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PARCEL DELIVERY FOR SMART CITIES: A SYNCHRONIZATION APPROACH FOR COMBINED TRUCK-DRONE-STREET ROBOT DELIVERIES

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ABSTRACT

The past decade saw many novel concepts for last-mile delivery. Particularly interesting is the concept in which trucks dispatch – from designated points – drones or robots that do the actual delivery. Generally, the role of the truck driver is underexposed. This paper proposes a last-mile delivery concept in which a truck carries a mixed fleet of drones and robots, and where the driver also has an active role in the delivery process. Our aim is to efficiently align the service time required by the truck driver with the back-and-forth delivery times of the drones and the robots. To this end, we design a street delivery model using continuous approximation. We evaluate our approach using a flexible and reusable simulation model to enable tactical decision-making for logistics service providers to determine which neighborhoods are suitable for drones, street robots, or combinations, in terms of makespan and energy consumption.

1 INTRODUCTION AND RELATED WORK

Drones constitute an emerging technology that provides opportunities in such diverse areas as construction (Phung et al. 2017), agriculture (Bandeira et al. 2015), disaster management (Sandvik and Lohne 2014), entertainment and media (Guerriero et al. 2014), and, last but not least, transportation (Murray and Chu 2015).

The effectiveness and efficiency of drones can be significantly enhanced if drones are combined with other vehicles, e.g., trucks and automated guided vehicles. A review of the state of the art is given by Chung et al. (2020). In parcel delivery, the idea of assisting trucks by drones has proven to be promising. The same applies to assistance by street robots (Mathew et al. 2015; Simoni et al. 2020). Moeini and Salewski (2020) introduced a new concept in last-mile delivery in which a truck carries a mixed fleet of drones and street robots, such that the truck dispatches and collects drones or robots that do the actual delivery from designated points. The truck itself is not used for direct deliveries. Depending on the parcel's weight and the exact location of the customers, either a drone or a robot is used for delivering parcels (see Figure 1 for examples). Basically, the truck is used to extend the limited range of the robots and drones. The system is more versatile than the use of a truck with either drones or robots. In the above study, as well as in others, the role of the truck driver is underexposed.

In this paper, we propose a last-mile delivery concept, in which a truck carries a mixed fleet of drones and robots, but also a truck driver that has an active role in the delivery process. Thus, at designated locations (i) the co-driver monitors the dispatching and collecting of drones or robots that perform deliveries, (ii) the truck driver services customers himself. In this way, we take care of the human factor. Not all customers appreciate drones or robots at their doorstep. In addition, there may be services such as unwrapping parcels that require manual handling. Our aim is to efficiently align the service time required by the truck driver with the back-and-forth delivery times of the drones and the robots. In a multi-truck

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situation, customers are allocated to trucks in such a way that the delivery area of the drones and the robots is proportional to the length of the service window of the truck driver, related to a particular designated location. We perform a simulation study in order to test the usability of our ideas. Moreover, we present a modelling approach to develop a flexible and reusable simulation model to speed up tactical decision-making for logistics service providers for different locations (e.g., which neighborhoods are suitable for drones, street robots, or combinations).

The remainder of this paper is composed as follows: Section 2 provides a synchronization approach for tactical decision-making. In Section 3, the conceptual model is described, and the simulation model is described in Section 4. The results are discussed in Section 5. The paper closes with conclusions and directions for further research in Section 6.

Figure 1: Examples of drones and street robots for parcel delivery.

2 SYNCHRONIZATION OF DELIVERIES

The key to an efficient cooperation between a truck driver and a fleet of street robots and drones is synchronization: We aim for a total delivery processing time that is equal per truck driver, per street robot, and per drone. Clearly, the delivery process consists of handling as well as travelling. For simplicity, this paper focuses on synchronization of travel times, only. We distinguish two types of parcels: heavy parcels and light parcels. Without entering technicalities, let us call a parcel light when it can easily be transported by a drone. Conversely, heavy parcels cause safety risks, lift-off problems, and excessive consumption of energy when transported by a drone. They can, however, conveniently be transported by a street robot or by a truck driver, provided the latter uses a hand trolly. Moreover, many municipalities ban trucks from narrow streets in the city center and increasingly deploy zero-emissions zones. Our idea of truck use is in line with that. The truck is not allowed to enter the street, but parks at a designated location near the beginning of the street. Next, parcels are delivered by the transport modes (i.e., the truck driver, the street robots, and the drones) in a *single command* fashion: Each parcel is retrieved from the truck by one of the modes and delivered at the doorstep of the customer. Then, the mode returns to the truck empty and retrieves the next parcel.

Section 2.1 introduces a simple street delivery model using continuous approximation. Section 2.2 derives the corresponding expected total travel times per truck driver, per street robot, and per drone. These are synchronized in Section 2.3. In Section 2.4, we discuss a slight adaptation from the model given in Section 2.1. Section 2.5 discusses the accuracy of the continuous approximation.

2.1 A Simple Street Delivery Model: Continuous Approximation

Let us model a street as an interval $[0, L]$. We assume two types of parcels: heavy parcels and light parcels. For simplicity, we assume uniformly distributed demand for heavy as well as light (parcel) deliveries. Let the constants ρ_1 and ρ_2 denote the heavy and light delivery densities, respectively, i.e., the number of deliveries per meter. The truck parks at point 0. From there, three delivery modes depart, servicing their own specific zone:

(i) the truck driver with speed v_1 servicing the heavy deliveries in the interval $[0, \alpha L]$ with $0 < \alpha < 1$
(ii) s street robots, each with speed v_2 servicing the heavy deliveries in the interval $[\alpha L, L]$
(iii) d drones, each with speed v_3 servicing the light deliveries in the interval $[0, L]$

2.2 Expected Total Travel Times per Truck Driver, per Street Robot, and per Drone

Below, we derive the expected total travel times per truck driver, per street robot, and per drone:

1. *Truck driver.* The expected number of (heavy) delivery visits amounts to $\alpha L\rho_1$. The expected travel time (forth and back) per delivery visit is $\alpha L/v_1$. Hence, the total expected travel time per truck driver to visit all customers in the interval [0, αL] is α^2/C_1 with $C_1 = v_1/\rho_1 L^2$
2. *Street robot.* The expected number of (heavy) delivery visits per street robot is $(1-\alpha)L\rho_1/s$. The expected travel time (forth and back) per delivery visit is $(1+\alpha)L/v_2$. Hence, the total expected travel time per street robot to visit all customers in the interval $[\alpha L, L]$ is $(1-\alpha^2)/C_2$ with $C_2 = sv_2/\rho_1 L^2$
3. *Drone.* The expected number of (light) delivery visits per drone is $L\rho_2\ /d$. The expected travel time (forth and back) per delivery visit is L/v_3. Hence, the total expected travel time per drone to visit all customers in the interval $[0, L]$ is $1/C_3$ with $C_3 = dv_3/\rho_2 L^2$

2.3 Synchronizing the Expected Total Travel Times

Let us determine the model parameters (among which α) in such a way that the expected travel time ETT per truck driver, per street robot, and per drone is equal. In other words, we need to synchronize these modes. For this purpose, we require that $ETT = \alpha^2/C_1 = (1-\alpha^2)/C_2 = 1/C_3$. Hence $\alpha^2 = C_1/(C_1 + C_2) = C_1/C_3$. Substituting back, we arrive at: $\alpha^2 = v_1/(v_1 + sv_2) = \rho_2 v_1/\rho_1 dv_3$. Hence, in order to synchronize, we need to adapt at least one of the speeds. Roughly speaking, the speeds of the truck driver and the street robot can be identified. Furthermore, these speeds are hard to change. Conversely, the drone speed v_3 is quite flexible. Hence, we aim to adapt v_3 to hold the above equality. To exemplify, let us fix v_1 and v_2 at 5 km/h. Suppose we have 2 street robots. Then $v_3 = 15\rho_2/\rho_1 d$. Now assume that $\rho_1 = 0.2\rho_2$. Then, $v_3 = 75/d$. Incidentally, $ETT = \rho_1 L^2/(v_1 + sv_2) = \rho_2 L^2/dv_3$
On the one hand, $ETT = (total\ number\ of\ heavy\ deliveries\ in\ the\ street) * ETTHP$, where ETTHP $= expected\ travel\ time\ per\ heavy\ parcel =\ L/(v_1 + sv_2)$. On the other hand, *ETT=(total number of light deliveries in the street)*ETTLP*, where $ETTLP\ = expected\ travel\ time\ per\ light\ parcel = L/dv_3$. These expressions may be seen as a general estimate, under the condition of mode synchronization. They are intuitively clear, since e.g., per heavy parcel you travel on average a (back and forth) distance of 2*($L/2$) and you do so with combined speed $v_1 + sv_2$. Interestingly, ETTHP is independent of the zone sequence, e.g., interchanging the zones of the truck driver and the street robots gives the same expression.

2.4 Swapping the Driver

For ergonomic reasons, we may consider reassigning the driver from heavy to light parcel deliveries:

(i) the truck driver executes the light deliveries in the interval [0, βL] with $0 < \beta < 1$
(ii) d drones execute the light deliveries in the interval $[\beta L, L]$
(iii) s street robots execute the heavy deliveries in the interval $[0, L]$

Then, we find $\beta^2 = v_1/(v_1 + dv_3) = \rho_1 v_1/\rho_2 sv_2$. In this swapped case, we find for the expected travel time per truck driver, per street robot and per drone: *ET – swapped* = $\rho_2 L^2/(v_1 + dv_3) = \rho_1 L^2/sv_2$, where the equality is realized by adapting v_3. Thus, we conclude that $ETT - swapped =\ \rho_1 L^2/sv_2 > ETT =\ \rho_1 L^2/(v_1 + sv_2)$. Hence, for economic reasons it is preferred to keep the truck driver assigned to the heavy parcel deliveries.

2.5 Accuracy of the Continuous Approximation

In practice, obviously, demand for parcels occurs at discrete locations, say at $j = 1,\ 2, \ldots, M$ for the heavy parcels and at $j = M+1, \ldots, N$ for the small parcels. Consequently, the expected travel times found in the previous section constitute a lower bound for the travel times related to real-life synchronization. One may wonder how tight this lower bound is. The discrete synchronization problem for the *heavy* parcels can be modelled as a simple resource constrained scheduling problem (Pinedo 2005). The resources $i =$

$1, 2, \ldots, 1+s$ are the truck driver and the street robots. We identify each location with a job $j = 1,2, \ldots, M$ requiring one single resource. The processing time p_{ij} for job j on resource i is equal to the travel time (forth and back) to visit location j. In order to maximize synchronization, we aim to find the job allocation that minimizes the makespan T. Here, the variable T denotes the time when the latest job is completed. This minimization problem can conveniently be modeled as an integer linear programming problem (ILP) by introducing the binary variables x_{ij} that assume the value 1 if and only if job j is allocated to resource i. These variables are connected to the variable T by the constraint $\sum_{j=1}^{M} p_{ij}x_{ij} \leq T$ for all i. For the *small* parcels, we proceed as follows. Given the makespan T obtained for the heavy parcels, we intend to adapt the drone speed v_3 such that the light parcels have this same makespan. To this end, we first take $v_3 = 1$ and solve a resource-constrained scheduling problem where the resources are the drones, whereas the processing time for job j on resource i is equal to the travel time (forth and back) to visit location j by drone. Thus, we obtain the light-parcel makespan – let us denote it by T_1 – for drone speed $v_3 = 1$. Next, let us consider a general drone speed v_3. By proportionality, the corresponding light-parcel makespan is equal to T_1/v_3. Hence, in order to synchronize with the heavy parcels, we take for v_3 the value T_1/T. To get an impression of the accuracy of our continuous approximation, we solved the resource-constrained scheduling problem for a limited number of parcels and found promising results. Our simulation is used to test the accuracy of this practically convenient approximation for larger problem instances.

In our simulation, we compare the relative improvement in service time of using drones and street robots – in combination with the truck driver – compared to the base case of using only the truck driver. We employ the continuous approximations introduced in Section 2.1. On the one hand, our simulation indicates whether the continuous approximation yields sufficient synchronization. On the other hand, our simulation gives a lower bound for the potential improvement obtained by the drones–robots–driver system compared to the base case.

3 CONCEPTUAL MODEL

Before presenting the simulation model, an abstraction is required using a conceptual model. Given our focus on tactical decision making and our aim to develop a reusable and highly configurable simulation model (e.g., quickly analyze different neighborhoods), we require some abstraction. The following elements are described: the inputs (Section 3.1), outputs (Section 3.2), experimental factors (Section 3.3) and model assumptions (Section 3.4).

3.1 Input

Regarding the inputs, we distinguish between (i) the road infrastructure, (ii) the houses, (iii) the trucks, (iv) the drones, and (v) the street robots.

1. *Road infrastructure.* In order to model a neighborhood, we require a road infrastructure that trucks, street robots, and drones can use to deliver parcels. For a useful abstraction without losing too many details, we use the following logic. Many (European) city planning departments utilized a similar approach to design road infrastructure in neighborhoods for decades. Typically, there are one or a few main roads through the area, connecting the area with other neighborhoods and with higher capacity roads. From this main road, the streets that make up the neighborhood (i.e., side-streets) are more or less perpendicularly oriented to the main road and the side-streets occur on opposite sides of the main road. The side-streets typically have various lengths across the area. Such a neighborhood can be seen as a fishbone structure. Although this is not entirely correct for some instances, as typically there are also alleys, courtyards, or differently oriented streets in a neighborhood, for the purposes of tactical decision making it suffices to model the road infrastructure on this abstraction level. This allows the user of the simulation to quickly model different areas or cities, to prioritize which are most promising for truck-drone-street robot deliveries. On an operational level, the road infrastructure can be further detailed for final analysis, but this is beyond the scope of this paper. An example of the abstraction of a part of a neighborhood to a fishbone structure is shown in Figure 2.

Figure 2: Example of neighborhood represented as a fishbone structure. The red line represents the main road and the grey lines the side-streets.

Given this abstraction, we can model a neighborhood as a collection of side-streets that are connected to the main road, similarly to Figure 2. In our model, a road network consists of two parts. First, we model a main street with a fixed length in the middle of the neighborhood. Second, we model side-streets on both sides of the main road, branching off the main road at fixed intervals. To exemplify, if a main road has a length of 1 kilometer and the distance between side-streets is 100 meters, we have 10 side-streets at each side of the main road, summing up to 20 side-streets in total. Each side-street has a certain length, drawn from a uniform distribution with a minimum and maximum. The minimum denotes the shortest street in the neighborhood and the maximum the longest street. This approach allows us to, although stylized, quickly model different neighborhoods without losing too much detail. Incidentally, the above notions may easily be extended or upscaled. For example, a main road may denote a highway and the corresponding side-streets may denote villages along that highway, in whose centers trucks are not welcome, which for modeling purposes are represented as a function of time and distance.

2. *Houses.* Every side-street has houses on both sides of the street. These houses are the delivery locations. To model the density of a neighborhood, we use a parameter to determine the distance between houses. This can be a fixed value (i.e., the distance between houses is the same in the entire network) or drawn from a probability distribution function to model fluctuations in the network. Moreover, it is possible to 'stack' houses on top of each other, to resemble apartment buildings or flats. Using a *delivery density* parameter between 0 and 1, we randomly determine which houses need to be visited for delivery, i.e., if the delivery density is 0.2, then 20 % of the houses need to be visited. Moreover, the parameters *AccesibleByStreetRobot* and *AccessibleByDrone* denote which portion of houses can be visited by a specific delivery vehicle, e.g., not accessible due to physical obstructions like gates or specific customer preferences.
3. *Trucks.* A delivery van, or truck, is used to carry the parcels, drones, and street robots into the neighborhood from, e.g., a local distribution center. In current operations, the delivery van visits the houses, traversing through the neighborhood. The delivery van has a fixed speed and a limited capacity to carry drones, denoted by d, and street robots, denoted by s. The delivery van is operated by a driver, who is also able to deliver parcels with a fixed speed $\boldsymbol{v_1}$ and is able to carry one parcel at a time. In current operations, the driver stops in front of each house it has to visit, carries out the delivery and continues to the next house. When drones or street robots are deployed, the truck is not allowed to enter the side-streets anymore, but has to stay on the main street (see Section 4.3).
4. *Street robots.* The street robots can be used to deliver parcels as a ground vehicle and are stored and dispatched from the delivery van. A maximum of s street robots are available, as this is the maximum capacity of the delivery van. A street robot can carry one parcel at a time and travels with a fixed speed of $\boldsymbol{v_2}$.

5. *Drones***.** The drones can be used to deliver parcels through the air and are stored and launched from the delivery van. As stated, a maximum of d drones can be carried by the delivery van. Each drone can carry one parcel and travels with a fixed speed $\boldsymbol{v_3}$. The drone first needs to reach high enough in the sky, in order to fly safely throughout the neighborhood and is denoted by the parameter *SafeFlyingDistance*.

3.2 Output

The simulation model has the following two outputs: (i) total completion time (makespan), and (ii) working time per delivery type, to evaluate our synchronization approach.

3.3 Experimental Factors

For the purposes of this paper, we mainly experiment with different combinations of the available delivery vehicles: The truck driver delivers all parcels by traversing the network (Scenario 1), the truck driver delivers the heavy parcels and drones delivery the light parcels (Scenario 2), street robots deliver the heavy parcels and drones delivery the light parcels (Scenario 3), or the truck driver together with street robots delivers the heavy parcels and the drones deliver the light parcels (Scenario 4). We use Scenario 1 as a benchmark, as this is the current way of working for many parcel deliverers. For this first study, we fix the number of drones and street robots a delivery van can carry. Moreover, utilizing our flexible modeling approach, we experiment with different neighborhoods: small, medium, and large as well as with different delivery densities. We deploy the synchronization approach as described in Section 2, to determine who serves which house in scenarios 2 to 4.

3.4 Model Assumptions

To reduce the complexity of the simulation model, several assumptions are introduced. First, we assume that all speeds of the delivery vehicles are deterministic, e.g., we do not model congestion, traffic lights, or influence by wind for drones. Second, every house that needs to be visited only requires one parcel and after each delivery the driver, drone, or street robot needs to return to the delivery van to pick up the next parcel (if required). For the driver this may not be realistic, as a hand trolley can be used to carry multiple parcels. We presume that allowing tours for the driver helps to minimize the makespan, but we leave the inclusion of tours to further research. Third, when street robots or drones are deployed (i.e., scenarios 2–4), the delivery van is no longer allowed to enter the side-streets for parcel delivery. The delivery van positions itself strategically at the junction of the main street and two (opposite) side-streets, and all deliveries in those two side-streets need to be served before the delivery van moves to the next junction. Moreover, all street robots and drones need to have returned to the delivery van, before it is allowed to move. Also, *all* street robots and drones are used for delivery, unless there are fewer deliveries in a street than the size of the fleet. In Scenario 1, we assume that the driver traverses the entire neighborhood in an s-shape, starting from the main road, delivering one house at a time. In order to create an s-shape, we assume that the delivery van can drive from the end of a side-street to the end of the next side-street, that is, it does not have to return to the main road to access the next side-street. Lastly, in all scenario's there is only one delivery van.

4 SIMULATION MODEL

Based on the conceptual model described, a discrete-event simulation model is proposed. The simulation model is used to evaluate (a) the performance of our synchronization approach and (b) the impact of combined truck-drone-street robot deliveries under various conditions. Below the three main components of the model are described: (i) road infrastructure, (ii) houses, and (iii) modalities (i.e., deliveries by driver, drone, and street robot). The model is implemented in the discrete event simulation tool Plant Simulation and is illustrated in Figure 3. The model relies heavily on visualization to let the user quickly verify whether the driver, drones, and street robots are allocated to the right houses (e.g., red houses are for heavy parcels, green houses for light parcels), whether they are all visited (i.e., houses already visited turn white) and whether the synchronization approach yields similar arrival times back at the truck (visualized as a white delivery van on the main road, in the middle of the network).

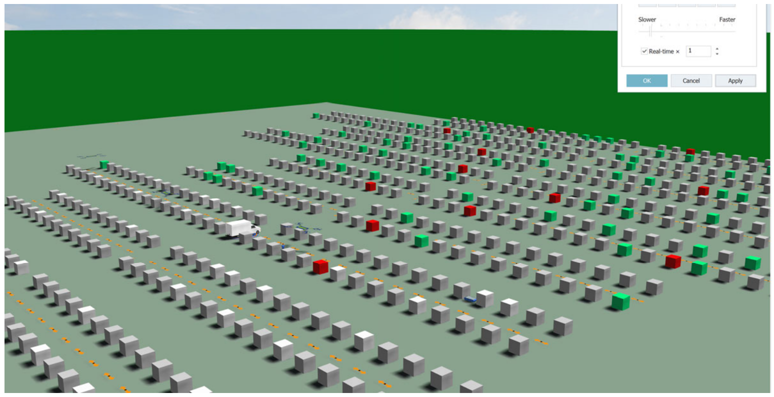

Figure 3: Visualization of the simulation model.

4.1 Road Infrastructure

The simulation model allows the user to quickly create different networks of so-called *Markers*. The amount and position of the markers are automatically created at the initialization of the simulation using a custom-built method and depend on various input parameters. The most important are: the length of the main road, the average length of a side-street and corresponding standard deviation, the distance between houses, and the *SafeFlyingDistance*. The markers are used by the truck, driver, drones and street robots to find their way through the neighborhood. As discussed, in Scenario 1 the truck traverses the network and markers are placed at the end of every side-street in order for the truck to turn around and enter the next side-street. Depending on the scenario, either the driver, street robots, or both use the markers to enter the side-street (visualized as orange arrows in Figure 3). The drones use a similar grid of markers, but these are placed on *SafeFlyingDistance* above the ground (not visualized). All in all, this results in a grid of markers, where every side-street has a corresponding marker on the main street (i.e., where the truck needs to stop in scenarios 2–4) and every house has a marker in front of it, both on the ground and in the air.

4.2 Houses

The houses (i.e, destinations) are also modelled as *Markers*, but visualized as a square box. They are modeled as markers such that the driver, street robots, or drones can move from the road infrastructure to their final destination. At initialization of the simulation, the houses are automatically created at each side of the side-street, alongside the creation of the 'road' markers. Moreover, at initialization, the jobs (i.e., houses to visit) are generated using the built-in random number generator and the input parameters *delivery density* and *percentage of heavy parcels* (see Section 6.1). If a house is selected, it is color-coded green for light parcels and red for heavy parcels. Lastly, the houses also contain a duration parameter, such that the (variable) on-site delivery time can be modelled.

4.3 Truck, Driver, Drones, and Street Robots

All movable units in the model, i.e., the truck, driver, drones and street robots are modeled as standard Transporter objects. They are characterized by dimensions, speed, acceleration, deceleration, and energy consumption. The characteristics are fixed, with the exception of the speed of the drones. This is determined by the synchronization approach discussed in Section 2. The movable units originate from separate instances of the *AGVPool* (e.g., *DronePool* and *RobotPool*), which allow movable units to freely navigate the network of *Markers*. In Scenario 1, the truck traverses the network and stops in front of every house it needs to visit. The *DriverPool* is automatically moved to the current location of the truck and the driver originates from this pool, delivers a parcel to a house, and returns (empty) to the truck, after which the truck moves to its next location. In the other scenarios, the truck stops at the beginning of every side-street on the main road. The *DriverPool, DronePool* and *RobotPool* are moved accordingly. The dispatching and loading of the drones and street robots is performed by the co-driver in the truck, i.e., not the driver who delivers the parcels. Depending on the scenario and the number of drones and street robots deployed, the synchronization approach determines which movable unit needs to visit which house (i.e., the green and red houses). Only after each house is visited (on both side-streets of the main street), and all movable units have returned to the truck, the truck is allowed to continue to the next side-street.

5 RESULTS

This section presents the simulation results for the four scenarios under consideration. First, the experimental design is discussed in Section 5.1. We present the results varying the street length variability (Section 5.2), varying the pick density (Section 5.3), and varying the percentage of heavy parcels (Section 5.4). Then, the accuracy of the synchronization approach is discussed in Section 5.5 and lastly the impact of the fleet composition on makespan and drone energy consumption is discussed in Section 5.6.

5.1 Experimental Design

To evaluate the impact of combined truck–drone–street-robot deliveries, we focus on different combinations of delivery modes, different delivery densities, different percentages of heavy parcels, and different street sizes. Specifically, we experiment with all possible combinations as described in Section 3.3 and different delivery densities (10 %, 20 %, and 40 %), and percentage heavy parcels (5 %, 10 %, and 20 %). The delivery density denotes the fraction of houses that need to be visited in the neighborhood and are randomly allocated. Of this fraction we randomly select houses that have a ‘heavy delivery’, based on the percentage used in an experiment. Moreover, we experiment with the variability of the length of the side-streets. We do so, because we are interested in the impact of neighborhood design on the performance of the different delivery combinations and the performance of our synchronization approach. The neighborhoods that are generated in the simulation all consist of a total of 20 side-streets (i.e., 10 streets on each side of the main road). The average side-street length is set at 240 meters (i.e., 24 houses long), as this is the most common street length in the Netherlands (Kadaster 2021). We use a uniform distribution to create different street lengths and experiment with different levels of variation. We denote a *low* variability with a variation of +/- 10 %, a *medium* variability with +/- 50 % and a *large* variability with +/- 90 %. To exemplify, in the latter case, the neighborhood consists of 20 side-streets, 10 on each side of the main road and each with a length between 2.4 and 45.6 houses. In the simulation, the number of houses is rounded to the nearest integer. Lastly, we fix the maximum number of street robots and drones that can be used to a total of six, due to limited available space in the delivery van. When only drones are used, we deploy six drones and when street robots work alongside drones, then we deploy two street robots and four drones. Although this combination may not be optimal in terms of operational efficiency, we found that our synchronization approach gave the most feasible velocities with this combination, namely 14 km/h, which is in line with the maximum speed of 15 km/h in residential areas. Nevertheless, the other possible compositions of the fleet are analyzed and discussed in Section 5.6. Moreover, as we are interested in the added value of different variants of combined truck–drone–street-robot deliveries, we first focus on addressing the impact of these different fleet compositions and leave a cost-based comparison of the different scenarios to further research (e.g., the makespan may be minimal with a certain combination of drones and street robots, but the procurement costs involved may be higher than for other compositions of the fleet). Twenty replications are used for each experiment, resulting in a relative error of at most $\gamma = 0.02$ using a significance level $\alpha = 0.05$. For an overview of the input parameters and their values, see Table 1.

Table 2 shows an overview of the results in terms of the average and standard deviation of the makespan, expressed in hours. For statistical comparisons, we compare Scenario 2 (driver and drones) and Scenario 3 (street robots and drones) with Scenario 1 (the driver delivers all parcels by traversing through the neighborhood). To show the added value of the role of the driver, we compare Scenario 4 (driver, street robots, and drones) with Scenario 3. The green values show a significant positive impact (i.e., the makespan decreases) and the red values a significant negative impact when using a t-test with $\alpha = 0.05$. The values in bold green are significant differences when $\alpha = 0.10$ and the values in italics have no significant difference when using the same alpha.

Table 1: Input parameters and their values, sc = scenario.

Input	**Value**	**Input**	**Value**
Road-infrastructure-related		**House related**	
Length main street (m)	1000	Distance between houses (m)	10
# of side-streets	20	Delivery density	[10 %, 20 %, 40 %]
Length side-street *low* (m)	U~(216,244)	Percentage heavy parcels	[5 %, 10 % ,20 %]
Length side-street *med* (m)]	U~(120,360)	AccessibleByStreetRobot	100 %
Length side-street *large* (m)	U~(24,456)	AccessibleByDrone	100 %
Delivery mode related		**Scenario related**	
Speed delivery van (km/h)	15	Available drivers (sc. 1, 2, 4)	1
Drone capacity (d)	4 or 6	Available drivers (sc. 3)	0
Street robot capacity (s)	2 or 0	Available drones (sc. 2)	6
Speed drones (km/h)	variable	Available drones (sc. 3-4)	4
Speed street robots (km/h)	5	Available street robots (sc. 3-4)	2
Walking speed driver (km/h)	4		

Table 2: Simulation results.

		Low variability								**Medium variability**								**High variability**							
	Scenario	1		2		3		4		1		2		3		4		1		2		3		4	
Heavy parcels	Delivery density	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd
5%	10%	1.10	0.01	0.68	0.08	0.38	0.06	*0.36*	*0.07*	1.34	0.03	0.77	0.12	0.41	0.11	*0.40*	*0.08*	1.52	0.18	0.88	0.17	0.47	0.11	*0.44*	*0.12*
	20%	1.59	0.01	1.08	0.14	0.58	0.08	0.52	0.13	1.86	0.06	1.21	0.21	0.61	0.14	*0.57*	*0.14*	2.08	0.11	1.36	0.27	0.66	0.19	*0.64*	*0.19*
	40%	2.56	0.02	1.73	0.17	0.82	0.19	0.79	0.10	2.90	0.12	2.00	0.32	0.79	0.24	*0.83*	*0.22*	3.13	0.22	2.28	0.43	1.03	0.22	*0.92*	*0.26*
10%	10%	1.10	0.01	*1.16*	*0.02*	0.56	0.11	*0.54*	*0.07*	1.34	0.03	*1.35*	*0.15*	0.64	0.11	*0.60*	*0.11*	1.52	0.18	*1.51*	*0.24*	0.73	0.14	**0.64**	**0.17**
	20%	1.59	0.01	1.82	0.10	0.86	0.05	0.79	0.06	1.86	0.06	2.15	0.28	0.97	0.15	**0.90**	**0.16**	2.08	0.11	2.37	0.38	1.08	0.19	1.00	0.21
	40%	2.56	0.02	3.13	0.15	1.25	0.35	1.03	0.36	2.90	0.12	3.69	0.51	1.56	0.27	1.41	0.23	3.13	0.22	4.05	0.82	1.38	0.41	**1.40**	**0.36**
20%	10%	1.10	0.01	2.15	0.12	0.90	0.07	0.75	0.22	1.34	0.03	2.54	0.24	1.05	0.14	0.81	0.26	1.52	0.18	2.89	0.39	1.19	0.18	1.01	0.28
	20%	1.59	0.01	3.41	0.13	1.42	0.07	1.18	0.09	1.86	0.06	4.08	0.40	1.67	0.21	1.41	0.19	2.08	0.11	4.56	0.72	1.86	0.31	1.52	0.35
	40%	2.56	0.02	5.61	0.02	2.55	0.73	1.94	0.13	2.90	0.12	5.58	0.12	2.68	1.13	2.28	0.48	3.13	0.22	5.56	0.21	2.99	0.61	2.48	0.47

5.2 Varying the Street Lengths

When increasing the variability of the street lengths, the difference between short and long streets increases, resulting in a heterogeneous neighborhood. Increasing this variability slightly increases the average makespan in all combinations of the experimental factors. Thus, having highly diverse neighborhoods negatively impacts the makespan, as the synchronization of modalities becomes more difficult. However, the percentual differences when comparing Scenarios 2 and 3 with Scenario 1 as well as the percentual differences between Scenarios 3 and 4 remain more or less constant. This indicates that our synchronization approach provides a promising and robust solution to neighborhood variability. This is particularly interesting for applying our conceptual model to higher abstraction levels (e.g., no side-streets, but neighborhoods or even cities) as these typically have a high variability in composition.

5.3 Varying the Delivery Density

By increasing the delivery density, the makespan obviously increases for all scenarios under consideration. When comparing Scenario 2 with Scenario 1 (as a base case), with low street variability and 5 % heavy parcels, the makespan decreases by roughly 37 %, 33 %, and 32 % when one increases the delivery density from 10 %, 20 %, and 40 %, respectively. A similar effect can be seen for the other street variabilities and when comparing Scenario 3 with Scenario 1. The opposite effect (i.e., increasing makespan) can be found when there are more heavy parcels. This can be explained by the fact that, particularly in Scenario 2, the driver has more tasks (i.e., heavy parcels) and transports these from the main street to the various houses as the truck is no longer allowed to enter the side-streets. In scenario 1 this is not the case, thus it makes more sense, efficiency wise, to traverse the neighborhood with the truck. This, however, does not solve the congestion issue in the side-streets, one of the aims of this paper. In general, we can conclude that when the delivery density increases, the impact of Scenarios 2 to 4 in terms of makespan is reduced. In Scenario 2, the makespan in fact increases when the percentage of heavy parcels increases, while in Scenario 3 and 4 the makespan still decreases significantly; only the decrease is less when the delivery density goes up. Neighborhoods with low delivery densities and relatively light parcels are, thus, ideal candidates for robot-and-drone-assisted deliveries.

5.4 Varying the Percentage of Heavy Parcels

When there are only a few heavy parcels (5 %), Scenarios 2 and 3 work well, decreasing the makespan by roughly 35 % and 67 %, respectively. Particularly the latter, where street robots carry the heavy parcels and the drones the light parcels, is a promising solution. Including the driver in this solution (i.e., Scenario 4), is only fruitful when the percentage of heavy parcels increases, the delivery density increases or both. When there are more heavy parcels, the driver is a useful addition to the two street robots, and this effect is enlarged when the delivery density increases. However, when only the driver carries the heavy parcels (Scenario 2), the makespan increases drastically compared to Scenario 1, especially when the delivery density is high. This suggests that in situations with a relatively high share of heavy parcels, it is interesting to explore parcel delivery combinations where the driver takes an active role or reevaluate the composition of the fleet, e.g., by increasing the share of street robots compared to drones. Another approach would be to allow drones to carry heavy parcels, but besides payload restrictions, this is beyond our scope.

5.5 Accuracy of the Synchronization Approach

This section explores the accuracy of our synchronization approach as discussed in Section 2 in the simulated environments. For brevity, we focus on a single experiment: medium street variability, with 20 % pick density and 10 % heavy parcels. The results, expressed in the percentage of the time each modality (including the driver) is working, are shown in Figure 4.

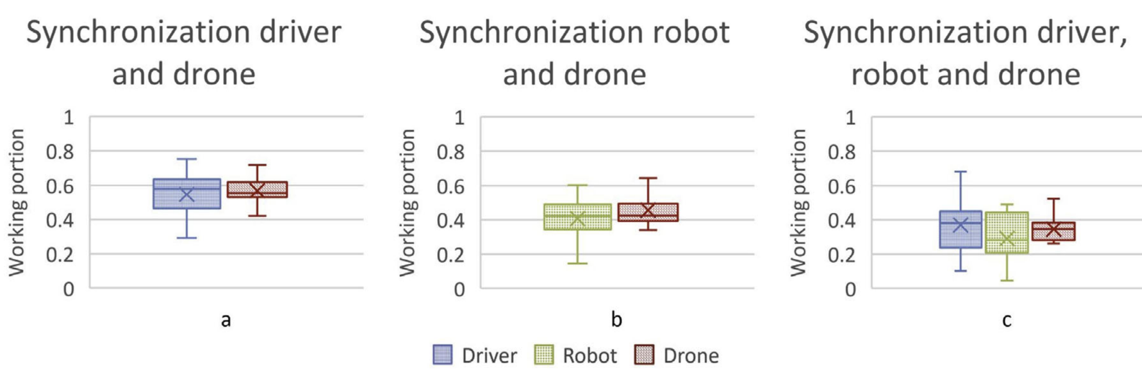

Figure 4: Synchronization for a) Scenario 2 (left; driver and drone), b) Scenario 3 (middle; robot and drone), and c) Scenario 4 (right, driver, robot, and drone).

From Figure 4 we see that there is some fluctuation in the working portions (i.e., percentage of the time actually devoted to delivery) of the modes deployed in the various scenarios. However, no significant differences were found using $\alpha = 0.05$, showing the accuracy of our synchronization approach. Although the synchronization is based on the assumption that demand is distributed continuously, while in practice demand is distributed on a discrete level (i.e., per house), the approach holds well. Although not substantiated here, the same conclusions were found using the other experiments, underlining the usefulness of our approach.

5.6 Varying the Fleet Composition

In previous experiments, we either had six drones available (Scenario 2) or two street robots and four drones (Scenario 3 and 4). These choices are motivated by the fact that they yielded feasible speeds for the drones. However, other compositions may influence the makespan, the (synchronized) drone speeds and resulting energy consumption. For brevity, we limit this analysis to medium street variability, with 20 % pick density and 10 % heavy parcels and focus on Scenario 4 only. The results are shown in Figure 5.

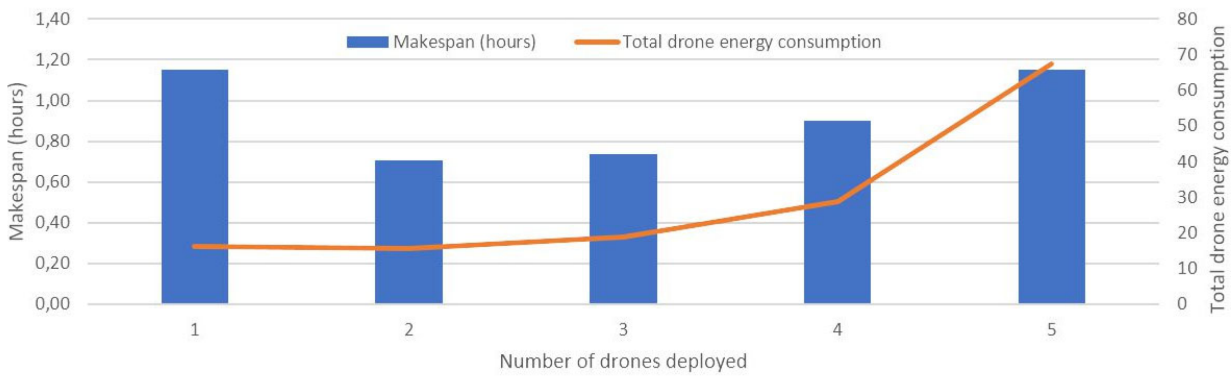

Figure 5: Impact fleet composition on makespan and total drone energy consumption.

When only one drone is deployed and, thus, needs to deliver all light parcels, it results in a high makespan, as well as a high drone velocity (i.e., 20 m/s). The minimum makespan is achieved when two drones and four street robots are deployed. Interestingly, increasing the number of drones increases the makespan, even though the majority of parcels are light and drones are fast compared to street robots. This is due to our synchronization approach, where the speed of the drones decreases when more drones are deployed. Interestingly, for the present densities, the drones are sometimes slower than the street robots when more drones than street robots are deployed. Moreover, according to Stolaroff et al. (2018), the velocity of the drone impacts its energy consumption. Flying either very slow or very fast has a high energy consumption, with a minimum energy consumption around 5-10 m/s. Using the simulation, we calculated the total energy consumption of the fleet of drones, accounting for the velocity of the drone, the percentage of the time it is flying, and the number of drones deployed. The results are shown as a line graph in Figure 5.

Interestingly, the minimum makespan also has a low total drone energy consumption. For the setting discussed in this section, it is profitable to deploy fewer drones such that their velocity increases and simultaneously the least amount of energy is consumed. Further increasing the speed (i.e., by deploying fewer drones) needs to be avoided as the energy consumption goes up, but also the makespan goes up due to capacity problems. Although these specific numbers may be dependent on our specific network, it is noteworthy that when considering combined truck–drone–street-robot deliveries, the fleet composition is an important aspect to research, as the makespan and the total energy consumption are both impacted in a non-linear fashion. Thus, designing and configuring the system such that the drones always fly at their optimal speed (in terms of energy consumption), while maintaining a low makespan is a promising area of further research. This may for example be approached by allowing the drones to operate upcoming streets (e.g., by flying over houses), while the driver and the street robot are still operating the previous street.

6 CONCLUSIONS AND FURTHER RESEARCH

This paper proposes a last-mile delivery concept in which a truck driver cooperates with a mixed fleet of drones and robots in the delivery process. We present a synchronization approach that is evaluated using simulation for different combinations of drones, street robots, and the driver, where the use of trucks is no longer allowed near the delivery locations. Our simulation suggests that the synchronization approach is accurate enough to support tactical decision making to determine which networks are suitable for combined truck–drone–street-robot delivery. Moreover, we show that the delivery makespan can drastically be reduced when drones or street robots are deployed, particularly when – next to the street robots - the driver is employed to deliver heavy parcels. We illustrate that by adapting the fleet composition the makespan can be minimized, whilst also minimizing the total drone energy consumption. Further research directions include: (i) designing and configuring the system such that drones always fly at their optimal speed (in terms of energy consumption and makespan), (ii) introduce mode-specific properties (e.g., taking into account customer preferences or allowing drivers to carry multiple parcels), and (iii) introduce heterogeneous and dynamic fleets.

REFERENCES

Bandeira, T. W., W. P. Coutinho, A. V. Brito, and A. Subramanian. 2015. "Analysis of Path Planning Algorithms Based on Travelling Salesman Problem Embedded in UAVs". In *Proceedings of the 2015 Brazilian Symposium on Computing Systems Engineering (SBESC)*, edited by R. Bilof, 70–75, Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Chung, S.H., B. Sah, and J. Lee. 2020. "Optimization for Drone and Drone-Truck Combined Operations: A Review of the State of the Art and Future Directions". *Computers and Operations Research* 123:1–29.

Guerriero, F., R. Surace, V. Loscri, and E. Natalizio. 2014. "A Multi-Objective Approach for Unmanned Aerial Vehicle Routing Problem with Soft Time Windows Constraints". *Applied Mathematical Modelling* 38(3):839–852.

Kadaster. 2021. Basisregistratie Adressen en Gebouwen. https://www.pdok.nl/introductie/-/article/basisregistratie-adressen-en-gebouwen-ba-1, accessed 12th April.

Law, A. M., and W. D. Kelton. 2000. *Simulation Modeling & Analysis.* 3rd ed. New York: McGraw-Hill, Inc.

Mathew, N., S. L. Smith, and S. L. Waslander. 2015. "Planning Paths for Package Delivery in Heterogeneous Multirobot Teams". *IEEE Transactions on Automation Science and Engineering* 12(4): 1298–1308.

Moeini M., and H. Salewski. 2020. "A Genetic Algorithm for Solving the Truck-Drone-ATV Routing Problem". In *Optimization of Complex Systems: Theory, Models, Algorithms and Application*, edited by H. Le Thi, H. Li, and T. Pham Dinh, 1023-1032. Cham: Springer.

Murray, C. C., and A. G. Chu. 2015. "The Flying Sidekick Traveling Salesman Problem: Optimization of Drone-Assisted Parcel Delivery". *Transportation Research Part C: Emerging Technologies* 54:86–109.

Phung, M. D., C. H. Quach, T. H. Dinh, and Q. Ha. 2017. "Enhanced Discrete Particle Swarm Optimization Path Planning for UAV Vision-Based Surface Inspection". *Automation in Construction* 81:25–33.

Pinedo, M. L. 2005. *Planning and Scheduling in Manufacturing and Services*. New York: Springer.

Sandvik, K. B., and K. Lohne. 2014. "The Rise of the Humanitarian Drone: Giving Content to an Emerging Concept". *Millennium* 43(1):145–164.

Simoni, M., E. Kutanoglub, and C. Claudel. 2020. "Optimization and Analysis of a Robot-Assisted Last Mile Delivery System". *Transportation Research Part E: Logistics and Transportation Review* 142:1-18.

Stolaroff, J. K., C. Samaras, E. R. O'Neill, A. Lubers, A. S. Mitchell, and D. Ceperley. 2018. "Energy Use and Life Cycle Greenhouse Gas Emissions of Drones for Commercial Package Delivery". *Nature Communications* 9(409):1–13.

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