



Unmanned Aerial Vehicles in Logistics: Efficiency Gains and Communication Performance of Hybrid Combinations of Ground and Aerial Vehicles

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Abstract—Unmanned Aerial Vehicles (UAVs) have drastically gained popularity in various Intelligent Transportation System (ITS) applications to improve the safety and efficiency of transportation systems. In this context, the combination of ground vehicles, such as delivery trucks, with drones to assist in the last-mile pick-up and delivery of the parcels has been recently proposed. While aerial vehicles promise increased efficiency based on flexible routes and parallelized operation, highly reliable wireless communication is also required for the control and coordination of potentially many drones acting in a self-organized way. In this paper, we analyze the improvements procured by drone usage in parcel delivery compared to traditional delivery and propose a simulation framework to further quantify the efficiency gains of the parcel delivery logistics and to analyze the performance of different wireless communications options. To this end, we consider a heterogeneous vehicle routing problem with various constraints. We consider two approaches regarding the dispatching and recovery of drones and evaluate their benefits as opposed to parcel delivery with a classic truck only. Furthermore, we compare two networking technologies for enabling coordination of the self-organizing teams of drones with a realistically modeled environment: one approach relying on base station oriented Long Term Evolution (LTE) vs. a more decentralized Cellular Vehicle-to-Everything (C-V2X) solution. The results show time savings of nearly 80% can be achieved through drone usage and that the negative impact of urban shadowing on network communications in the base station oriented LTE approach can be compensated by leveraging decentralized C-V2X communications.

I. INTRODUCTION

As transport is one of the main pillars of modern economy, last mile delivery has become fundamental to the E-Commerce industry [1] thus requiring new solutions in order to face the challenges of Pickup and Delivery (PDP). Integrating UAVs into ITSs yields tremendous potential regarding the development of new applications and services [2] as they offer more flexibility in motion than conventional terrestrial vehicles. Most of these novel applications are enhancements of already existing ones by deploying autonomous vehicles to decrease operation costs. Such is the case of UAV-empowered PDP which consists of carrying out parcel delivery logistics with a truck aided by a fleet of drones.

Parcel delivery with one vehicle already yields a non negligible complexity. Therefore, enhancing it with autonomous UAV support adds to the preexisting logistics complexity [3] and threatens to tone down the benefits of UAV assistance in this application context. Several studies were conducted to

ascertain the logistics benefits of UAV assistance in parcel delivery scenarios and proof-of-concept implementations have already been introduced [4]. They formulate the drone-aided parcel distribution as an optimization problem to which they suggest heuristic approaches [5].

Furthermore, being an ITS application, the performance of UAV-enhanced near-field delivery heavily depends on a suitable communication infrastructure. There are still few studies investigating this specific ITS use case with its dependency to network communications.

The integration of UAVs into existing and upcoming cellular networks is an active field of research [6] as it is expected to facilitate wireless broadcast and support high rate transmissions [7]. It also requires the use of anticipatory networking in order to forecast the evolution of network conditions and offer the best achievable connectivity at any times [8].

A comprehensive summary of the recent advances in UAV communications and the challenges they bring about, with an emphasis on how to integrate UAVs into the forthcoming fifth-generation (5G) and future cellular networks is provided by [9].

In this paper we investigate the benefits of UAV-empowered near-field delivery by analyzing the influence of various UAV deployment schemes on the total completion time of the delivery tour and the mean energy consumption per drone. We further compare the performance of two network communication technologies in the parcel delivery application context. This paper provides the following contributions:

- Logistics **simulation** of **UAV-empowered PDP**.
- Comparison of **communication technologies** LTE and C-V2X in parcel delivery application context.

The paper is structured as follows: After discussing state of the art approaches in Sec. II, we present the proposed UAV-empowered PDP and introduce the methodological setup for the evaluation campaign in Sec. III. Finally, the results of different evaluations are presented and discussed in Sec. IV.

II. RELATED WORK

The idea of enhancing parcel delivery with drones is currently trending and several implementation approaches have already been discussed. These all entail solving the problem of finding the optimal route for a delivery truck, taking into account the mobility of its associated UAVs, thus enabling

them to autonomously deliver parcels up to a certain distance from the truck.

One of the problem's earliest introductions [10] labeled it as the Flying Sidekick Travelling Salesman Problem (FSTSP) and introduced a Mixed Integer Programming (MIP) formulation and a heuristic approach. Their heuristic begins with an initial Travelling Salesman Problem (TSP) tour and iteratively considers whether a node should be served by a drone or not. The FSTSP is handled with different approaches in [11] [12] to minimize the total traveling time. A cost function that considers an energy consumption model and drone reuse is therefore proposed in [13]. The importance of reusing drones and optimizing battery size in drone delivery routing problems is confirmed. As far as our observation goes, all of the mentioned studies make a basic assumption: drone dispatching and recovery must take place at a delivery node. [5] presents a novel approach aiming to maximize the drone usage in parcel delivering. The authors consider that a truck can deliver and pick up a drone not only at a delivery target but also along a route arc.

The key role played by UAVs in enabling the next generation of ITSs [2] has induced research momentum regarding UAV related ITS applications. For modeling such applications, the lightweight vehicular simulation framework Lightweight ICT-centric Mobility Simulation (LIMoSim) [14] was developed following a shared codebase approach to allow a seamless integration with other simulators, in contrast to the state-of-the-art Interprocess Communication (IPC)-based coupling methods. It focuses on highly dynamic traffic scenarios where decision processes and routes are determined at runtime [14]. LIMoSim is further extended in [15] with UAV mobility and an integration with Network Simulator 3 (ns-3) to support simulations of aerial and ground-based vehicular networks. As the mobility is simulated in a discrete event fashion, LIMoSim integrates particularly well with discrete event network simulations. The shared code base approach allows to natively bring together mobility and network simulators. This enables the development of novel context-aware optimization methods that exploit interdependencies between both domains.

A realistic model for simulating communications between UAVs and ground vehicles is proposed in [16]. It supports the usage of mobile infrastructure to broadcast alerts in situations of emergency. The use of UAVs to build an aerial-ground cooperative vehicular networking architecture is proposed in [17]. Multiple UAVs, forming an aerial sub-network, aid the ground vehicular sub-network through air-to-air (A2A) and air-to-ground (A2G) communications. UAVs can be dispatched to areas of interest to collect data and share it with ground vehicles. The flexible mobility of UAVs while being one of their key features is also a challenging point for their integration in the communication infrastructure. In [18], an approach which leverages application layer knowledge derived from mobility control algorithms guiding the behavior of UAVs to fulfill a dedicated task is presented. It thereby enables the integration of a UAV trajectory prediction with the routing protocol to avoid unexpected route breaks and packet loss.



Fig. 1. Simulation scenario at the Dortmund technology center with an exemplary drone-aided parcel delivery illustration.

Finally, the problem of UAV docking station placement for ITS is investigated in [19]. The objective is to determine the best locations for a given number of docking stations that the operator aims to install in a large geographical area.

III. SIMULATION OF UAV-ENABLED PICKUP AND DELIVERY

In this section, we give a detailed presentation of the methods and tools which were used to carry out our analysis.

A. Simulation Environment

To model UAV-assistance in near-field delivery, a suitable simulation environment supporting hybrid vehicle scenarios is required. The platform devised in [15], which relies on ns-3 for the network simulation and the LIMoSim kernel for mobility as proposed in [15] was selected due to its shared codebase approach, thereby allowing for a bidirectional influence between mobility and communication.

The simulation scenario entails the buildings and road network around the Dortmund technology center and features a delivery truck and a specific number of UAVs.

The default UAV mobility model proposed by LIMoSim is used for the delivery drones: a simplified version of the proposed model of [20]. With the angular vector $\eta = [\theta \ \phi \ \psi]^{-1}$, which entails the values for *pitch*, *roll* and *yaw*, motion in cartesian space is expressed as

$$\begin{bmatrix} \ddot{x} \\ \ddot{y} \\ \ddot{z} \end{bmatrix} = -g \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} + \frac{T}{m} \begin{bmatrix} C_\psi S_\theta C_\phi + S_\psi S_\phi \\ S_\psi S_\theta C_\phi - C_\psi S_\phi \\ C_\theta C_\phi \end{bmatrix} \quad (1)$$

where $C_x = \cos(x)$, $S_x = \sin(x)$, g is the gravitation, T is the thrust and m the vehicle mass. The angular accelerations are additionally modeled as

$$\ddot{\eta} = \mathbf{J}^{-1}(\tau_B - \mathbf{C}(\eta, \dot{\eta})\dot{\eta}) \quad (2)$$

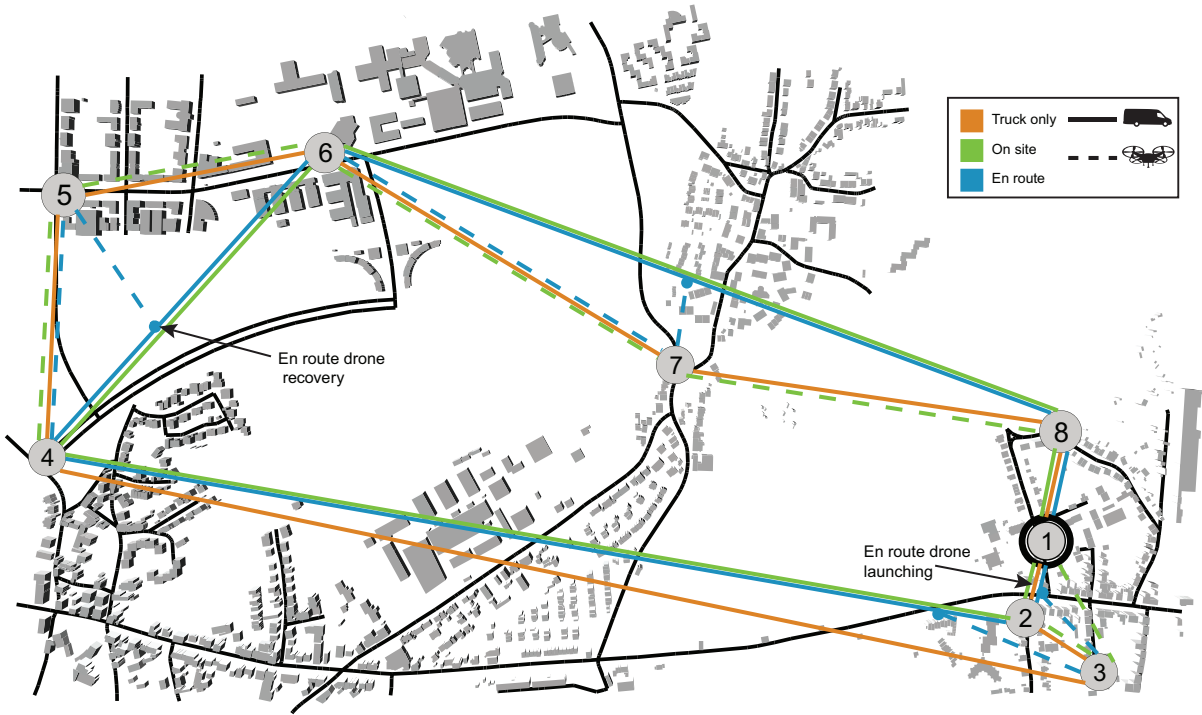


Fig. 2. Exemplary delivery scenario with the computed delivery plans of the **truck only**, **on site** and **en route** approaches.

where \mathbf{J} is a Jacobian matrix, which maps the angular velocities to angular accelerations, τ_B being the torque and $\mathbf{C}(\eta, \dot{\eta})$ being the Coriolis term, which accounts for gyroscopic and centripetal effects.

For the delivery truck, a new vehicle model which extends the standard car model proposed by LIMoSim with specialized parcel delivery navigation logic was developed. Inheriting from the existing car model allows the delivery truck to rely on a hierarchical mobility model for considering different decision levels and control routines.

The truck must start from the depot center, visit each delivery location once and return to its start position. A suitable route is therefore needed to complete the delivery as fast as possible.

B. TSP-Modeling

In order to generate the delivery route, the delivery scenario is treated as a TSP and modeled as a graph $G = (V, E)$ where the node v_0 represents the depot and the nodes (v_1, \dots, v_n) stand for the delivery recipients. An optimal solution must satisfy the following constraint:

$$\min \sum_{i=1}^n \sum_{j \neq i, j=1}^n c_{ij} \cdot x_{ij} \quad (3)$$

with the cost c_{ij} being the distance between v_i and v_j and x_{ij} a path selection variable obeying:

$$x_{ij} = \begin{cases} 1 & \text{if path goes from } v_i \text{ to } v_j \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

The following additional constraints must apply to an optimal solution:

$$\forall j \in (1, \dots, n) \sum_{i=1, i \neq j}^n x_{ij} = 1 \quad (5)$$

The constraint in Eq. 5 enforces that each node is visited exactly once. The cost of each edge c_{ij} is determined by taking the shortest route between the edge's nodes, based on the OpenStreetMap (OSM) road network data which is loaded in LIMoSim [15]. While searching for the shortest route between two nodes, u-turns are only allowed at dead ends or just after completing a delivery.

The Lin-Kernighan heuristic is used to solve the thus modeled TSP instance, as it produces nearly optimal solutions for large TSP instances with less computational effort than the optimal integer programming method [21]. The TSP solution is then transformed into a LIMoSim route for the delivery truck consisting of a sequence of gates, which must be taken to leave each encountered intersection.

C. Enhancement through Drone Delivery

The TSP solution is then enhanced to account for drone support in two different variants, thus producing two Travelling Salesman Problem with Drone (TSP-D) tours.

The first variant is **on site** drone dispatching and recovery, which means the drones are only dispatched and recovered at truck delivery nodes.

The second variant is **en route** drone dispatching and recovery, which as opposed to the first variant, allows for

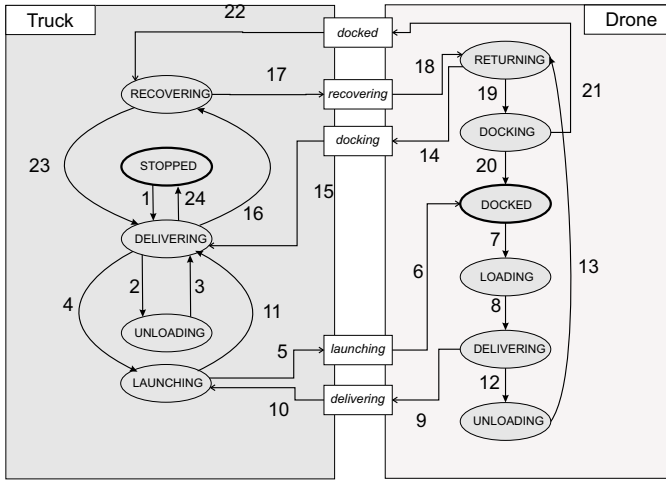


Fig. 3. Interaction protocol used to coordinate the heterogeneous fleet of delivery agents.

drones to be deployed and recovered at any location on the truck's route, this variant may yield delivery efficiency gains over the on-site variant, but can at the same time be difficult or not always possible to perform. For instance, recovering a drone en route while the truck is riding on a highway may prove to be a tedious landing task.

A basic job scheduling scheme is used to determine which delivery jobs are assigned to UAVs. A job gets allocated to a UAV if it is available and when the total estimated travel time for the job is smaller than the maximal allowed travel time for a drone. As a consequence, the job scheduling scheme does not disrupt the truck nodes order as it simply removes jobs from the truck's list and assigns them to UAVs. The truck route is then constructed from the TSP-D solution analog to the TSP case. The generated solutions for the TSP, TSP-D and TSP-D with en route operations for our example scenario are illustrated in Fig. 2 and the associated Gantt charts are presented in Fig. 4.

To further mimic the logistics of delivery, execution parameters are used to control the waiting time for unloading the parcel at a delivery target once the agent - the truck or a drone - reaches it (further referred to as unloading time), as well as the take-off and landing duration of the drones. Speed limitations on the different road segments are respected. However, traffic signaling and congestion were not considered.

To fully leverage the potential of a heterogeneous delivery fleet requires a means to synchronize the agents. To this end, we defined a protocol to coordinate the interactions between the delivery truck and the UAVs, which is graphically featured in Fig. 3.

The delivery truck may deliberately wander between the STOPPED, DELIVERING, UNLOADING and LAUNCHING states.

For instance, upon reaching a delivery target, the truck

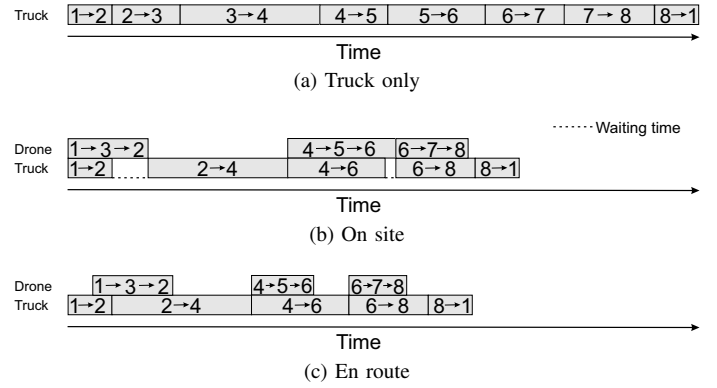


Fig. 4. Gantt charts of the different delivery methods applied on the example scenario.

switches to the UNLOADING state to unload the parcel and complete delivery. The truck then switches back to the DELIVERING state after the unloading time is up and resumes delivery.

Nearly the same cycle is observed for the LAUNCHING state on the truck side with the only exception that there is no launch timer. The delivery truck switches to the LAUNCHING state when it reaches a drone launch point and leaves it upon receiving a launch completion message from the launched UAV.

Entering and leaving the RECOVERING state is triggered by any UAV aiming to regroup with the delivery truck. Before recovery, the truck slows down upon sensing a returning drone within a specific range and stops once the drone initiates recovery.

The drones get started in the DOCKED state, where they are docked to the truck and can, therefore, travel through the scenario without exerting any effort. Upon receiving the launch message from the truck, they change in the LOADING mode, which they then leave for the DELIVERING state after the take-off timeout and notify the truck of launch completion.

Once they reach the delivery target, they switch to UNLOADING and continue in the RETURNING state once the unloading duration is spent.

While returning, the drones send a docking message to the truck as they get in docking range, causing the truck to stop for them to complete the docking maneuver after which they notify the truck of docking completion.

The en route delivery variant requires additional logic to keep the truck waiting in optimal launching or recovery range until the awaited events occur. In the on-site delivery variant, every truck delivery target is a potential drone launch or recovery point.

D. Energy Consumption

To assess the power efficiency of the various delivery methods, the internal energy monitoring of LIMoSim is used. The mobility-related energy consumption tracking in LIMoSim is

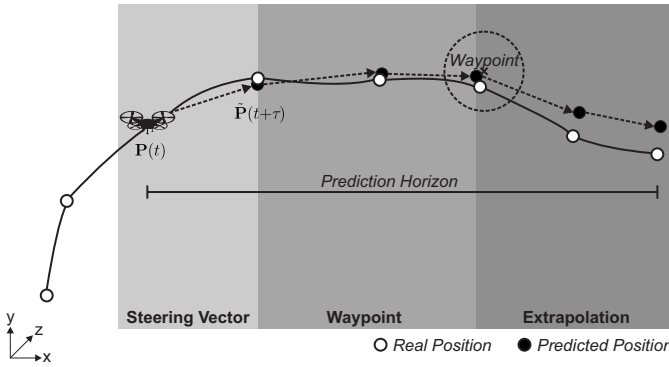


Fig. 5. Hierarchical mobility prediction model overview according to [15]. The method with the highest prediction accuracy is selected in each iteration step.

enabled through its hierarchical mobility model. The control inputs which are sent to the mobility's locomotion layer are forwarded to a numerical energy model which computes the resulting consumption, based on the time interval during which these inputs are applied on the locomotion.

The energy model used tracks only the mobility-related consumption of UAVs. Further details to the energy model have been published in [15].

E. Mobility Prediction

To further optimize the energy footprint of the drone delivery, we consider mobility prediction as it is one of the key enabling methods for anticipatory communication [22].

LIMoSim supports mobility prediction and allows the usage of a customized model. However it inherently provides an implementation of a hierarchical model which iteratively uses different prediction methods for forecasting successive future vehicle positions. At each prediction iteration, the method with the highest expected precision is used as illustrated in Fig. 5.

Specific extensions were made to the provided mobility prediction to leverage the routing information contained in the delivery route depending on the drone deployment scheme. These extensions are the following:

- In on site mode, the next waypoint is the delivery target where regrouping shall take place
- In en route mode, the next waypoint may be the next road intersection on the truck's route or the next delivery target

IV. EVALUATION OF THE DELIVERY APPROACHES

In this section, we evaluate the performance of different delivery approaches. LTE and C-V2X (Mode 4) are applied for communications among delivery agents. The C-V2X implementation developed in [23] is used.

The general simulation parameters common to all evaluations presented hereafter are listed in Tab. I

TABLE I
GENERAL SIMULATION PARAMETERS

Parameter	Value
Scenario size	3000 m x 1500 m x 250 m
Maximum speed (Truck)	13 ms^{-1}
Maximum speed (UAV)	16 ms^{-1}

A. Enhancement of Delivery Performance

In the first analysis, three delivery modes are analyzed: **truck only**, **on site** and **en route**. In the drone assisted modes, we study the effects of increased drone usage. A summary of the relevant simulation parameters of this evaluation is given in Tab. II.

TABLE II
PARAMETERS OF THE LOGISTICS ENHANCEMENT EVALUATION

Parameter	Value
Simulation duration	until delivery completion
Delivery sets	50
Deliveries per set	15
UAV count	{0, 1, 2, 3}

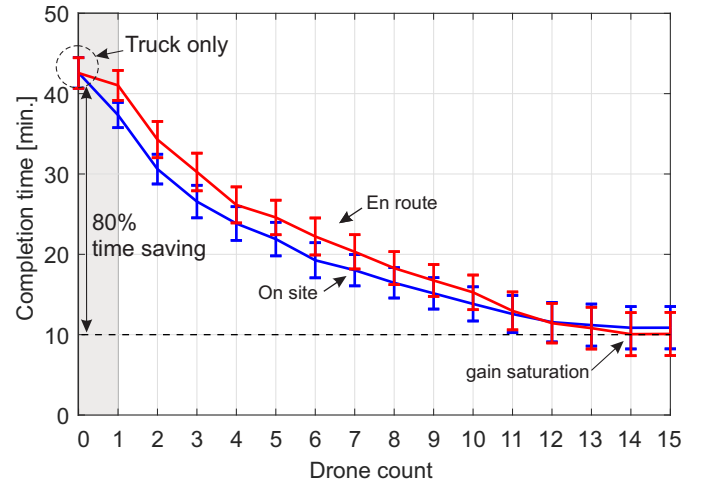


Fig. 6. Completion time of delivery using the truck only mode as well as the on site and en route approaches with an increasing number of drones.

The evolution of the completion time with an increasing number of deliverer drones in Fig. 6 shows that the delivery tour can be completed faster with the usage of more drones. However, the time gain decreases after each drone increase until saturation is reached. It can also be observed that switching the operations mode from **on site** to **en route** adds a supplementary delay on the overall completion time. This is due to the simplicity of the drone delivery scheduling scheme used. As mentioned in Sec. III, the used scheme assigns deliveries to the drones while keeping the order of the remaining truck deliveries consistent with the truck only delivery schedule, therefore, causing the truck to stop more often in en route mode. It was shown that the en route yields

better completion times than the on site approach [5], however, a more complex job scheduling scheme must be used to further leverage the mobility advantage induced by drone support.

B. Energy Savings and Mobility Prediction

In the second evaluation, we focus on the energy consumption of the delivery modes which were used in the previous evaluation. Furthermore, we investigate the impact of mobility prediction on energy consumption in en route drone operations. This is motivated by the fact that drone recovery, which requires a regrouping point with the truck, does not occur at fixed points in en route mode as opposed to on site mode.

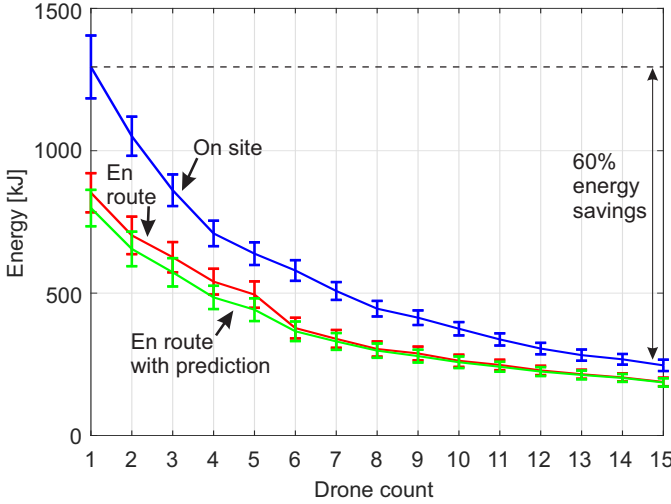


Fig. 7. Energy consumption per drone with increasing drone count for the different delivery approaches.

The mean energy consumption per UAV and grouped per delivery mode is shown in Fig. 7. An overall reduction of the energy footprint per drone is achieved when switching from on site to en route operations. Using more drones also decreases the average energy consumption per drone up to 60. Mobility prediction allows for further energy sparing, but its effects become less perceptible when more drones are

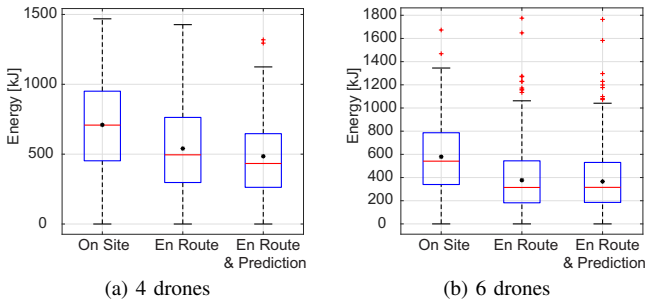


Fig. 8. Energy consumption per drone of the different delivery approaches, before and after the efficiency gain of mobility prediction wears off

relied upon. This is presented more explicitly in Fig. 8 for the evaluated scenario. When using less than 6 drones, for instance 4, the sparing effects of mobility prediction are noticeable. The energy saved through mobility prediction becomes negligible from 6 drones upwards.

C. Investigating Network Communication Standard Usability

In the second evaluation, we monitor mission-critical network metrics for UAV-empowered PDP applications: the transmission latency and the Packet Delivery Ratio (PDR). The criticalness of these metrics arise from the requirement of permanent monitoring of the UAVs. Therefore a reliable communication link between the delivery UAVs and the truck is needed.

To carry out our evaluation, standard Cooperative Awareness Messages (CAMs) are sent from the UAVs to the truck with a size of 190 Bytes every 100 ms [23]. These messages are likely safety-related, so the delay must be kept low and PDR should be high. Two communication technologies are applied: LTE and C-V2X. Common operating parameters values are used for the network configuration. An overview of the relevant simulation parameters to this evaluation is given in Tab. III.

TABLE III
PARAMETERS OF THE COMMUNICATION TECHNOLOGY EVALUATION

	Parameter	Value
General	Simulation duration	15 min
	Delivery sets	50
	Deliveries per set	15
	UAV count	{ 1, 2, 3, 4, 5 }
	Channel model	DeterministicObstacleShadowing
	Packet Size	190 Byte
C-V2X	Inter Packet Interval	100 ms
	Carrier frequency	5.9 GHz
	Bandwidth	20 MHz
	P_{TX} (UE)	23 dBm
LTE	Carrier frequency	2.1 GHz
	Bandwidth	20 MHz
	P_{TX} (UE)	23 dBm
	P_{TX} (eNB)	43 dBm

P_{TX} : Maximum transmission power

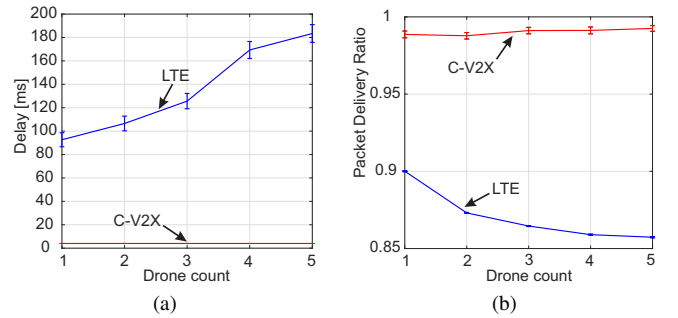


Fig. 9. Comparison between LTE and C-V2X for connecting the delivery drones to the truck.

The statistical evaluation of the results is illustrated in Fig.9 and shows that C-V2X achieves a significant smaller latency

than LTE. This stems from the applied C-V2X variant which implements *Mode 4* behavior [23]. The channel is accessed directly, which gives the intra-User Equipment (UE) processing the dominant share on the overall delay. Whereas LTE transmissions are subject to resource scheduling mechanisms of the evolved Node B (eNB). The direct channel access of C-V2X however increases the collision probability with a growing number of UEs operating in the same interference region but does not prevent C-V2X to achieve a higher PDR than LTE with an increased number of drones as UEs. The LTE link quality is affected by the shadowing of buildings present in the scenario. These have an average height of 20 m.

D. The Influence of Building's Height

In this last evaluation, we qualitatively investigate the influence of buildings height on the LTE communication link in the parcel delivery application context. The LTE simulation setup of the previous evaluation is used and the mean of the building's height distribution in the scenario is varied.

In order to model a deterministic and consistent interference behavior of the buildings the **deterministic obstacle shadowing model** provided in LIMoSim is used. An exemplary Reference Signal Received Power (RSRP) heatmap of the simulation scenario generated using this model is shown in Fig.10.

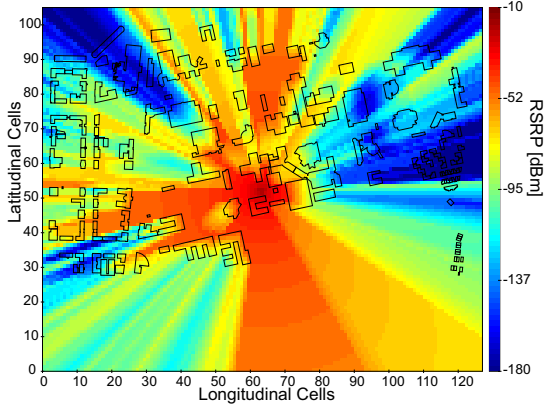


Fig. 10. Exemplary signal strength map at 10 m above ground derived by the obstacle shadowing model.

TABLE IV
PARAMETERS OF THE BUILDINGS INFLUENCE EVALUATION

Parameter	Value
Simulation duration	15 min
Delivery sets	50
Deliveries per set	15
UAV count	{ 1, 2, 3, 4, 5 }
Channel model	DeterministicObstacleShadowing
Mean building height	{ 10 m, 20 m, 30 m }

The increasing heights of buildings is shown in Fig. 11 to have a reinforcing effect on the network latency. This is due to the poor radio channel conditions associated with the

shadowing caused by tall buildings. A similar effect befalls the PDR, which gets smaller when buildings height is increased. Furthermore, having more drones access the channel increases the delay on a greater scale when surrounded by high buildings. The results show that the delay's growth rate is higher when increasing the drone count at bigger buildings height. The PDR also degrades faster with an increasing number of UEs around high buildings.

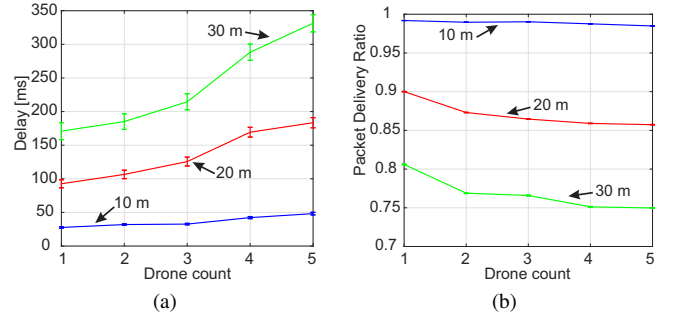


Fig. 11. Performance of the LTE link connecting drones to the truck with different mean height of buildings.

The penalties incurred by the increased drone usage on of the LTE-link is detailed further in Fig. 12. The average impact which adding one more drone to the scenario produces on the delay and PDR is analyzed for the different building heights. On average, going from 1 to 5 drones could incur 150 milliseconds delay, and 50 additional packets out of 1000 may not be delivered correctly within an environment featuring buildings of an average height of 30 meters. As opposed to an additional delay of about 20 milliseconds and an extra loss of approximately 5 packets out of 1000 at an average building height of 10m when increasing the drone count from 1 to 5.

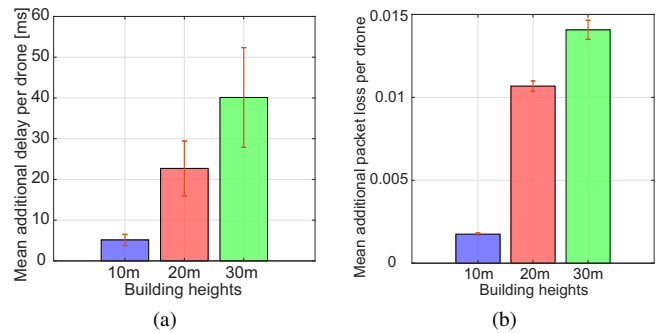


Fig. 12. Incremental average degradation of the LTE link performance for each added drone with different mean height of buildings.

V. CONCLUSION

In this paper, we investigated the use of relying on UAVs to enhance logistics applications. We analyzed the feasibility of such an enhancement from the network perspective by comparing the performance of LTE and C-V2X for reliable communications among the delivery fleet. The evaluations

were carried out using the system-level development platform for joint modeling of aerial and ground-based vehicular networks provided by the open simulation framework LIMoSim. It was shown that drone usage in parcel delivery can reduce the time taken to complete a delivery tour by up to 80%. Increased drone usage further reduces the completion time and the energy consumption per drone, however, speeding up the tour completion by increasing drone usage has limits. In a future work, the delivery performance could be enhanced further by using more efficient schemes to schedule delivery jobs for the drones. Such schemes could also consider energy efficiency as a scheduling criterion. An extension of the presented work could also account for more real-world interactions, such as traffic lights and congestion. Communication link deterioration around tall buildings still raises a challenge which could, however, be addressed by leveraging mobility prediction schemes, to forecast the channel conditions at future locations during the path planning procedure of the drone.

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