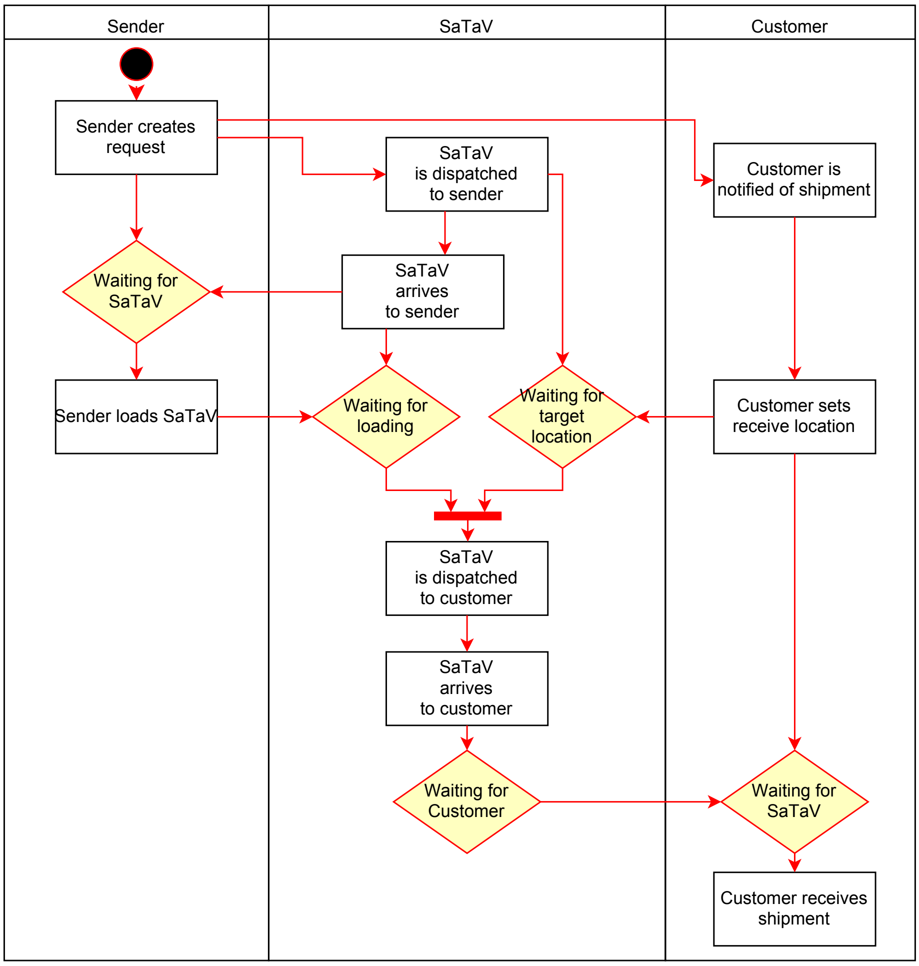

Fig. 1. Process of shipment with SaTaVs from sender and customer view

for expected demand and **high** - number of SaTaVs is far higher then expected demand for specified zone.

SaTaVs population index for specific zone is calculated according to minimum D_L and maximum D_H zone SaTaV expected requirement as follows:

$$x : ip_x = \frac{P_x - D_{Lx}}{D_{Hx} - D_{Lx}} \tag{1}$$

Population index is then used for cost equation of SaTaV movement as from point x to y with point 0 being SaTaV initial position by:

$$C_{xy} = Ca_{0x} + Ct_{xy} + Cp_y \tag{2}$$

Table 1. SaTaV population zones

ip	Population	Description
$(-\infty, 0)$	low	Population less then desired
$[0, 1)$	fair	Population has reserve as expected
$[1, \infty)$	high	Too many SaTaVs in zone

where:

$$Ca_{0x} = (1 - ip_0) * c_A + d_{0x} * c_d \tag{3}$$
$$Ct_{xy} = d_{xy} * c_d \tag{4}$$
$$Cp_y = ip'_y * c_P \tag{5}$$

where Ca_{0x} is allocation cost with c_A being allocation cost constant, Ct_{xy} is cost of transport with d_xy being distance from point x to y and c_d distance unit cost constant. Lastly Cp_y is cost ending in target zone with c_P being constant of parking cost and ip'_y is population index including traveling agents. Because ip is from interval $(-\infty, +\infty)$ part, or a whole cost equation can be negative – this is a wanted behavior for encouraging use of SaTaVs from over populated zones to underpopulated.

Let's imagine following situation - five zones with sender in zone 2 an customers in zones 4 and 5 (shown on Figure 2). When a sender puts in a request for package transport from zone 2 to zone 4 all SaTaVs will see request and can calculate their allocation and travel expanse. For agents in zone 1 initial allocation and travel cost will be $Ca_{12} = 1 - (-0.2) * c_A + d_{12} * c_d = 1.2c_A + d_{12} * c_d$ while for agents in zone 2 (let's suppose that d_{22} is 0) allocation cost will be $Ca_{22} = 1 - (0.4) * c_A = 0.6c_A$ and thus agents from zone 2 will be preferred over agents from zone 1. For the agents from zone 3 the allocation and initial cost will be $Ca_{32} = 1 - (-1.2) * c_A + d_{32} * c_d = -0.2c_A + d_{32} * c_d$. Agents from the zone 3 are by negative cost of allocation incentivized to further system zones population equilibrium. Similarly for cost of delivering packages transported to

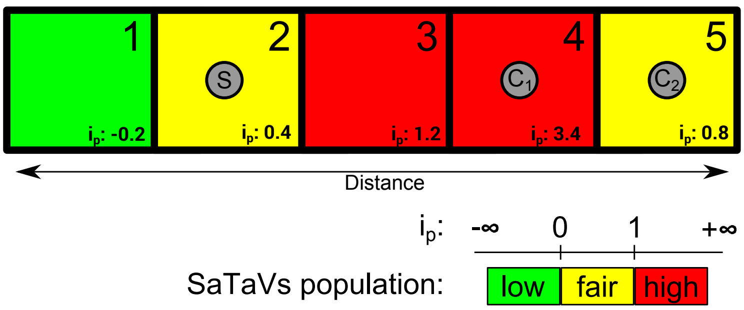

Fig. 2. Zoning example for determining SaTaVs desires.

the customer $1 : d_{24} * c_d + ip_4 * c_P$ and customer $2 : d_{25} * c_d + ip_5 * c_P$ and while $d_{24} < d_{25}$ the difference in $ip_4 = 3.4$ and $ip_5 = 0.8$ depending on c_P and c_d may cause longer distance delivery to customer no.2 to be cheaper in view of better system equilibrium reflecting agents future prospect for another delivery.

2.3 Empty trips

SaTaVs are also capable of empty trips with cost equation (2) in reduced form as:

$$Ce_{0t} = Ca_{0t} + Cp_t \tag{6}$$

intended for relocation of SaTaVs in case of large system imbalance when benefits from leaving the zone with high population and benefits from arriving to low population zone cover travel expanses.

3 SaTaVs auction system

All transactions in SaTaVs ecosystem are managed by auctions, thus allowing clients to chose their own priorities and keep prices for services in competitive perspective.

3.1 Allocation bidding

SaTaV agents offer their services through simple auction system where sender puts request for shipment and gets bids from available units in form of price and expected arrival time as can be seen in Figure 3.

bid_id	zone	distance	allocation_cost	approx_time
8561	D7	3.62	120	420
8565	B7	4.4	200	820
8567	D8	4.9	280	370
8563	D8	5.7	320	400
8562	C6	7.2	600	380
8566	B6	12.5	1300	840
8564	C7	0.2	1700	70

Fig. 3. Allocation table showing bids of near SaTaVs.

Client is presented with choices, where according to his priorities, he can choose allocation time versus cost ratio. After client makes makes his choice, SaTaV is notified of successful bid and starts his way to client.

3.2 Transportation hiring

When SaTaVs want to get to sender or transport package, they put up bid for transport with information on origin location, target location and price willing to pay for transport. Price B is set according to priority P_B of sender or customer depending on time sensitivity of the package, where priority $P_B = 1$ represents urgency and price is equal to full price of hired personal leading vehicle. SaTaVs with less time sensitive cargo are starting bidding for transport by fraction of full price and may use increments on price initiated by customer while SaTaVs with highly time sensitive cargo are using price expected to yield transportation as soon as possible.

Prices for transport, willing to be paid by SaTaVs, are then shown in the system, where driving agents (either human drivers with cars, motorbikes or even bicycles or fully autonomous vehicles) may purchase contract to lead SaTaV from its current location to desired destination.

3.3 Empty trips

When SaTaV is in high population zone ($ip \geq 1$) it automatically starts to scan for fair and low population zones ($ip < 1$) and calculates empty trip cost according (6). If result Ce_{0t} is negative the sum is used for transportation bid.

4 System parameters

In above mentioned equations is a lot of parameters (like allocation constant c_A, parking constant c_P or optimal zone population limits) without defining their value or relationship. This is intentional because this constants have highly specific nature depending on factors such as geography, traffic, zone input or output of packages and lot more.

This can be seen on specific example in Figure 4 showing disproportioned package flow in Brno city caused by high concentration of small businesses in city center in proportion to high consumption by residential areas on edges of city. This creates high demand for SaTaVs on one side and unwanted overpopulation on other. Such effects are countered by system constants causing SaTaVs to engage in empty trip migration from edges back to center funded by high parking costs on edges and high allocation costs in center.

5 Conclusion

This paper presented basic overview of delivery with Semi-autonomous Tag-along Vehicles representing alternative to now used package delivery systems.

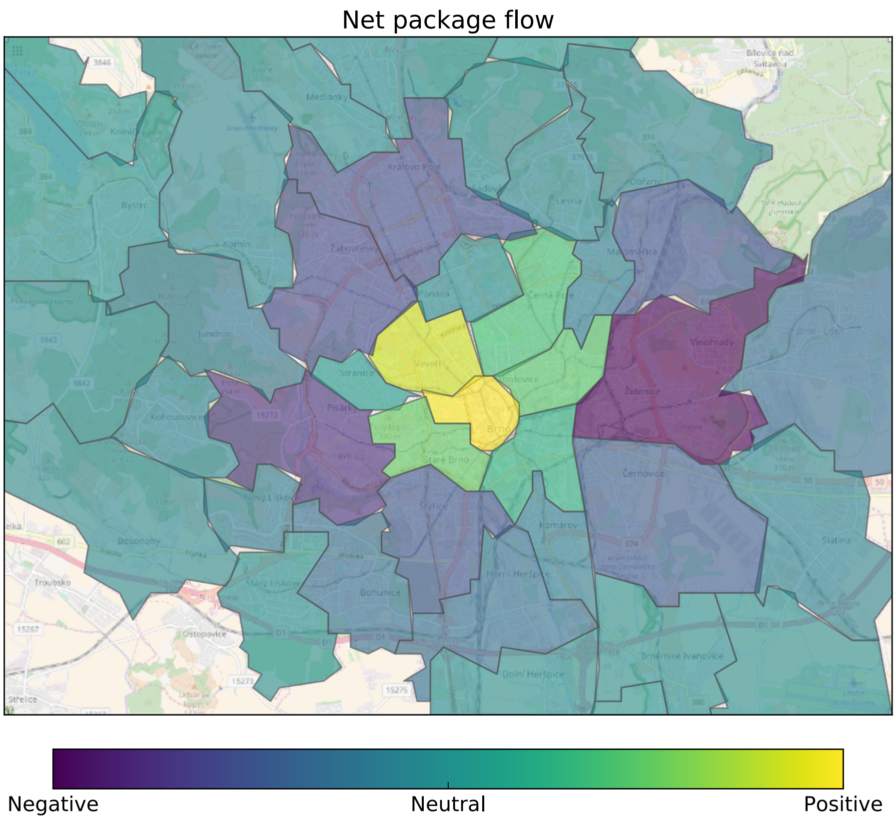

Fig. 4. Simulated package flow based on district type in Brno.

System is dependent on future technology of economically viable SaTaVs, but principle can be implemented on packages delivered by human drivers directly yet economical viability is depended on low time cost autonomous systems.

Future work should be directed to establishing parameters automatically based on feedback from simulation of particular zones using real-time traffic data and creating comparative studies to current distribution systems.

6 Acknowledgements

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