Time-Optimized Contextual Information Flow on Unmanned Vehicles

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Abstract— **Nowadays, the domain of robotics experiences a significant growth. We focus on Unmanned Vehicles intended for the air, sea and ground (UxV). Such devices are typically equipped with numerous sensors that detect contextual parameters from the broader environment, e.g., obstacles, temperature. Sensors report their findings (telemetry) to other systems, e.g., back-end systems, that further process the captured information while the UxV receives control inputs, such as navigation commands from other systems, e.g., commanding stations. We investigate a framework that monitors network condition parameters including signal strength and prioritizes the transmission of control messages and telemetry. This framework relies on the Theory of Optimal Stopping to assess in real-time the trade-off between the delivery of the messages and the network quality statistics and optimally schedules critical information delivery to back-end systems.**

I. Introduction

The use of unmanned vehicles is rising in areas of everyday life such as environmental monitoring [1], agricultural applications, disaster management, regardless of the domain that they belong to, i.e., aerial, ground or underwater. The characteristics that made them so popular are their degree of autonomy, i.e., the ability to make decisions without human intervention, the endurance and the payload they can support. As drones become more advanced they present greater value for commercial business use especially in case of mobile security monitoring or supporting crisis management activities. One example is the use of umnanned flying device, i.e. drone, equipped with video camera in order to recognize objects in real time, i.e. to cruise over forests to spot fires early, or to be sent to seek errant hikers who have failed to report in when expected.

UxVs ('x' can stand for 'a' aerial, 'g' ground or 's' sea vehicles) have, as a goal, the successful execution of a mission. A mission is often described as a trajectory with specific way-points in which the UxV is ordered to approach and gather various measurements from sensors or images from cameras. A Ground Control Station (GCS) is the terrestrial system, which acts as a coordinator/master node at distance responsible for data acquisition and transmission. The communication between the UxV and the GCS is established via wireless communications. A mission is created by the users and, then, GCS is responsible for the successful execution of the mission autonomously. GCS control messages shall be delivered with a high assurance of low or minimal time delay to enable real-time management, monitoring, control, and feedback loops. Therefore, this feature is transformed to a challenge in wireless multimedia sensor networks (WMSN) where providing better quality for images and videos is necessary under saturated and limited bandwidth. Multimedia applications with real time streaming needs require on-line assessment mechanisms in order to tackle uncertain wireless link capabilities while devices successful deliver messages to GCS.

The quality of the network has high importance for the mission because significant commands or sensor values can be lost. We can assume that even if control feedback is in high priority, telemetry can be paused for short time in need of crisis. When the quality of network changes, UxV/GCS can decide on-line to act accordingly in order not to overload a saturated network. For example GCS can pause the transmission of control a command rather than risks to loose completely the message under poor network conditions. In this work, we focus on an UxV with the following characteristics: (i) a user creates an outdoor mission for an UxV, (ii) a wireless multimedia network is established with nodes report telemetry and video streams, (iii) UxV consumes commands from GCS, (iv) GCS and UxV monitor the quality of the network and (v) the ultimate goal of UxV and GCS is to ensure the delivery of critical information exchanged. We provide the insights of adopting the principles of the Optimal Stopping Theory (OST) to establish an *optimal stopping rule*, which provides the best time instance to maximize an expected pay-off under network quality indicators. Our proposed optimal policy is based on an optimal stopping time series search algorithm for adjusting the transmission of control messages and telemetry.

This paper is organized as follows. Section 2 reports on the related work and the main contribution of this work. In Section 3, we present the preliminaries for our problem formulation and our solution. Section 4 presents the experiments performed followed by the conclusions in Section 5.

II. Related Work & Contribution

A. Related work

The dynamic control handling of messages in order not to overload a saturated network in device that is executinng an automatic remote mission is a new need for the researchers. For this reason we split the problems studied in literature in two main catergories, i.e 1) the message routing protocols area and 2) OST decision problems applied. Related to the first category, opportunistic networks are studied as long as they are capable of maintaining efficient operation in

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a wide range of network density and mobility conditions. In classifying the diversity of topological conditions in networking environments, one end of the spectrum corresponds to almost static dense topologies. For these, conventional topology-based protocols [2] function best; they use just node labels/identities. As the nodal density decreases and/or the mobility increases, and up to a point where the connectivity status between pairs of nodes remains stable, position-based families of protocols [3], [4] become more suitable. Additionally in networks of low nodal density, intense mobility becomes a prerequisite for the creation of contact opportunities. The aforementioned routing protocols have been designed to accommodate a restricted set of possible network conditions, corresponding to a particular sub-range and yield satisfactory performance only under these conditions. Another approach for resolving the connectivity issues in mobile devices and secure the delivery of the messages is to create a Decision Making Process (DMP) by explicitly considering the heterogeneous multimedia traffic characteristics, e.g., delay deadlines, distortion impacts and dependencies etc. Researchers in [5] develop a a cross-layer optimization framework for single-user multimedia transmission. In this work it is provided study on the network conditions and the adaptation mechanisms of a framework giving to our work a reference point of network characterization parameters.

Going a step further, we study methods derived from the OST that have been applied to contextual information dissemination in (mobile) ad-hoc networks. However, data delivery mechanisms have been studied in the literature from a different 'perspective' in mobile ad-hoc networks. The contextual data delivery mechanisms in [6],[7],[8] [9], and [10] deal with the delivery of quality information to context-aware applications in static and mobile ad-hoc networks, respectively, assuming epidemic-based information dissemination schemes.The mechanism in [9] is based on the probabilistic nature of the 'secretary problem' [11] and the optimal on-line search problem. The authors in [12] study a dynamic video encoder that detects scene changes and tunes the synthesis of Groups-of-Pictures . An OST mechanism is applied to multimedia streams in wireless multimedia sensor networks (WMSNs) where the size of groups-of-pictures (frames) is based on the possible detection. In [13], the authors determine the best time to switch from *decision* to *learning* phase of a Principal Component-based Context Compression model, while data inaccuracy is taken into account in wireless sensor networks. The main studied problem is that if data inaccuracy remains at low levels, then any deterministic switching from compression to learning phase leads to unnecessary energy consumption.

Change-point detection has its origins almost sixty years ago in the work of Page [14], Shiryayev [15], and Lorden [16], who focused on sequential detection of a change-point in an observed stochastic process. The stochastic process was typically a model for the measured quality of a continuous production process, and the change-point indicated a deterioration in quality that must be detected and corrected. In our case, we are adopting this methodology for finding the best

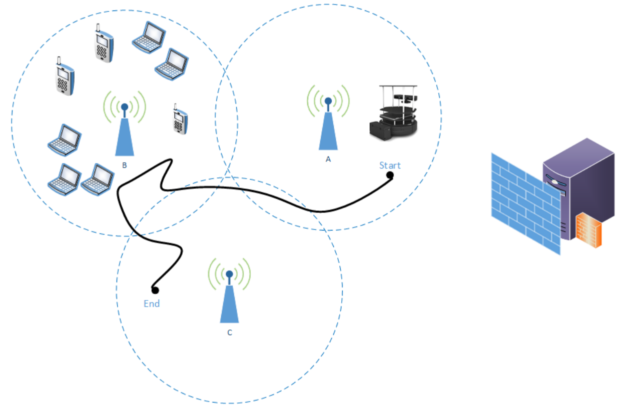


Fig. 1: Mission of a UxV in a saturated network.

time instance for the controller strategy in order to maximize the possibility of successful message delivery by observing runtime network statistics.

B. Contribution

We propose a model of on-line control unit adaptive to changes in network quality statistics by dynamically pause control/telemetry messages based on an OST rule in order to ensure the optimal delivery of critical information. We contribute with:

- *an on-line network quality change detection mechanism*,
- *an OST rule for time-optimized change detection*,
- *comprehensive performance evaluation of our mechanism.*

III. Time-Optimized Data Flow

We study a network-driven command and control contextual information flow adaptive to the network quality measurements. For example, an UxV is engaged in a mission probably and is tasked to explore places with full connectivity, with communication "blind spots", or with limited or saturated bandwidth, as shown in Figure 1. The main question in these situations is 'how we timely *identify* a change on network conditions and for how long the transitioning from one state to another lasts'. The time that a GCS shall adapt the commands production (by pausing the commands as long as the possibility of successful delivery of messages is considerably low) is provided by an OST rule based on the principles of optimality, which provides the best time instance to maximize our defined expected pay-off.

A. Preliminaries

Let $\mathbb{F}_n$ is defined as the σ-algebra generated by the random variables $Y_1, Y_2, \cdots, Y_n$ in a probability space $(\Omega, \mathbb{F}, P)$ [11]. A *stopping rule* is a random variable τ with realization values in a set of natural numbers such that $\{\tau = n \in \mathbb{F}_n\}$ for $n = 1, 2, \ldots$ and $P(\tau < \infty) = 1$. $\mathbb{M}(n, N)$ is the class of all stopping rules τ in which $P(n \leq \tau \leq N) = 1$ for any $n = 1, 2, \ldots$. The real-valued pay off function in OST is defined as the mapping $W : \mathbb{R} \to \mathbb{R}$ being a measurable function which values $W(y)$ define the trade off of a decision maker (the GCS in our case) when it stops the Markov chain $(Y_n, \mathbb{F}_n)$ at the state $y \in \mathbb{R}$.

Let assume that for a given state y and for a given stopping rule τ the expectation $\mathbb{E}[W(Y_\tau)|Y_1 = y]$ exists. Then, the expected pay-off $\mathbb{E}[W(Y_\tau)|Y_1 = y]$ corresponding to a chosen stopping rule τ exists for all states $y \in \mathbb{R}$, which refers to the value of the OST problem. Based on the *principles of optimality* the *value* $V_N(y)$of the optimal stopping problem is the supremum of the expected pay-off of all the stopping rules belonging to $\mathbb{M}(1,N)$, i.e.,

$$V_N(y) = \sup_{\tau \in \mathbb{M}(1,N)} \mathbb{E}[W(Y_\tau)|Y_1 = y] \quad (1)$$

where the $V_N(y)$ is calculated for all the stopping rules $\tau \in \mathbb{M}(1,N)$ for which the expectation $\mathbb{E}[W(Y_\tau)|Y_1 = y]$ exists for all $y \in \mathbb{R}$. Based on the optimal value $V_N(y)$, where the supremum in (1) is attained, the *optimal stopping rule* $t^* \in \mathbb{M}(1,N)$ satisfies the condition:

$$V_N(y) = \mathbb{E}[W(Y_t^*)|Y_1 = y], \forall y \in \mathbb{R}. \quad (2)$$

It is evident that the optimal value of $V_N(y)$ is the maximum value of the possible excepted pay-off that can be obtained observing the random variables $Y_1, \dots, Y_N$ up to N-th observation. Consider now that the expectations $\mathbb{E}[W(Y_\tau)|Y_1 = y]$ exist for all $y \in \mathbb{R}$ and, based on the principles of optimality, introduce the operator $\mathscr{Q}$ over the pay off function $W \in \mathbb{R}$ such that:

$$\mathscr{Q}W(y) = \max\{W(y), \mathbb{E}[W(Y_t^*)|Y_1 = y]\}. \quad (3)$$

Then, the optimal stopping rule t^* which attains the optimal value in (2) is estimated by the Theorem 1:

Theorem 1 Assume that $W \in \mathbb{R}$. Then:

- $V_n(y) = \mathscr{Q}^n W(y)$, $n = 1.2, \dots;$
- $V_n(y) = \max\{W(y), \mathbb{E}[V_{n-1}(Y_1)]\}$, where $V_0(y) = W(y)$
- The stopping rule t_n^* evaluated as

$$t_n^* = \min\{0 \le k \le n : V_{n-k}(y) = W(y)\}, \quad (4)$$

refers to an optimal stopping rule in $\mathbb{M}(1,n)$. If $\mathbb{E}[|W(Y_k)|] < \infty$, for $k = 1, \dots, n$, then the stopping rule t_n^* in (4) is *optimal* in the class $\mathbb{M}(1,n)$.

Proof: See [11]. ■

Let us assume a prediction scheme inside the GCS and UxV that is used to foresee any network changes. In our case, we claim that in good network conditions the transmission of telemetry messages from and to GCS/UxV can be large and infinite. This means that GCS can continuously sends commands without any stop. The main goal is to continue to send telemetry messages if the quality of network is *acceptable*. Otherwise each node, i.e. GCS or UxV, pauses the transmission and waits for a finite horizon to send all the messages in order not to overload a saturated network or to risk to loose completely messages. At the change point detection, a network change is identified based on the probability density functions of the network measurements, as explained later.

B. Time-Optimized Change-Point Decision Making

Let us assume that network readings $X_1, X_2, \dots, X_n$ are independent and identically distributed (i.i.d.) random variables and are observed sequentially in real time. Consider also that there are two known probability density functions f_0 and f_1, where $f_0 \neq f_1$. We are interested in finding the *stopping time* that detects a change from one distribution to another with the *minimum* delay based only on the realization of the random values $x_1, x_2, \dots, x_n$. To estimate f_0 and f_1, a probability density function comparison method was adopted to derive the closest distributions to our introduced Quality Network Indicator (QNI) values. A QNI is derived by the normalization of two important network metrics: the SNR and Quality Indicator. Quality indicator is exported by an access point in scale $[0, 100]$ and depends on on the level of contention or interference, like the bit or frame error rate, or other hardware metric. Values α_1 and α_2 normalize QNI sum in $[0, 1]$.

$$QNI = \alpha_1 * \frac{SNR(i) - max(SNR)}{max(SNR) - min(SNR)} + \alpha_2 * \frac{Q(i) - max(Q)}{max(Q) - min(Q)} \quad (5)$$

The chosen method returns the model fitting of all the parametric probability distributions to the SNR and compare them graphically as shown in Figure 2a for f_0 and Figure 2b for f_1.

Based on these observations, we model f_0 and f_1 through the Normal distribution. Given such distributions f_0 and f_1, the log-likelihood ratio $L^*(X_i)$ is then:

$$L^*(X_i; \mu_0, \sigma_0, \mu_1, \sigma_1) = \ln \frac{\sigma_1^2}{\sigma_0^2} + \frac{(X_i - \mu_1)^2}{2\sigma_1^2} - \frac{(X_i - \mu_0)^2}{2\sigma_0^2}, \quad (6)$$

We performed an independent analysis of the distribution values of SNR and Quality. The possible states of our analysis are (a) good SNR - good Quality, (b) good SNR - poor Quality, (c) poor SNR - good Quality, and (d) poor SNR - poor Quality. As shown in Figure 3, our problem can be defined as binary in which the 'good SNR - poor Quality' and 'poor SNR - good Quality' states are not dominant and can be considered as a subset of ' poor SNR - poor Quality' state. Therefore the change detection problem is approached by Page's [14] introduced method of cumulative sum change detection algorithm with among two states f_0 and f_1.

We allow n to the state to the infinity denoting by this case that no change occurs. Let $\mathscr{F}_n$, $n \ge 1$ be the σ-algebra generated by random variables (realizations) $\{X_1, X_2, \dots X_n\}$ and $\mathscr{P}_i$ equal to the uncertainty class of distribution f_i, where i denotes the i-th distribution. A sequential change point detection rule is derived by stopping time τ of the observation stream. The stopping time τ is the output of two different characteristics:

- the detection delay and D_n
- the frequency false alarm FAR, as denoted in [17]. A false alarm is a wrongly detection of a change from one distribution to the other. A false positive rate is calculated as the ratio between the number of negative events wrongly categorized as network changes. In the

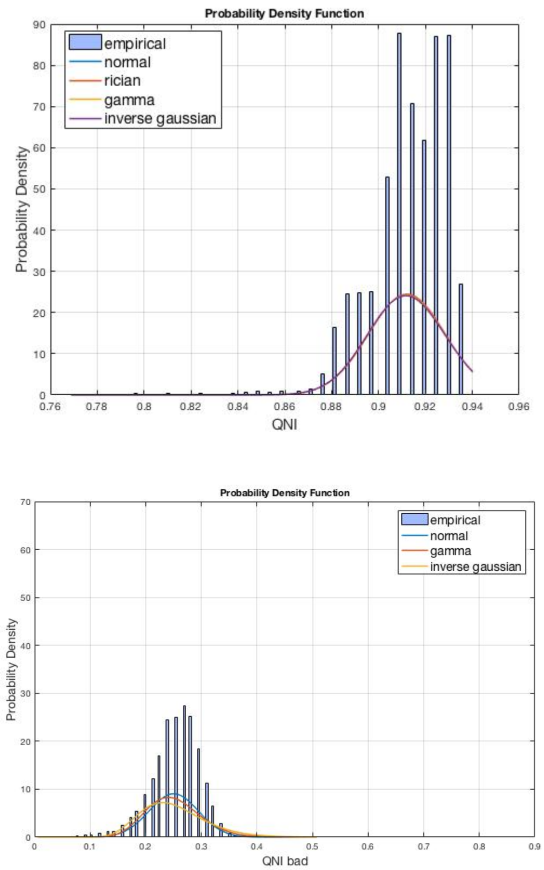


Fig. 2: (up) probability density function f_0 and (down) f_1 model fitting for *good* and *bad* quality of QNI values.

minimax formulation of Lorden [16], the change point is assumed to be an unknown deterministic quantity.

The worst-case detection delay is measured as:

$$D_n(\tau) = \sup_{n\geq 1} ess \sup \mathbb{E}_k[(\tau - k + 1)_+ | \mathscr{F}_{k-1}] \tag{7}$$

where $x^+ = max\{x, 0\}$ and the False Alarm Rate (FAR) is defined in [17] as:

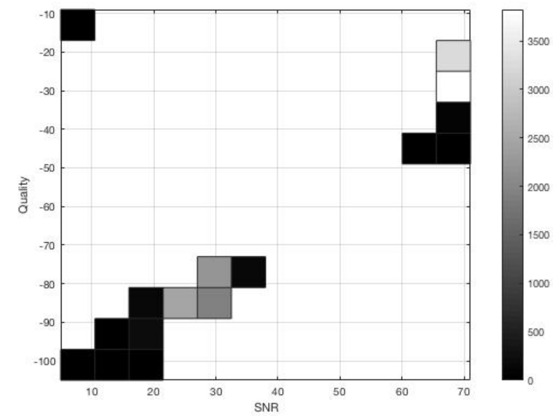
$$\text{FAR}(\tau) = \frac{1}{\mathbb{E}_\infty[\tau]}.$$

Here $\mathbb{E}_\infty[\tau]$ defines the expected time between false alarms. Under the Lorden criterion, the objective is to find the stopping rule that minimizes the worst-case delay subject to an upper bound on the false alarm rate. An example is shown in Figure 4*b*:

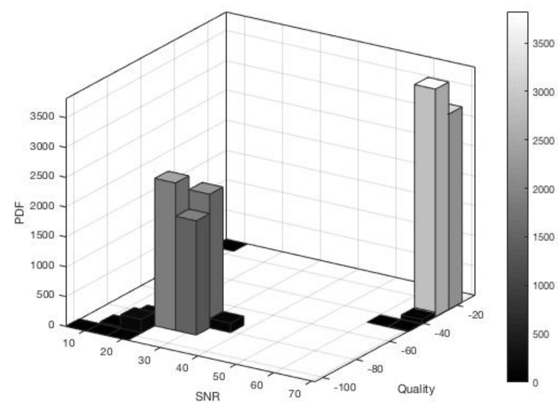
$$\text{min.} \quad D(\tau) \quad \text{s.t.} \quad \text{FAR}(\tau) \leq \alpha. \tag{8}$$

The optimal solution to (8) was proved by [18] that it is given by the Cumulative Sum (CUMSUM) test proposed by Page [14]. Hence the optimal stopping time is given by:

$$\tau = \inf\{n \geq 1, \max_{1\leq k\leq n} \sum_{i=k}^{n} L(X_i) \geq \eta\} \tag{9}$$



(a) Joint probability density function in 2D



(b) Joint probability density function in 3D

Fig. 3: Heatmap of probability density function for SNR and Quality.

Let L denote the log-likelihood ratio between $f_0(X)$ and $f_1(X)$ defined as the Radon-Nikodym derivative, i.e., $L(X) = \log \frac{f_0(X)}{f_1(X)}$. The threshold η is chosen so that $\mathbb{E}_\infty[\tau] = \frac{1}{\alpha}$.

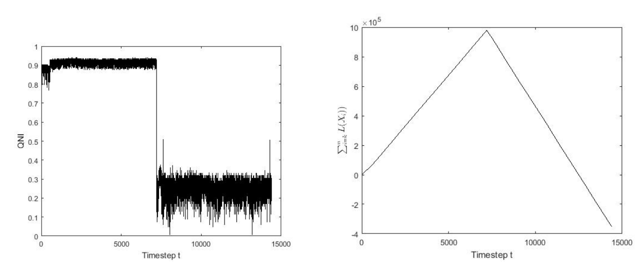


Fig. 4: The behavior of the cumulative log-likelihood ratio corresponding to a change.

Theorem 2: It holds true that:

- Uncertainty classes of distributions $\mathbb{P}_0$, $\mathbb{P}_1$ are jointly stochastically bounded by $(\bar{f}_0, \bar{f}_1)$.
- All distributions $f_1 \in \mathbb{P}_1$ are absolutely continuous with

respect to $\bar{f}_1$, i.e.

$$f_1 << \bar{f}_1, \quad f_1 \in \mathbb{P}_1 \tag{10}$$

- Function $L^*(.)$ of the log-likelihood ratio between $\bar{f}_0$ and $\bar{f}_1$ is continuous over the support of $\bar{f}_1$.

The optimal stopping rule which is derived by [18] applying the CUMSUM test is:

$$\tau^* = \inf\{n \geq 1 : \max_{1 \leq k \leq n} \sum_{i=k}^{n} L^*(X_i) \geq \eta\} \tag{11}$$

where threshold η is chosen so that $\mathbb{E}^*_\infty(\tau^*) = \frac{1}{\alpha}$.

Proof: Let us assume the conditions in Theorem 1. Since the CUMSUM test is optimal for known distributions it is clear that the test given in (11) is optimal when the pre- and post-change distributions are $\bar{f}_0$ and $\bar{f}_1$ respectively. Therefore it would be enough to show that the values of $D(\tau^*)$ and $FAR(\tau^*)$ are obtained under any $f_0 \in \mathbb{P}_0$ and any $f_1 \in \mathbb{P}_1$. Y_i^* is defined as the random variable $L^*(X_i)$ where the pre-change and the post-change distributions of the observations from the sequence $X_1, X_2 \cdots X_n$ are $\bar{f}_0$ and $\bar{f}_1$ respectively. It is defined Y_i as the random variable $L^*(X_i)$ when the pre- and post- change distributions are f_0 and f_1. In our case f_0 and f_1 distributions are known and the observations are referring to SNR measurements, i.e., each time instance k the controller measures the SNR variable X_k. These measurements are stochastically drawn under the distribution f_0 with mean μ_0 and variance σ_0^2. Their distribution changes to a distribution f_1 with mean value μ_1 and variance σ_1^2 at some *unknown* point m so that SNR variables $X_k \sim f_0$ for $k \leq m-1$ and $X_k \sim f_1$ for $k \geq m$.

It is evident that the FAR obtained by using the stopping rule τ^* is independent of the true value of the post-change distribution. Let us assume that the change point is set to a timestep λ. Hence we must prove that for all $\lambda \geq 1$

$$\mathbb{E}^\infty_\lambda[(\tau^* - \lambda + 1)^1 | \mathscr{F}_{\lambda-1}] \succ \mathbb{E}_\lambda[(\tau^* - \lambda + 1)^1 | \mathscr{F}_{\lambda-1}], \tag{12}$$

which establishes that the value of $D(\tau^*)$ obtained under any $f_1 \in \mathbb{P}_1$ is no higher than the value when the true post-change distribution is $\bar{f}_1$. The $A \succ B$ operator denotes that A is jointly stochastically bounded by B. We can show, without the loss of generality, that for all $i < \lambda$, Y_i holds with probability 1. Under this assumption it is sufficient to prove that:

$$P^\infty_\lambda((\tau^* - \lambda + 1)^+ \leq N | \mathscr{F}_{\lambda-1}) \leq P_\lambda((\tau^* - \lambda + 1)^+ \leq N | \mathscr{F}_{\lambda-1}) \tag{13}$$

which would then establish (12). Since τ^* is a stopping time, the event $(\tau^* - \lambda + 1)^+ \leq 0$ is $\mathscr{F}_{\lambda-1}$- measurable. Therefore with probability 1 (13) holds with equality for $N = 0$. For $N \geq 1$ we know that under stochastic ordering condition on $\mathscr{P}_1$ it is true that:

$$Y_i \succ Y_i^\infty, \forall i \geq \lambda. \tag{14}$$

Hence, between a change, the following equation holds:

$$\begin{aligned} \{\tau^* \leq N\} &= \{max_{1 \leq n \leq N} max_{1 \leq k \leq n} \sum_{i=k}^{n} L^*(X_i) \geq \eta\} && (15) \\ &= \{max_{1 \leq k \leq n \leq N} \sum_{i=k}^{n} L^*(X_i) \geq \eta\}. && (16) \end{aligned}$$

It is easy to see that the function $\sum_{i=k}^{n} L^*(X_i)$ is a non-decreasing function for all the $i < \lambda$.

Hence for $N \geq 1$ the following holds:

$$\begin{aligned} P^*_\lambda((\tau^* - \lambda - 1)^+ &\leq N | \mathscr{F}_{\lambda-1}) \\ &= P^\infty_\lambda(\tau^* \leq N + \lambda - 1 | \mathscr{F}_{\lambda-1}) \\ &= P_\lambda((Y_1^*, \cdots, (Y^*_{N+\lambda-1}) \geq \eta | \mathscr{F}_{\lambda-1}) \\ &\leq P_\lambda((Y_1, \cdots, (Y_{N+\lambda-1}) \geq \eta | \mathscr{F}_{\lambda-1}) \\ &= P_\lambda(\tau^* \leq N | \mathscr{F}_{\lambda-1}) \\ &= P_\lambda((\tau^* - \lambda + 1)^+ \leq N | \mathscr{F}_{\lambda-1}) \quad (17) \end{aligned}$$

This denotes that the equation $D(\tau^*)$ (8) under any pair of distribution $(f_0, f_1) \in P_0 \times P_1$ is no larger than $(\bar{f}_0, \bar{f}_1)$ and thus τ^* is the optimal solution. ■

IV. Performance Evaluation

We report on an experimental evaluation to compare the performance of our framework. We have used a UGV named 'turtlebot' and the role of GCS was handled by a fixed server. UGV and GCS are part of the *Road-, Air- and Water-based Future Internet Experimentation* (RAWFIE) [1] platform which offers a framework for interconnecting numerous testbeds over which remote experimentation can be realized. RAWFIE platform originates in a H2002 EU-funded (FIRE+ initiative) project which focuses on the mobile IoT paradigm and provides research and experimentation facilities through the ever growing domain of unmanned networked devices (vehicles). The simulation setup has as follows: The simulation takes places in an outdoor space as depicted in figure 1. A GCS is a fixed server communicating with a moving UxV. The messages are sent via UDP protocol, which is widely used in unmanned missions. GCS initializes a mission of an UGV following a specific trajectory. The mission contains a sequence of way-points in an outdoor infrastructure which are being sent to UGV with specific control messages. These commands are produced by following the exponential distribution. UGV during the mission sends back to GCS telemetry messages from its on board sensors, like health status, battery, temperature and video streaming. When UGV approaches one goal point then the next command containing location indicators is sent to the UGV. Unfortunately UGV is in outdoor facility faces saturated network conditions. The measured QNI in this outdoor testbed is shown in Figure 5. Figure 5 also contains the profiling between poor and excellent QNI.

The design parameter of the problem is the upper bound of the false alarm rate α in 8. The α parameter is highly connected with false alarm rate (FAR). We run a number of missions in order to study the performance of the OST decision module for the different values of α. Different values of α were evaluated by the number of the false alarms detected in $N = 100$ executions of the mission. The different α values were generated randomly in the intervals presented in Table I. It is shown the lower the α values the performance of FAR reaches better scores. However for values lower than

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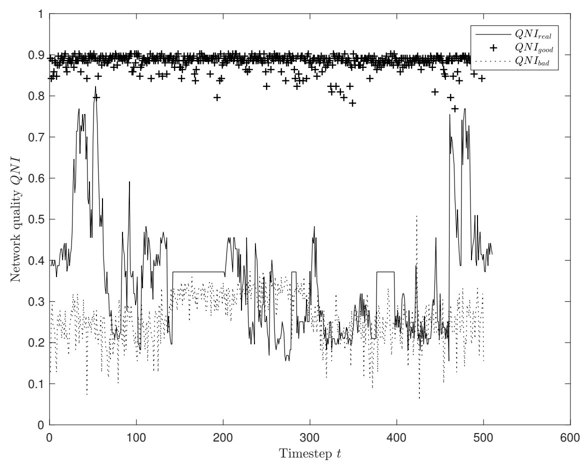

Fig. 5: The quality measured for real saturated network.

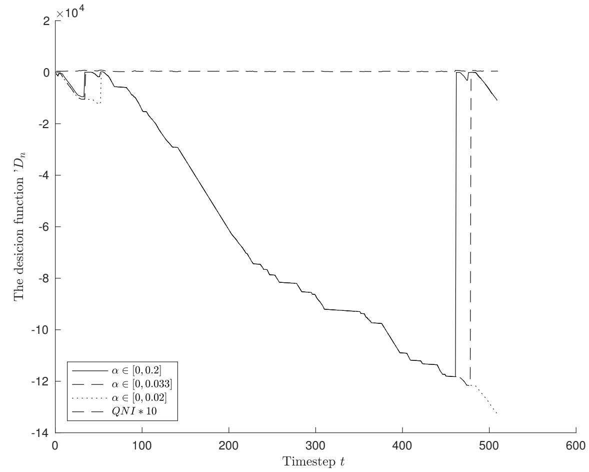

Fig. 6: The value of the D function vs. different α.

TABLE I: Simulation Parameters

α	False Alarms
$[0,1]$	0,5
$[0,0.2]$	0.32
$[0,0.01]$	0.27
$[0,002]$	0.18
$[0,0.033]$	0.23

TABLE II: Packets Produced and Consumed

ModelName	*PacketsProduced*	Packets Consumed	Lost Packets
Nopolicy	3716	2253	1463
HeuristicPolicy	3719	2074	1645
OST $\alpha = 0.002$	2550	2478	72
OST $\alpha = 0.001$	1914	1707	207

0.01 the experiment can gain similar values. The chosen interval is the $[0, 0.002]$. This is can be shown in Figure 6, in which the function D based on different values of α is compared. The changes of network based on SNR is presented in the same figure -the initial QNI values were multiplied by 100 in order to be readable.

Taking α values in the interval $[0, 0.02]$, D_n function was studied similarly for $N = 100$ experiments. Four different models were evaluated as follows

- A non policy model, i.e GCS and UxV continuously send and receive messages having indifference to network conditions
- A heuristic theshold-based model, in which the transmission of messages is paused when QNI falls under the interval of $[0.2, 0.3]$ and messages are stored in a queue.
- OST model with α values $\in [0, 0.02]$
- OST model with α values $\in [0, 0.01]$

The performance metrics of the proposed model with dynamic adoption of transmission of exchanged messages taking into account the real-time networks conditions are i) the number of produced messages by the producers exist in GCS and UxV, ii) the consumed messages by the consumers in both units and iii) the lost number of messages. In this way we are trying to map the differences between the different approaches related to saturated networks with the upper goal the successful execution of a mission. It is evident that in table II the OST model outperforms related with the rest models. The heuristic model and the original version of receiving and transmitting messages lost messages close to 24%, in other words close to 1 to 4 messages were lost, while only 4% of the messages were lost in OST model with $\alpha \in [0, 0.001]$ and this percentage is minimized to less of 2% in OST model with $\alpha \in [0, 0.002]$.

In figures 7a and 7b an overview of the messages produced and consumed by the four different models. It is expected that "network-agnostic" models produce a great amount of exchanged models and especially in threshold model the messages are displaced due to the latency of queue. In case of OST models, producers and consumers have a more moderate and normal distribution of messages in time hence the messages are delivered even if the existence of network disconnections.

The latency issues is more evident in figure 8. The difference in each timestep of the messages produced and consumed by the two units is studied in the main cases, i.e. in the original case where no algorithm is implemented and in the case of the OST model. It should be noted that we have 3 main network disconnections in the timestep $t = 600$, $t = 1000$ and $t = 1200$. Until $t = 600$ the OST model, although it works in saturated network, the differences between the produced and consumed messages are zero. After the first disconnection it can be noticed a small shift of the messages paused and consumed in a later time. This latency imported by the stopping time of the producers is balanced in the next time steps and finally close to all messages are delivered successfully. This is not the case for the original model in which the producers continually and burdens the network and consumers with messages that are not delivered.

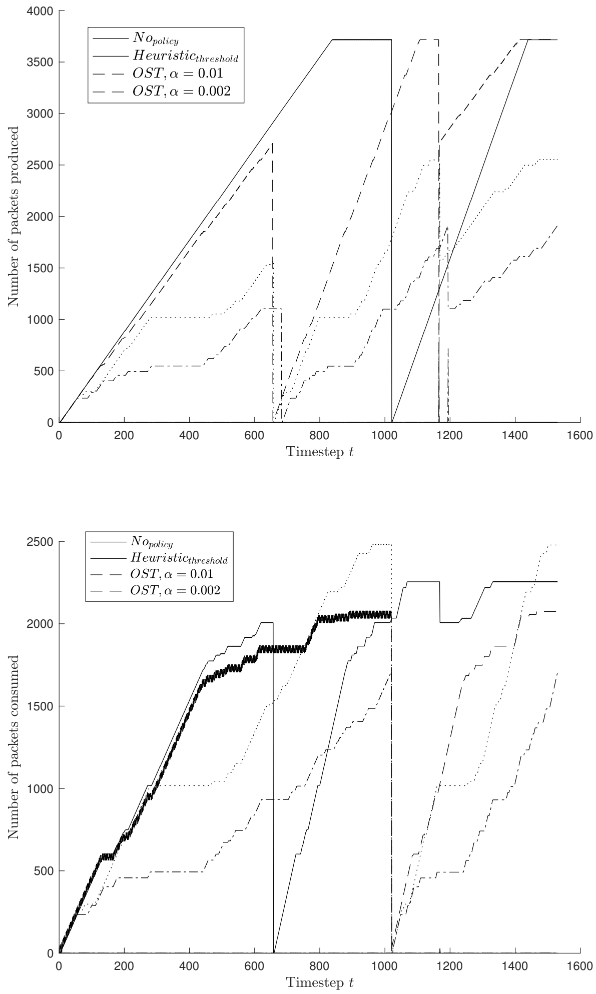

Fig. 7: The behavior of (up) produced and (down) consumed packets in a saturated network

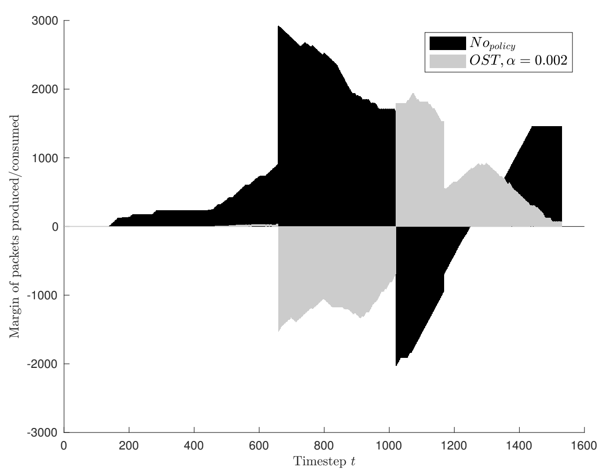

Fig. 8: The differences between produced and consumed data with No policy applied (black area) and with OST model, $\alpha \in [0, 0.002]$ (grey area).

V. Conclusions

This paper describes a framework that monitors network conditions and changes the UxV transmission of control message and telemetry trying not to overload the network in which the devices operate and move. We propose a model of dynamic decision making, adaptive to changes in network conditions, by dynamically adjusting the transmission of control messages and telemetry based on an optimal stopping rule. The performance evaluation showed the successful delivery of messages in poor network conditions and the moderate production of messages so as not to burden an already saturated network. Our future agenda includes a time-constraint approach with an additional OST problem of finite horizon in order to include a trade-off for the 'pausing' strategy.

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