Simulation of Data Losses, Nonlinearity and Modulation Impact in RPAS/UAV Swarms

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Abstract

Intelligence of Remotely Piloted Air System (RPAS) swarms depends on reliable communications. The parallelism and distributed characteristics of swarm intelligence provide self-adapting and reliable capabilities. This article is devoted to the calculation of packet losses and the impact of traffic parameters on the data exchange with swarms. Original swarm models were created with the help of MATLAB and NetCracker packages. Dependences of data packet losses on the transaction size are calculated for different RPAS number in a swarm using NetCracker software. Data traffic with different parameters and statistical distribution laws was considered. The effect of different distances to drones on the base station workload has been simulated. Data transmission in a swarm was studied using MATLAB software depending on the signal-to-noise ratio, nonlinearity levels of base station amplifier, signal modulation types, base station antenna diameters, and signal phase offsets. The data obtained allows foresee the operation of RPAS communication channels in swarms.

1. Introduction

Remotely Piloted Air Systems (RPASs) or Unmanned Aerial Vehicles (UAVs) shown in Figure 1 [1, 2] are attracting attention and are used in civilian, community and military purposes for a variety of surveillance, environmental monitoring or communications missions. Many applications are implemented using RPAS/UAV swarms, for which it is necessary to develop perfect structures for transmission of information in real time. Therefore, the number of publications devoted to these issues is constantly increasing. In recent years, many books, reviews, tutorials [3–14] and articles [15–27] have been published.

RPAS/UAV swarms are a multi-agent system and jointly perform tasks of different scale and complexity. In simple cases, a swarm can include a group of non-interacting drones. Strategies that are more sophisticated might include interactive links of drones in a swarm and even multiple swarms connected through ground or satellite platforms to exchange information. Autonomous and cooperative cluster RPAS systems need new communication and networking technologies. The choice of a suitable communication technology is highly dependent on fault tolerance, aggregate data rate, and antenna arrangements. Currently, there is not enough research in this area.

Quantitative information about the impact of drone traffic parameters on channels operation is required for correct prediction the reliability and quality of drones' communication in a swarm. How do packet losses quantitatively change with increasing number of drones in a swarm? How does message size affect the amount of losses? How does the difference in distance to drones affect the workload of the Base Station (BS)? What are the effects of nonlinearity, modulation type, radiation phase characteristics and antenna sizes? There are no answers to such questions in the literature.

In this article, a centralized two-way Radio Line of Sight (RLOS) connection of a ground BS with all RPASs in a swarm is considered. RPASs are not directly connected in this case. The connection between the two

RPASs can be made through the BS. The behavior prediction of these systems is impossible without the theoretical foundations of data transmission in such systems. To achieve this goal, the following was done in the work.

First, original cluster models were created for swarm data exchange simulation using MATLAB and NetCracker packages.

Secondly, packet losses for different RPAS number in a swarm were calculated for the first time using NetCracker software. Data transmitting with different parameters and statistical distribution laws was considered. The influence of distances to drones in a swarm on the BS workload was simulated.

Third, channels parameters estimation was carried out for the first time using MATLAB software. Data transmission in a swarm was investigated depending on the Signal-to-Noise Ratio (SNR), nonlinearity levels of the BS High Power Amplifier (HPA), the type of signal modulation, the BS antenna diameters, and the signal phase offset.

Fourth, it is possible to predict the features of data transmission in swarms based on the obtained results, which is of practical value. From this point of view, this work is the development of theoretical methods for predicting the operation of RPAS communication channels in critical conditions.

The rest of this article is organized as follows. Section 2 covers related works. Section 3 presents swarm model parameters, the algorithm for modeling, data traffic description and results obtained using NetCracker software. Section 4 presents impact of nonlinearity, modulations, antenna diameters and phase offsets obtained using MATLAB software. At the end of the article, the results are discussed in Section 5 and conclusions are given in Section 6.

2. Related Works

Mobile ad hoc networks (MANETs) and vehicular ad hoc networks (VANETs) are considered in a review [3] without taking into account the peculiarities of UAV networks, which can vary from slow dynamic to dynamic and have intermittent connections. It is noted that multi-UAV networks has been an understudied area. High mobility, dynamic topology, intermittent links, power constraints, changing link quality, latency and fault tolerance should be considered when designing communication systems for RPAS/UAV swarms.

An overview of the characteristics and requirements for communications in UAV networks is carried out in a work [4]. General networking related requirements such as connectivity, safety, privacy, security, and scalability are considered. Suitability of existing communication technologies for supporting reliable aerial networking is examined.

UAVs must communicate effectively with each other using UAV-to-UAV (U2U) communications and with existing network infrastructure using UAV-to-infrastructure (U2I) communications. This requirement for effective communication is caused by errors in navigation, guidance and control systems, introduced at

each step. First, navigation systems introduce errors to the current coordinates and attitude parameters determination [5 - 8]. Then guidance and control system may have correspondent imperfections in placing single drone to the required position [9]. Therefore, effective and reliable communication inside of UAVs' swarm plays a crucial role. The article [10] defines the functions, services and requirements for communication systems based on UAVs. Network architectures, basic structures and requirements for data traffic in these systems are presented. Services of the middleware level for uninterrupted communication and support of heterogeneous network interfaces are discussed. A new area of research is considered, which includes the use of UAVs to collect data from Wireless Sensor Networks (WSN).

Single small UAV has limited payloads, flight times and requires external control. Coordinating multiple drones into swarm increases their functionality. A swarm is defined as a group of behaving entities that coordinate their actions together to achieve the desired result. A swarm of UAVs can distribute tasks in principle without operator intervention. The article [11] provides a review of UAV swarms and proposes a swarm architecture using cellular communication. The authors note that the use of cellular mobile infrastructure removes the limiting factors of drone use, including range and network problems.

Multi-UAVs are predicted to be an important element in the development of advanced cyber-physical systems (CPS) with synergistic interactions between computing and physical capabilities. The main advantages of using UAVs in the CPS application are their exceptional characteristics (mobility, dynamism, ease of deployment, adaptive height, maneuverability, adjustability and effective assessment of real functions anytime, anywhere). The review [12] describes the fundamental problems of designing systems with several UAVs for CPS applications. Various algorithms for fixed and mobile coverage and target tracking have been investigated, and comparisons have been made between them on complexity, share of open area and number of surveillance cameras.

Understanding how multiple drones can coordinate and interact is essential for the advancement of multi-agent robotics. The review [13] illustrates existing flight control and communication systems for multi-agent drone deployments. Articles with experimental results and analysis of the used communication equipment are considered. It is noted that most of the work in this area remains at the modeling stage, since the coordination of UAVs is a complex issue. Choosing communication and coordination strategies is very difficult and designers must consider range, throughput, data rate, power requirements, payload weight, compatibility, and cost.

The review article [14] presents a study of UAVs with a discussion of the mechanics, functionality, organization, modeling, applications and aspects of drones' autonomy.

Communications play an important role in the control and coordination of RPASs/UAVs swarm. The communication architecture defines the exchange of information between drones and the control center. Routing protocols help ensure reliable end-to-end communications. The review article [15] describes four communication architectures and provides a systematic overview and feasibility study of routing protocols. It is concluded that layered architecture, combined with mesh architecture within the swarm, is currently the most applicable communication architecture.

The article [16] provides an overview of typical Swarm Intelligence (SI) algorithms and summarizes their application in the Internet of Things (IoT). The focus is on analyzing SI-enabled applications for the WSN and discussing research issues at WSN. Authors generally divide the UAV-aided wireless network into three categories according to their principles, and their applications based on SI are analyzed.

When using UAVs, there are many problems that need to be solved, and the main one is communication. The review [17] explores the latest UAV communication technologies by examining suitable task modules, antennas, resource processing platforms, and network architectures. Explored techniques such as machine learning and path planning. Encryption methods to ensure long-term and secure communication are discussed. Applications of UAV networks are investigated for a variety of contextual purposes, from navigation to surveillance, URLLC (Ultra-Reliable Low Latency Communication), edge computing and work related to artificial intelligence. The complex interaction between UAVs, cellular communications and the IoT is one of the main topics of this article. This literature review demonstrates the need for additional research in the field of drone-to-drone and drone-to-device communications.

There are many complex issues in the design of UAV swarm networks, such as the integration of hardware and software for large-scale UAV network management, long distance data transmission between UAVs, swarm shape/formation control, and intelligent UAV mobility/position prediction. Engineering developments and designs of network protocols for dynamic large-scale UAV networks are considered in the book [18]. It provides technical models/algorithms and protocol specifications for the practical deployment of UAV swarms.

Automating swarms' management is challenging as every drone operates under fluctuating wireless, networking and environment constraints. In the review [19], drone swarms are considered as Network Control Systems (NCS), in which the control of the entire system is carried out within the wireless communication network. This is based on a tight interconnection between the networking and computational systems, aiming efficiently support data collection, information exchanging, decision-making, and the distribution of commands. The development of self-organized drone swarms as NCS through the integration of networking and computing systems is described. Their integration is analyzed to improve the performance of drone swarms.

UAVs swarm is usually used to solve the problems of finding survivors, monitoring and tracking several targets. This requires complex mechanisms for their control, communication and coordination. However, these mechanisms are difficult to test and analyze in the context of flight dynamics. Such multi-UAV scenarios are inherently well suited to be simulated as multi-agent systems. The article [20] presents an approach for modeling the UAV as an agent in terms of multi-agent system. Sensors and communication devices allow interaction with other drones in the swarm and the environment. Proposed flight dynamics model reflects limitations and uncertainties.

Data congestion control is used to expand network capabilities, improve the reliability of VANETs by reducing packet loss and communication delays. The study [21] proposes a distributed congestion control strategy based on an intelligent swarm. This maintains channel utilization below the network

failure threshold and maintains high quality of service. Experiments have shown that the proposed strategy improves network throughput, channel utilization, and link stability when compared to other competing congestion management strategies.

Due to the uncertainty of wireless links, communications between UAVs experience transmission delays that impair the swarm's ability to stabilize the system. The article [22] examines the problem of joint communication and control for a group of three UAVs connected by cellular communication. A new approach is proposed to optimize the swarm operation while taking into account the wireless network latency and the stability of the control system. The maximum allowable delay required to prevent swarm instability is determined. The simulation results help to get recommendations for the formation of a stable UAV swarm.

Traffic monitoring is considered in the paper [23] using a swarm that continuously monitors traffic in SwarmCity. It is a simulated city built on the Unity game engine, where drones and cars are modeled realistically. The swarm control algorithm is based on six modes of behavior with twenty-three parameters that are configurable. Parameters optimization is performed using a genetic algorithm in a simplified and fast simulator. The best resulting configurations are tested at SwarmCity and perform well in terms of the number of vehicles monitored versus the total number of vehicles over time windows.

Mini-UAVs should be grouped using swarm coordination algorithms to perform tasks in a scalable and reliable manner. The article [24] uses biological mechanisms to coordinate unmanned aerial vehicles searching for a target with imperfect sensors. Coordination can be achieved by combining stigmergic and flocking behavior. Stigmergia occurs when a drone releases a digital pheromone when it detects a potential target. Such pheromones can aggregate and spread between flocking drones, creating a spatially attractive potential field.

A multi-layer model of network communication and message management is proposed in the article [25] developing a communication system for UAVs swarm. The model implements the communication infrastructure of the swarm in the form of a communication node, in which scheduling algorithms and message management schemes are applied. Experimental results show that communication node meets the requirements of swarm communications with unstable bandwidth changes.

The work [26] considered the scenario, in which several UAVs with one antenna simultaneously exchange data with a ground station (GS) equipped with a large number of antennas. The achievable performance of the uplink communication (UAV - GS) throughput in the case of line-of-sight conditions is discussed. The geometric model includes an arbitrary orientation of the GS and UAV antenna elements and estimates the polarization mismatch losses that arise due to the UAV's movement and orientation. For homogeneous linear and rectangular arrays, the optimal distance between the antennas has been determined.

The data transfer from the RPAS swarm was modeled using MATLAB Simulink in our work [27]. RLOS and Beyond Radio Line of Sight (BRLOS) link models included: 1) "Base Station Transmitter"; 2) RLOS

channel: "Uplink Path", "RPAS Receiver"; 3) BRLOS channel: "Uplink Path", "Satellite Transponder", "Downlink Path"; "RPAS Receiver". The dependences of the BER on the SNR were obtained for different levels of BS transmitter nonlinearity, its gain, diameters of BS and satellite transponder antennas.

Models of "Base Station - Satellite - RPASs" communication channels were built using the NetCracker Professional 4.1 software [28]. We analyzed the dependences of average utilization on the size of the transaction, satellite channels with different bandwidths and the number of RPAS, as well as the impact of the likelihood of satellite failure.

The article [29] proposes the UAV-Edge-Cloud model as a new hybrid computing platform to provide powerful resources for supporting resource-intensive applications and real-time tasks in edge networks. Potential applications of the model for smart cities and the routing problem for latency-critical applications are discussed. Simulation results show that this approach can improve Quality of Service (QoS).

The paper [30] describes experiments with small drones, a real-time big data platform, and an operating system that interacts with 4G cellular mobile services. The purpose of the experiment is to collect data for testing obstacle avoidance algorithms and to evaluate communication performance.

In the literature, there is generally no data on the loss of data packets when exchanging information with drones in swarms. In the article [31] we published the first packet losses estimation for single drone. The article [32] is actually the first publication containing numerical experimental data on the traffic of single drone.

3. Base Station Data Losses When Rpass/uavs Number In Swarm Increases

3.1. Swarm Model Architecture

Swarm model architecture is based on ICAO documents [1, 2] and is designed using Professional NetCracker 4.1 software. Models with different numbers of RPASs ($N = 1 - 4$) are built and considered. Models' parameters are given in Table 1. Swarm model "BS – RPASs" (Figure 2) contains the BS and the RPASs each on the distance 10 km for case Radio Line-of-Sight (RLOS).

Table 1
Swarm model parameters

Parameters →	Bandwidth	Length	BER
Model elements ↓	(Mbps)	(m)	(%)
Model: “BS – RPASs”			
Base Station			
BS – Switch link	10	1	0
Switch	10	-	-
Switch – Antenna link	44.736	10	0
Antenna	10	-	-
BS – RPAS wireless links	1.544	10^5	0 – 0.06
RPAS	10	-	-

3.2. Algorithm

The algorithm for modeling channel characteristics is described in our paper [Modelling]. Characteristics are divided into internal (obtained using mathematical modeling tools) and external (on which the internal characteristics depend). The internal characteristics were the average channels utilization (load), the packets travel time, and the number of dropped packets. The external characteristics are the transaction size, the time between transactions, the bit error rate, and the link bandwidth. During simulation, it is possible to calculate internal characteristics using specified external characteristics.

NetCracker as analytical simulator provides real-time “what-if” simulation using mathematical equations. Its core is written in Java EE, the native application server is Weblogic, and Oracle is used as a database.

3.3. Calculation Methods

The models’ parameters were simulated taking into account different statistical distributions for TS and TBT parameters, the BER, the links bandwidth and the data transfer protocols. The following probability distribution laws were used: Const law - $\omega(x) = Const$, Exponential law - $\omega(x) = \lambda e^{-\lambda x}$, and LogNormal law –

$$\omega(x) = \frac{1}{x\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(\ln x - a)^2}{2\sigma^2}\right)$$

Formulas for the average length of the transmitted packets, the average time interval between two adjacent packets, the average utilization of the communication link, and the average packet travel time are given in our paper [33].

3.4. Data Traffic

A traffic with Local Area Network peer-to-peer protocol is specified for the created models with the topology according to Figure 2. This means decentralized network based on the equal rights of participants. There are no dedicated servers in such a network, and each peer is both a client and acts as a server. Such an organization allows maintaining the network's operability for any number and any combination of available RPASs. Swarm communication traffic is performed as two-way communication.

3.5. Results

Packet losses during exchanging data between a base station and drones is a critical factor, as it can make the mission itself impossible. Packet losses can be caused by channel errors during data transmission and conversion, insufficient channel capacity, or network congestion. Particularly relevant is the issue of traffic losses in RPAS swarms with an increase in the number of drones. How much does the loss increase quantitatively when additional RPAS is added? How does the loss depend on the mode of data transfer and the size of the transactions? How does the type of statistical distribution law of traffic parameters affect the amount of data loss? How does the number of bit errors during transmission affect the average workload of communication channels BS and RPAS? The answers to these questions are presented in Fig. 3 - 6.

The average workload and average utilization of channels, the messages travel time, and the number of dropped packets were calculated during the simulation. Quantitatively packets loss is estimated as the percentage of packets lost in relation to sent packets. The dependences shown in Figures 3 - 5 differ in the statistical distribution law of the TBT parameter, but have the same value $TBT = 0.01$ s and the same Const distribution law for the TS parameter. The numerical values of the parameters were chosen on the basis of the experimental data presented in the work [32]).

The PER dependences on the TS parameter (Figures 3–5) were investigated for different amounts of RPAS ($N = 1–4$). Comparative assessment of packet losses at the BS are given. Distribution laws and values of TS and TBT parameters are shown in Figures 3–5.

Figure 3 demonstrates PER dependences for the BS on the packet size with Const distribution law for TBT parameter. It can be seen from the graphs that for all $N = 1 - 4$ the nature of the dependences is similar. For TS values from 1 Kbits to 4 Kbits, the PER values practically do not change, beginning substantially increase for $TS > 4$ Kbits. An increase in the number of RPASs from $N = 1$ to $N = 4$ leads to an increase in the PER parameter by more than 4 times and reaches $\approx 70\%$ for $TS = 6$ Kbits. As the number of RPASs in the swarm increases, packet loss increases. The difference in the PER for $N = 1$ and $N = 4$ is $\approx 45\%$ in the entire range of the considered TS values.

Figure 4 features an Exponential distribution for TBT. At $TS = (1 - 4)$ Kbits, the PER values for $N = 1, 2, 3, 4$ do not differ very much, but, unlike the previous case, the monotonic growth of the PER values begins immediately. The PER value reaches $\approx 68\%$ at $TS = 6$ Kbits for $N = 4$. It should be noted that at $TS = 1$

Kbits the difference in PER for $N = 1$ and $N = 4$ is less than $\approx 10\%$, and at $TS = 6$ Kbits it reaches values $\approx 20\%$.

Figure 5 shows the data for the LogNormal distribution law of the TBT parameter. In the range of $TS = (1 - 4)$ Kbits, the PER values for $N = 1, 2, 3, 4$ take the same values as for $TS = 5$ Kbits in the figure. The PER value reaches $\approx 65\%$ at $TS = 10$ Kbits for $N = 4$.

($BER_{BS-RPAS\ 1} = 0\%$, $BER_{BS-RPAS\ 2} = 0.02\%$, $BER_{BS-RPAS\ 3} = 0.04\%$, $BER_{BS-RPAS\ 4} = 0.06\%$)

It is of interest to compare the results obtained for four RPASs with different BERs in the communication channel with the BS. This situation is possible at different distances between RPASs in a swarm and the BS. The dependences of the AW parameter on the TS parameter are presented for Const distribution law of TS and TBT parameters in Figure 6. At the same time, AU parameter values at 100 Kbits reach the values $\approx 6\%$ for RPAS 1, $\approx 26\%$ for RPAS 2, $\approx 47\%$ for RPAS 3, $\approx 90\%$ for RPAS 4, and the PER value on the BS is $\approx 23\%$.

4. Impact Of Nonlinearity, Modulation, Antenna Diameter And Phase Offset

4.1. Swarm model “BS – RPASs” in MATLAB

RPAS swarms can have various architectures and organizations for communication with the BS. To study the features of data transmission in swarms, we built original models containing up to 30 RPASs with different channels for communication with the BS - Additive White Gaussian Noise (AWGN), Free Space Path Loss, Rician Frequency-Flat and Frequency-Selective Fading. When simulating data transmission, different types of modulation (BPSK, QPSK, 16QAM, 64QAM) with and without Doppler shift were considered. In this paper, we present only results obtained for AWGN channel with BPSK and QPSK1/2 modulations.

Figure 7 shows a swarm of four RPASs with RLOS communication with the BS. The model consists of “Base Station” (Bernoulli Random Binary Generator, Convolutional Encoder, BPSK/QPSK Baseband Modulator, High Power Amplifier with a memoryless nonlinearity, Transmitter Dish Antenna Gain); “AWGN channels”; “RPAS Receivers” (Receiver Dish Antenna Gain, RPAS Receiver System Temperature, Viterbi Decoder), “Error Rate Calculation” blocks and “Displays”.

In the “Base Station Transmitter” the Bernoulli Binary Generator block generates random binary numbers using a Bernoulli distribution with parameter p , produces “zero” with probability p and “one” with probability $1-p$ (the value $p=0,5$ is used).

The model uses forward error correction coding in the form of convolutional encoding with Viterbi decoding [34]. A model uses a rate $3/4$, constraint length 7, ($r=3/4$; $K=7$) convolutional code on both transmission and reception.

BPSK/QPSK Baseband Modulator block modulates a signal using the binary phase shift keying method.

The HPA block applies Saleh model [35]. The following backoff is used to set the input and output gain of the Memoryless Nonlinearity block: 30 dB - the average input power is 30 decibels below the input power that causes amplifier saturation; and 1 dB - severe nonlinearity.

The relationship between the antenna gain, the antenna diameter and the wavelength is determined by the relation $G = \eta(\pi D/\lambda)^2$, where η is the antenna efficiency. For calculations (here $\eta = 1$), the following parameters in the model were set up: RPAS antenna gain was taken 1.55 (an antenna diameter ≈ 0.2 m at 1 GHz), for the BS the following antenna gains were taken 6.2, 7.8 and 9.3 (an antenna diameters ≈ 0.8 m, ≈ 1.0 m and ≈ 1.2 m correspondently at 1 GHz).

“AWGN Channel” blocks add white Gaussian noise to the input signal. In the previous paragraph, the modeling of different distances between the BS and RPASs was carried out by setting different BER values for different communication channels of the RPAS with the BS (see Figure 6). In the case of the MATLAB software package, the “effect of different distances” was modeled by setting different SNR values. The values were varied only in AWGN Channel 1. At the same time, the SNR values in other channels were set constant, with the help of which a decrease in the SNR level was simulated for each subsequent RPAS. Such situation actually happens when the signal travels a greater distance (AWGN Channel 2 – $E_s/N_0 = -5$ dB, AWGN Channel 3 – $E_s/N_0 = -3$ dB, AWGN Channel 4 – $E_s/N_0 = -1$ dB). These SNR values for the channels were chosen arbitrarily from considerations of the approximate “equidistance” of the curves with negligible nonlinearity of the HPA for both considered modulations. In this case, it is possible to trace the influence of severe nonlinearity and phase offset in the modulated signal with an increase in the range to the RPAS.

In “RPAS Receivers”, signals are decoded and the BER is determined. The Viterbi Decoder block decodes input symbols to produce binary output symbols. Unquantized decision type parameter was used.

4.2. Results

The calculations were carried out using the MATLAB R2014a package. Figures 8-11 show data for BPSK modulation, Figure 12 compares data for BPSK and QPSK modulations, and Figures 13-16 illustrate QPSK modulation. An important problem in communication with RPASs is related to the nonlinearity of the BS HPA, which is associated with the small size of the drone antennas and the need to maximize the range of the drones. Therefore, the key issue is to compare the cases of negligible and severe nonlinearities (Figures 8, 9 for BPSK modulation and Figures 14, 15 for QPSK modulation).

Figure 8 shows data for BPSK modulation with negligible HPA nonlinearity. When the SNR in AWGN Channel 1 changes from -34 dB to -30 dB, the BER decreases from $\approx 3.9 \cdot 10^{-2}$ to $\approx 1.1 \cdot 10^{-6}$. In this case, for each next channel, the BER values turn out to be large due to long distances and worse SNR values. With $E_s/N_0 = -30$ dB, the BER value for AWGN Channel 2 is $\approx 5.0 \cdot 10^{-6}$, for AWGN Channel 3 is $\approx$

$4.0 \cdot 10^{-5}$, and for AWGN Channel 4 is $\approx 1.9 \cdot 10^{-4}$. This means that AWGN Channel 4 will be closed, and AWGN Channel 3 may be unstable.

In the case of strong HPA nonlinearity, the situation changes dramatically (Figure 9). For the operation of RPAS communication channels in these conditions, much higher SNR values are required. When the SNR in AWGN Channel 1 changes from -13 dB to -10 dB, the BER decreases from $\approx 4.8 \cdot 10^{-3}$ to $\approx 1.1 \cdot 10^{-6}$. The BER for AWGN Channel 2 reaches a value of $\approx 1.4 \cdot 10^{-6}$ at $E_s/N_0 = -8$ dB, and for AWGN Channels 3 and 4 at the same time $\approx 2.0 \cdot 10^{-5}$ and $\approx 9.0 \cdot 10^{-5}$ respectively. The distance between the graph of AWGN Channel 1 and the curves for the remaining channels increased compared to the negligible HPA nonlinearity (see Figure 8), although for the latter the SNR “shift” remained the same. This means that with an increase in the level of nonlinearity, communication with the RPAS at large distances suffers first of all. This is a seemingly obvious conclusion, but the data obtained allow us to quantify the degree of such deterioration.

The plots in Figures 10 (BPSK modulation) and 16 (QPSK modulation) demonstrate the dependences of the BER on the SNR for different diameters of BS antennas (RPASs antenna diameter ≈ 0.2 m in all cases) with a high degree of HPA nonlinearity. The high sensitivity of bit errors number in the transmitted data in dependence of the antenna size is obvious. The data are given only for the first RPAS, and for the rest, the situation is even more critical for the given SNR range. At $E_s/N_0 = -11$ dB, the change in the BER for both modulations reaches more than one order of magnitude.

The predefined M-ary Gray-coded signal constellation assigns the binary representation to the Mth phase. The zeroth phase in the constellation is the phase offset parameter. If the block input is the natural binary representation, the block output has phase $j\theta + j2\pi m/M$, where θ is the phase offset parameter and m is an integer between 0 and $M-1$. Figure 11 (BPSK modulation) and Figure 15 (QPSK modulation) show the dependences of the BEP on the SNR for different phase offset parameters with a high degree of HPA nonlinearity (in both cases, for simplicity, data are given only for the first two RPASs). Phase offset values equal to 0 radians lead to the least number of bit errors. In the case of QPSK modulation, higher SNR values are required for the communication channels compared to BPSK modulation.

A comparison of the differences between BER versus SNR dependences for the first two RPASs for BPSK and QPSK modulations is shown in Figure 12. The AWGN Channel 1 is open for BPSK modulation at $E_s/N_0 = -13$ dB, and at $E_s/N_0 = -11$ dB, the second is also open. For QPSK modulation both considered channels are closed in this case.

Comparison of negligible and severe HPA nonlinearities for BPSK modulation is considered above in Figures 8 and 9. Figure 14 shows the data for QPSK modulation with negligible HPA nonlinearity. When the SNR in AWGN Channel 1 changes from -33 dB to -28 dB, the BER decreases from $\approx 9.5 \cdot 10^{-2}$ to $\approx 4.8 \cdot 10^{-6}$. For each next channel, the BER values turn out to be larger due to long distances and worse SNR values. At $E_s/N_0 = -28$ dB, the BER values for AWGN Channel 2 are $\approx 9.8 \cdot 10^{-6}$, for AWGN Channel 3 $\approx 2.4 \cdot 10^{-5}$, and for AWGN Channel 4 $\approx 5.0 \cdot 10^{-5}$.

In the case of severe HPA nonlinearity, the situation is shown in Figure 15. High SNR values are required for RPAS communication links operation under these conditions. When the SNR in AWGN Channel 1 changes from -13 dB to -8 dB, the BER decreases from $\approx 7.0 \cdot 10^{-2}$ to $\approx 5.1 \cdot 10^{-6}$. The BER for AWGN Channel 2 reaches a value of $\approx 4.1 \cdot 10^{-3}$ at $E_s/N_0 = -8$ dB, and for AWGN Channels 3 and 4 at the same time, respectively, $\approx 1.3 \cdot 10^{-2}$ and $\approx 1.8 \cdot 10^{-2}$. The distance between AWGN Channel 1 graph and the curves for the remaining channels increased compared to the negligible HPA nonlinearity (see Figure 14). An increase in the level of nonlinearity leads to a deterioration in communication with the RPAS over long distances.

5. Discussion

There are practically no theoretical studies devoted to the development of predictive analysis methods in the field of RPAS/UAV swarms data synthesis. There are no methods for assessing the efficiency and traffic parameters for swarms. Our research focuses on the development of such methods. To understand the ways to fulfill the requirements for drone swarms delay, reliability, bandwidth, and QoS this study was undertaken.

The data presented in Figures 3–6 (Const distribution law for TS parameter) allow analyzing the advantages of a certain mode for data exchange between RPASs in a swarm with BS. For one RPAS: at Const law for TBT parameter $PER \approx 0\%$ up to $TS = 4$ Kbits and at $TS = 6$ Kbits it reaches $\approx 25\%$; at LogNormal law, $PER \approx 0\%$ up to 5 Kbits, with $TS = 6$ Kbits it becomes $\approx 22\%$, from $TS = 6$ Kbits to $TS = 8$ Kbits there is a "plateau", and then an increase up to $PER \approx 50\%$ at 10 Kbits; at Exponential law, there is an almost linear increase up to $PER \approx 22\%$ in the range (1 - 5) Kbits and at $TS = 6$ Kbits PER reaches $\approx 52\%$. For four RPASs in a swarm: at Const law for TBT parameter $PER \approx 42\%$ from 1 Kbits to 4 Kbits and then an increase to $\approx 70\%$ at 6 Kbits; at Exponential law, there is an increase from $PER \approx 8\%$ at 1 Kbits to $PER \approx 68\%$ at 6 Kbits without a "plateau"; at LogNormal law $PER \approx 42\%$ from 1 to 9 Kbits, and with 10 Kbits it becomes $\approx 65\%$.

It is possible to conclude that in a swarm for "small" packets up to 4 Kbits it is "more profitable" (less losses) to use Exponential law for TBT parameter ($\approx 25\%$ losses compared to $\approx 42\%$ for Const and LogNormal laws), but for "large" packets (4 – 9) Kbits is more profitable to use the LogNormal law ($\approx 42\%$ losses).

The nonlinearity in the communication channel is critical for wireless communication systems in general, and for drones in particular. Therefore, the obtained data allow quantitatively compare the features of data transmission using the dependences of the BER on the SNR for different levels of BS transmitter nonlinearity (Figures 8-16). It is shown that data transmission with an increase in the nonlinearity and the transition to QPSK modulation requires an increase in the SNR. So, for BPSK modulation (phase offset $\pi/8$ rad, BS antenna diameter 1 m) with the negligible nonlinearity $BER \approx 1.0 \cdot 10^{-6}$ at $E_s/N_0 = -30$ dB, and with the severe nonlinearity $BER \approx 1.0 \cdot 10^{-6}$ at $E_s/N_0 = -10$ dB. For QPSK modulation (phase offset

$\pi / 4$ rad, BS antenna diameter 1 m) with the negligible nonlinearity $\text{BER} \approx 4.8 \cdot 10^{-6}$ at $E_s/N_0 = -28$ dB, and with the severe nonlinearity $\text{BER} \approx 5.1 \cdot 10^{-6}$ at $E_s/N_0 = -8$ dB.

The given dependences of the BER on the diameter of the BS antenna for the severe nonlinearity allow analyzing and predicting the behavior of communication channels for various signal modulations during data transmission.

It should be noted such aspects in our article as the original architecture of channel models and the possibility of using the results to assess the quality of data transmission. The study is a continuation of our work and expands it to modeling RPAS communication channels in swarms. In the future, we plan to include an estimate of packet loss and parameters of telecommunication channels in RPAS swarms with satellite radio access networks.

6. Conclusions

This work is the first study with the calculation of data packet losses and the effect of nonlinearity for RPASs in a swarm. Results can be considered as a way to estimate the parameters of such channels using the MATLAB Simulink and NetCracker packages.

The significance of the results obtained lies in the ability not only to identify problems at the early stages of designing RPAS channels, but also to minimize errors, reduce time, costs and ensure scalability in new projects. It is already clear to many that such calculations are becoming a necessary tool for a researcher and developer of RPAS communication systems in clusters.

Abbreviations

AWGN: Additive White Gaussian Noise; BER: Bit Error Rate; BPSK: Binary Phase Shift Keying; BRLOS: Beyond Radio Line of Sight; BS: Base Station; CPS: Cyber-physical systems; GS: Ground Station; HPA: High Power Amplifier; MANETs: Mobile Ad hoc Networks; NCS: Network Control Systems; PER: Packet Error Rate; QAM: Quadrature Amplitude Modulation; QoS: Quality of Service; QPSK: Quadrature Phase Shift Keying; RLOS: Radio Line of Sight; RPAS: Remotely Piloted Air System; SNR: Signal-to-Noise Ratio; TBT: Time Between Transaction; TS: Transaction Size; UAV: Unmanned Aerial Vehicle; U2I: UAV-to-infrastructure; U2U: UAV-to-UAV; URLLC: Ultra-Reliable Low Latency Communication; VANETs: Vehicular Ad hoc Networks; WSN: Wireless Sensor Networks.

Declarations

Availability of data and materials: All data generated or analysed during this study are included in this published article.

Competing interests: The authors declare that they have no competing interests.

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Figures

Figure 1

ICAO aeronautical RPAS communication links [1]

Remotely Piloted Air Systems

Figure 2

Swarm model with four RPASs:

Figure 3

Dependences of PER for BS on TS for different RPAS number in swarm (BER = 0)

Figure 4

Dependences of PER for BS on TS for different RPAS number in swarm (BER = 0)

Figure 5

Dependences of PER for BS on TS for different RPAS number in swarm (BER = 0)

Figure 6

Dependences of AW for BS – RPASs links on TS with different BER (BERBS-RPAS 1 = 0%, BERBS-RPAS 2 = 0.02%, BERBS-RPAS 3 = 0.04%, BERBS-RPAS 4 = 0.06%)

Figure 7

Model of RPASs swarm

Figure 8

Dependences of BER on SNR (BPSK modulation, phase offset $\pi/8$ rad, BS antenna diameter 1 m)

Figure 9

Dependences of BER on SNR (BPSK modulation, phase offset $\pi/8$ rad, BS antenna diameter 1 m)

Figure 10

Dependences of BER on SNR for different BS antenna diameters (BPSK modulation, phase offset $\pi/8$ rad)

Figure 11

Dependences of BER on SNR for different phase offsets (BPSK modulation, BS antenna diameter 1 m)

Figure 12

Dependences of BER on SNR for different modulations (Phase offset 0 rad, BS antenna diameter 1 m)

Figure 13

Dependences of BER on SNR for different phase offsets (QPSK modulation, BS antenna diameter 1 m)

Figure 14

Dependences of BER on SNR (QPSK modulation, phase offset $\pi/4$ rad, BS antenna diameter 1 m)

Figure 15

Dependences of BER on SNR (QPSK modulation, phase offset $\pi/4$ rad, BS antenna diameter 1 m)

Figure 16

Dependences of BER on SNR for different BS antenna diameters (QPSK modulation, phase offset $\pi/4$ rad)