Timely Ship Monitoring via Satellite: a Perspective on Age of Incorrect Information

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***Abstract*—The ability to collect via satellite status updates from vessels is a key enabler for a number of maritime applications. In these settings, maintaining an up to date perception of the state of a ship is paramount, yet challenging due to the large number of vessels in the satellite coverage. To tackle the problem, we study the impact of different transmission policies, capturing system performance in terms of age of incorrect information (AoII). Modelling channel contention as slotted ALOHA, we consider a benchmark inspired by the de-facto AIS/VDES transmission standard in which ships periodically report their state, and compare it to solutions that adapt the transmission probability to current ship-to-satellite channel conditions and to relevant changes in the ship state. By means of a Markovian analysis, we derive closed-form expressions for the average AoII, and discuss the performance in settings of representative of practical conditions. The potential of solutions that tie channel access to the evolution of the process to be tracked clearly emerges. The work aims at stimulating further research in this domain, having in mind future enhancements of ship communication standards.**

I. Introduction

The steady growth of maritime traffic is triggering an increased demand for vessel connectivity [1]. The ability to track ships as well as to enable communication among them and with port authorities is indeed paramount, with implications ranging from safety to environmental sustainability [1], [2]. Yet, stable connectivity through conventional networks is often not available [3], and many applications rely on maritime-specific communications systems. A practically relevant example in this perspective is the automatic identification system (AIS) [4], together with its evolutions (VDES [5]). Originally developed in the ′90s for collision avoidance, AIS relies on a simple self-organized TDMA (SOTDMA) protocol to foster periodic data exchange among nearby vessels about heading, position, speed and other relevant information [4], [6]. On the other hand, its field of application widened dramatically with the possibility to collect messages sent by ships via low-Earth orbit (LEO) satellites [1]. As a result, AIS data is nowadays used both commercially, e.g., for real time monitoring, data analytics and prediction methods, as well as by authorities, e.g., for the orchestration of just-in-time port calls [2].

The potential of AIS via satellite comes though with some challenges. In particular, the wide field of view of a LEO receiver may cover thousands of ships [6], which in turn communicate leaning on protocols that were designed for small clusters of nodes. Due to this, the satellite perceives an overloaded channel, prone to packet collisions and interference which may lead to losing track of vessels for extended periods of time. Devising improvements to the basic AIS communication scheme is thus key to fully reap the capabilities of ship monitoring. In this perspective, a promising approach consists in tying the transmission of data to the value of the information being sent, e.g., prioritizing reports of changes in bearing or speed that could be critical. The idea is aligned with the notion of *data relevance* and *information freshness*, which received a large deal of attention for internet of things and cyber-physical systems, e.g., [7], [8]. In these settings, protocol design based on novel metrics such as age of incorrect information (AoII) has proven to be a key enabler in maintaining an up-to-date perception at a monitor collecting data from a number of sources over a multiple-access channel [9]–[12]. On the other hand, the application of such principles to vessel monitoring via satellite is still largely unexplored. In fact, although the basic notion of adapting the periodicity of messages to the current speed or to a bearing change is somewhat embedded in the AIS specifications [4], the communication system is typically studied considering traditional performance indicators.

Based on these remarks, we tackle the problem of timely vessel monitoring by focusing on a setting in which ships in a receiver's field of view contend for the channel following a slotted ALOHA policy [13]. The model was shown to capture very accurately the traffic pattern induced by SOTDMA when reception is performed at a satellite [6], [14], and is thus representative of AIS data collection. We then study different variations of the protocol, considering a channel access probability that depends on changes in the vessel state (e.g., velocity or bearing) and on current link conditions. By means of a Markovian first-step analysis, we derive closed form expressions for the AoII at the satellite, and optimize the channel access probabilities in order to minimize the metric. Several insights are derived, showing the potential of tying vessel transmissions to state changes. The work aims at stimulating further research in the area, considering the notion of data relevance and the use of novel metrics such as AoII as performance indicators for future enhancements of AIS as well as other maritime communication solutions via satellite.

II. System Model

Throughout this work we focus on a set of M terminals (nodes) that share a wireless channel to communicate with

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a common receiver (sink). Time is divided in slots of equal duration, allowing transmission of a single data packet (possibly with guard intervals), and all nodes are assumed to be slot synchronized. At the link layer, we model medium contention as slotted ALOHA [13]. Accordingly, at every slot a terminal accesses the channel with a certain probability, transmitting a packet regardless of the activity of other nodes. The receiver provides no feedback on whether the message was successfully received or not, and no retransmission is performed by the sender. This model has been shown to accurately capture the behavior of a LEO satellite attempting collection of AIS/VDES messages exchanged among vessels in its footprint [6], [14].

Packets sent by terminals may undergo attenuation and other channel impairments, e.g., due to obstructions, fading or atmospheric losses. Following a well-established modeling approach for slotted ALOHA systems [15], we assume that a sent message can either be erased, delivering no power at the receiver, or reach the sink unfaded. Moreover, the links between terminals and the receiver (ship to satellite) are described as independent and identically distributed Gilbert-Elliot processes [16], allowing to capture in a simple way temporal correlation in the evolution of wireless channels [17]. Specifically, at each slot a sender-receiver channel may be either in a *bad* or *good* state. In the former case, a sent message undergoes an erasure with probability ε_b, whereas the event takes place with probability ε_g under good conditions. Clearly, $\varepsilon_b \gg \varepsilon_g$. Formally, each channel is characterized by a two-state discrete-time Markov chain C_n, $n \in \mathbb{N}$. The process updates its value at the beginning of each slot, transitioning from bad to good or good to bad state with probability γ and β, respectively. For the ergodic Markov chain, the stationary probabilities of being in state good and bad readily follow as $\pi_g = \gamma/(\gamma+\beta)$ and $\pi_b = 1 - \pi_g$, respectively. In the remainder, we assume that a terminal is aware of the current quality of its link with the sink. Finally, at the receiver side, the presence of two or more non-erased packets over the same slot results in a collision, not allowing retrieval of any information. Conversely, a slot in which a sole message arrives unfaded leads to successful decoding (*collision channel model* [13]).

In the monitoring applications under study, ships transmit messages containing time-stamped information, e.g., relevant for localization, collision avoidance and route planning. We refer to the set of such parameters as the *state* of the terminal, and assume that, at each slot, a node experiences a change in its state with probability α. This may correspond to variations in velocity, bearing, or any other feature which is needed to properly track the behavior of the sender. In turn, the receiver maintains an estimate of the state of a terminal, set to the content of the last successfully received message from that node. Accordingly, whenever a change in the state of a ship occurs, the sink remains with an erroneous knowledge until being informed from the terminal of the current conditions. We formalize the aspect by introducing the discrete time random process E_n, $n \in \mathbb{N}$, taking value 0 if the estimate at the receiver is correct at slot n, and 1 otherwise.

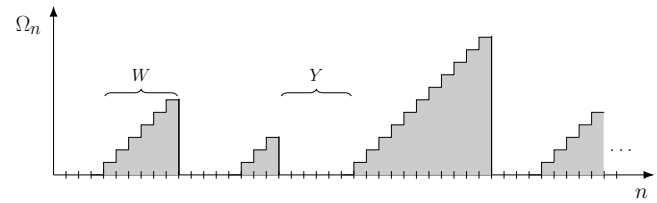


Fig. 1. Example of evolution of the instantaneous AoII Ω_n over time. Shaded areas denote periods during which the receiver has an erroneous knowledge of the state of the reference terminal. Instances of the random durations W and Y of a period with erroneous and correct knowledge are also reported.

In this setting, we aim to gauge the ability of different communication strategies to provide the sink with an accurate knowledge. To this end, focusing without loss of generality on a reference ship of interest, we define the age of incorrect information (AoII) at the receiver at time n as

$$\Omega_n := E_n \cdot (n - s(n))$$

where $s(n)$ is the last time at which the sink started having an erroneous estimate for that terminal. An example of the time evolution of Ω_n is reported in Fig. 1. Here, the metric is reset to 0 whenever a message from the reference ship is received, and remains so until the ship changes its state. When this happens, a linear growth in AoII is experienced as long as the receiver remains with an erroneous knowledge. In the remainder, we will focus on the average value of the stochastic process, which can be shown to be ergodic:

$$\overline{\Omega} = \mathbb{E}[\Omega_n] = \lim_{\ell\to\infty} \frac{1}{\ell} \sum\nolimits_{i=1}^{\ell} \Omega_\ell.$$

We consider three variations of the slotted ALOHA policy:

Random transmission policy (RAN): in this case, a terminal transmits an update containing its current state at each slot with probability τ. The simple approach serves as a reference benchmark, epitomizing strategies in which ships periodically report information, oblivious of the evolution of their state;

Channel-aware transmission policy (C-AW): following this approach, a node can tune its access probability based on the current channel conditions. Specifically, an update message is sent over a slot with probability τ_g if the channel is in *good* state, and with probability τ_b if the channel is in *bad* state.

State-aware transmission policy (S-AW): here, a terminal not only leverages knowledge of channel conditions, but also prioritizes delivery attempts when its state has changed. Specifically, whenever the channel is good, access is performed with probability $\tau_{g,c}$ if the node state changed over that slot, and with probability $\tau_{g,s}$ if the state has remained the same. Accordingly, the terminal remains silent with probability $1-\tau_{g,c}-\tau_{g,s}$. Similarly, the behavior when the channel is bad is captured by the pair of probability values $\tau_{b,c}$ and $\tau_{b,s}$.

III. Average AoII Characterization

For the slotted ALOHA system under study, the average AoII at the receiver for a reference terminal can be shown via

geometric arguments to take the form [10]

$$\overline{\Omega} = \frac{\mathbb{E}\left[W^2\right] + \mathbb{E}[W]}{2(\mathbb{E}[W] + \mathbb{E}[Y])} \tag{1}$$

where W and Y are the r.v.s describing the duration (in slots) of a period during which the receiver has erroneous and correct knowledge of the state of the node, respectively (see Fig. 1). In turn, the statistics of the involved r.v.s depend on the specific variation of the access protocol being implemented. From this standpoint, we observe that both the random and the channel-aware policies can be seen as special cases of the state-aware scheme. Indeed, the RAN setup is obtained by setting all the transmission probabilities equal to τ, whereas the C-AW one follows for $\tau_{g,c} = \tau_{g,s} = \tau_g$ and $\tau_{b,c} = \tau_{b,s} = \tau_b$.

Leaning on this, we focus in the remainder of our analysis on the S-AW policy, and introduce for convenience the probability that a node with good (ρ_g) and bad (ρ_b) channel conditions transmits over a slot:

$$\begin{aligned} \rho_g &:= (1-\alpha)\tau_{g,s} + \alpha\,\tau_{g,c} \\ \rho_b &:= (1-\alpha)\tau_{b,s} + \alpha\,\tau_{b,c}. \end{aligned} \tag{2}$$

Without loss of generality, let us then focus on a reference terminal, and assume that over the current slot the node has experienced a state change, and is enjoying *good* channel conditions. The probability to deliver an update in these conditions can easily be written as

$$\mathsf{p}_{g,c} = \tau_{g,c}\,(1-\varepsilon_g)\,\mathbb{P}(I=0) \tag{3}$$

where the r.v. $I \in \{0,\ldots,\mathsf{M}-1\}$ denotes the number of messages other than that of the reference terminal that reach the receiver unfaded over the observed slot. In (3), the first two factors require the node to send an update and for this not to undergo an erasure, whereas the final one defines the decoding condition under the collision channel model. In turn, by the law of total probability, we have

$$\mathbb{P}(I=0) = \sum\nolimits_{n_g=0}^{\mathsf{M}-1} \mathbb{P}(I=0\,|\,N_g=n_g)\,\mathbb{P}(N_g=n_g) \tag{4}$$

where N_g is the r.v. describing the number of users other than the reference one that are currently experiencing good channel conditions. The conditional probability in (4) follows as

$$\begin{aligned} &\mathbb{P}(I=0\,|\,N_g=n_g) = \\ &\qquad (1-\rho_g(1-\varepsilon_g))^{n_g}\cdot(1-\rho_b(1-\varepsilon_b))^{\mathsf{M}-1-n_g}. \end{aligned} \tag{5}$$

On the other hand, the probability mass function of N_g can be obtained using the stationary distribution of the channel as

$$\mathbb{P}(N_g=n_g) = \binom{\mathsf{M}-1}{n_g}\pi_g^{n_g}\,(1-\pi_g)^{\mathsf{M}-1-n_g}. \tag{6}$$

Plugging (5) and (6) into (4) finally allows to derive a closed form expression for the update delivery probability in (3). Similarly, the probabilities of delivering a message with good channel yet no state change ($\mathsf{p}_{b,s}$), as well in the presence of a bad channel ($\mathsf{p}_{b,c}$, $\mathsf{p}_{b,s}$) immediately follow from (3) by simply replacing $\tau_{g,c}$ and ε_g with the appropriate probabilities.

Remark: We observe that the presented approach introduces an approximation, epitomized by (6) *and* (2)*. Indeed, for the considered Gilbert-Elliot channels, the distribution of the number of incoming messages at the receiver is in general correlated over time as soon as $\beta \neq \gamma$. An exact characterization of the system would thus require to jointly track the state of all the channels, becoming cumbersome for large* M*. The tightness of the approximation will be verified in Sec. IV.*

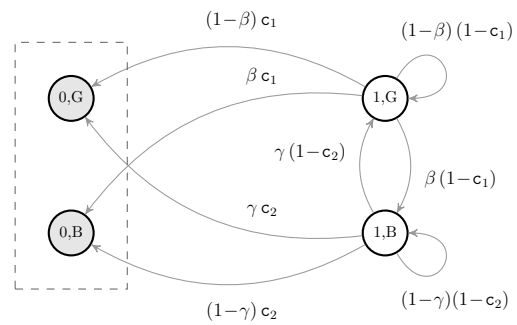


Fig. 2. Markov chain to derive the statistical moments of the time spent with erroneous knowledge of the state of the reference source, i.e., W.

A. Statistical moments of W

Consider now the r.v. W, which describes the duration of a period during which the receiver has an erroneous knowledge of the state of the reference node. To capture its statistics, it is convenient to introduce the discrete time Markov chain $X_n = (E_n, C_n)$, $n \in \mathbb{N}$, jointly tracking the knowledge error at the receiver and the channel conditions for the reference node-receiver pair over time. The chain is reported in Fig. 2, highlighting the transitions of interest for our discussion. Specifically, the two rightmost states denote conditions in which the receiver estimate is wrong ($E_n = 1$) and the channel conditions are either good or bad. In turn, the leftmost part of the chain, denoting conditions in which the receiver has a correct knowledge, are modeled as absorbing states. The one-step transition probabilities for the process can easily be derived leaning on the probability of successfully delivering an update computed earlier. For instance, the chain moves from $(1,\mathsf{G})$ to $(1,\mathsf{B})$ if i) the channel transitions from good to bad (probability β), and ii) no update is delivered in the slot by the reference terminal. The latter event has probability $1-\alpha\mathsf{p}_{g,c}-(1-\alpha)\mathsf{p}_{g,s}$, accounting for the possibility of the terminal to both change its state or not and considering the corresponding update probabilities. Similarly, if the chain is in state $(1,\mathsf{G})$, the channel transitions to bad conditions (β) yet an update is delivered (probability $\alpha\mathsf{p}_{g,c}+(1-\alpha)\mathsf{p}_{g,s}$), a transition to $(0,\mathsf{B})$ is experienced. All other probabilities are reported in Fig. 2, introducing the auxiliary quantities $\mathsf{c}_1 = \alpha\mathsf{p}_{g,c}-(1-\alpha)\mathsf{p}_{g,s}$ and $\mathsf{c}_2 = \alpha\mathsf{p}_{b,c}-(1-\alpha)\mathsf{p}_{b,s}$.

More interestingly, for this chain W represents the time of absorption (i.e., first visit to one of the states $(0,\mathsf{B})$ or $(0,\mathsf{G})$) when starting either in $(1,\mathsf{G})$ or in $(1,\mathsf{B})$. Accordingly, the first and second order moments of the r.v. can be computed resorting to a first-step analysis [18]. Consider first $\mathbb{E}[W]$.

Without loss of generality, let $n = 1$ denote a time slot at which the receiver starts having an erroneous knowledge of the state of the source. With this notation, we can write

$$\mathbb{E}[W \mid X_1 = (1, \mathsf{G})] = 1 + \mathsf{E}[W \mid X_1 = (1, \mathsf{G})] \cdot (1-\beta)(1-\mathsf{c}_1) + \mathsf{E}[W \mid X_1 = (1, \mathsf{B})] \cdot \beta(1-\mathsf{c}_1). \quad (7)$$

In the equation, the first addend accounts for the one slot elapsed in the current step, whereas the Markov property ensures that the average duration, once the transition to either state $(1, \mathsf{G})$ or $(1, \mathsf{B})$ has occurred, is equal to the one that we would have by starting from such state. A similar condition holds when starting from $X_1 = (1, \mathsf{B})$, so that

$$\mathbb{E}[W \mid X_1 = (1, \mathsf{B})] = 1 + \mathsf{E}[W \mid X_1 = (1, \mathsf{G})] \cdot \gamma(1-\mathsf{c}_2) + \mathsf{E}[W \mid X_1 = (1, \mathsf{B})] \cdot (1-\gamma)(1-\mathsf{c}_2). \quad (8)$$

We thus have with (7)-(8) a full-rank system of two linear equations, whose solution provides the expected value of W conditioned on whether the period of erroneous knowledge started in good or bad channel conditions. Finally, let us denote by $k_{(1,\mathsf{G})}$ and $k_{(1,\mathsf{B})}$ the probability of starting a the period in the two cases. The quantities can readily be expressed as

$$k_{(1,\mathsf{G})} = \frac{(1-\beta)(1-\mathsf{p}_{g,c})\,\pi_{(0,\mathsf{G})} + \gamma(1-\mathsf{p}_{b,c})\,\pi_{(0,\mathsf{B})}}{(1-\mathsf{p}_{g,c})\,\pi_{(0,\mathsf{G})} + (1-\mathsf{p}_{b,c})\,\pi_{(0,\mathsf{B})}}$$

and $k_{(1,\mathsf{B})} = 1 - k_{(1,\mathsf{G})}$, where $\pi_{(0,\mathsf{B})}$ and $\pi_{(0,\mathsf{G})}$ are the stationary probabilities for the Markov chain (E_n, C_n).[1] By the law of total probability we finally have

$$\mathbb{E}[W] = k_{(1,\mathsf{G})}\,\mathbb{E}[W \mid X_1 = (1, \mathsf{G})] + k_{(1,\mathsf{B})}\,\mathbb{E}[W \mid X_1 = (1, \mathsf{B})]$$

which provides the sought quantity.

A first-step approach can also be applied for the derivation of the second order moment of the r.v. W [19]. In this case, the procedure leads to the set of two independent linear equations reported in (9)-(10) at the top of next page. Once more, the sum of the two conditional expectations weighted by $k_{(1,\mathsf{G})}$ and $k_{(1,\mathsf{B})}$ provides a closed-form expression of $\mathbb{E}[W^2]$.

B. Statistical moments of Y

To conclude our analysis, we derive the expected duration of the time spent with correct knowledge at the receiver for the state of the reference source, i.e., $\mathbb{E}[Y]$, needed to evaluate (1). Focusing on the Markov chain (E_n, C_n), the same reasoning followed to characterize $\mathbb{E}[W]$ can be applied, and we simply highlight the key differences. In this case, we regard $(1, \mathsf{G})$ and $(1, \mathsf{B})$ as absorbing states, and are interested in the time of first visit to any of them when starting from $(0, \mathsf{G})$ and $(0, \mathsf{B})$. A graphical representation of the process, together with the relevant one-step transition probabilities, is reported in Fig. 3, where for convenience we introduced the ancillary quantities $\mathsf{d}_1 = \alpha(1 - \mathsf{p}_{g,c})$ and $\mathsf{d}_2 = \alpha(1 - \mathsf{p}_{b,c})$. As done for (7)-(8),

[1]The stationary distribution follows by solving the balance equations for the chain, and is not reported due to space constraints. The outgoing transition probabilities from the two states $(0, \mathsf{G})$ and $(0, \mathsf{B})$ are provided in Fig. 3.

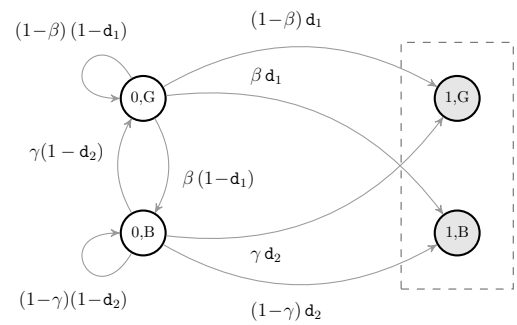


Fig. 3. Markov chain to derive the statistical moments of the time spent with correct knowledge of the state of the reference source at the source, i.e., Y.

a first-step analysis provides the conditional expectations as solution of the system of equations

$$\mathbb{E}[Y \mid X_1 = (0, \mathsf{G})] = 1 + \mathsf{E}[Y \mid X_1 = (0, \mathsf{G})] \cdot (1-\beta)(1-\mathsf{d}_1) + \mathsf{E}[Y \mid X_1 = (0, \mathsf{B})] \cdot \beta(1-\mathsf{d}_1)$$

$$\mathbb{E}[Y \mid X_1 = (0, \mathsf{B})] = 1 + \mathsf{E}[Y \mid X_1 = (0, \mathsf{G})] \cdot \gamma(1-\mathsf{d}_2) + \mathsf{E}[Y \mid X_1 = (0, \mathsf{B})] \cdot (1-\gamma)(1-\mathsf{d}_2).$$

In turn, $\mathbb{E}[Y]$ follows as the sum of the solutions weighted by the coefficients $k_{(0,\mathsf{G})}$ and $k_{(0,\mathsf{B})}$, denoting the probability of starting a period with correct knowledge in state $(0, \mathsf{G})$ and $(0, \mathsf{B})$, given by $k_{(0,\mathsf{B})} = 1 - k_{(0,\mathsf{G})}$ and

$$k_{(0,\mathsf{G})} = \frac{(1-\beta)\mathsf{c}_1\,\pi_{(1,\mathsf{G})} + \gamma\mathsf{c}_2\,\pi_{(1,\mathsf{B})}}{\mathsf{c}_1\,\pi_{(1,\mathsf{G})} + \mathsf{c}_2\,\pi_{(1,\mathsf{B})}}.$$

IV. Results and Discussion

To gauge the effectiveness of the proposed transmission strategies in enabling an up-to-date tracking of vessels via satellite, we implement the analysis of Sec. III in configurations that are inspired by practical settings. In particular, we consider data collection performed by a LEO satellite flying at an altitude of 524 km, with coverage range of 1250 km, assuming a minimum elevation angle of $11.5°$. The density of ships sending messages is derived from real data collected by the operating satellite-AIS system of exactEarth [20], for the month of January 2013. More details on the dataset are omitted due to space constraints, and can be found in [14]. Based on this, we focus on a reference density $6.75 \cdot 10^{-4}$ [ship/km^2], corresponding to intermediate conditions which can often be experienced. Accordingly, we consider $\mathsf{M} = 10000$ vessels in the satellite field of view that contend for the channel.

To derive the duration of a slot in our system model, we take as reference the AIS/VDES standard [5], where terminals send messages of 256 information bits, encoded with a rate $3/4$ code and QPSK-modulated over a channel bandwidth of 50 kHz. As a result, a packet transmission lasts for $T_p = 3.5$ ms. Unless otherwise stated, we assume that a ship-to-satellite channel remains in good conditions on average 80% of the time ($\pi_g = 0.8$), and consider bursts of bad channel states of

$$\mathbb{E}\left[W^2 \,|\, X_1 = (1,\mathsf{G})\right] = 1 + 2\left\{\mathbb{E}[W \,|\, X_1 = (1,\mathsf{G})](1-\beta)(1-\mathsf{c}_1) + \mathbb{E}[W \,|\, X_1 = (1,\mathsf{B})]\beta(1-\mathsf{c}_1)\right\} + \mathbb{E}\left[W^2 \,|\, X_1 = (1,\mathsf{G})\right](1-\beta)(1-\mathsf{c}_1) + \mathbb{E}[W^2 \,|\, X_1 = (1,\mathsf{B})]\beta(1-\mathsf{c}_1) \tag{9}$$

$$\mathbb{E}\left[W^2 \,|\, X_1 = (1,\mathsf{B})\right] = 1 + 2\left\{\mathbb{E}[W \,|\, X_1 = (1,\mathsf{G})]\gamma(1-\mathsf{c}_2) + \mathbb{E}[W \,|\, X_1 = (1,\mathsf{B})](1-\gamma)(1-\mathsf{c}_2)\right\} + \mathbb{E}\left[W^2 \,|\, X_1 = (1,\mathsf{G})\right]\gamma(1-\mathsf{c}_2) + \mathbb{E}[W^2 \,|\, X_1 = (1,\mathsf{B})](1-\gamma)(1-\mathsf{c}_2) \tag{10}$$

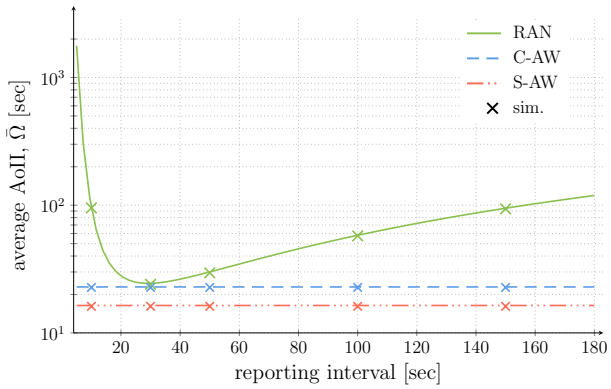
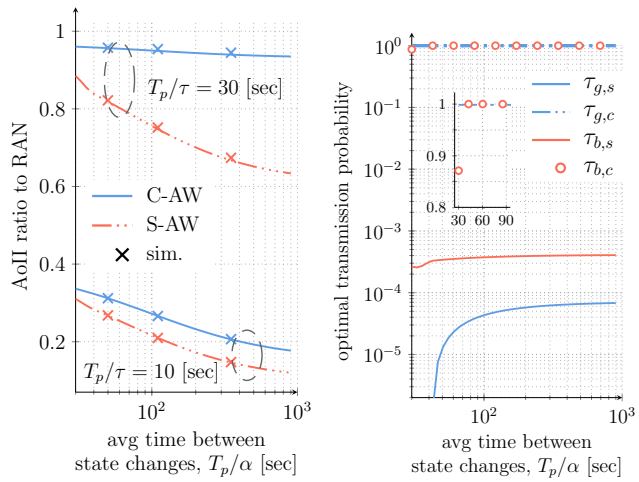


Fig. 4. Average AoII vs reporting interval T_p/τ for the RAN strategy. For C-AW and S-AW, results refer to the transmission probabilities that minimize AoII. The average time between ship state changes is $T_p/\alpha = 5$ minutes.



(a) Ratio of AoII to RAN (b) Optimal tx probabilities, C-AW

Fig. 5. Ratio of AoII of C-AW and S-AW to that of RAN and optimal transmission probabilities for S-AW, vs. T_p/α.

average duration $T_p/\gamma = 30$ sec. The two conditions readily define the values of γ and β as discussed in Sec. II. Finally, the packet erasure rate under bad and good channels are set as $\varepsilon_b = 0.8$ and $\varepsilon_g = 0.01$, respectively. In all plots, cross-markers ($\times$) denote the outcome of detailed simulations, which do not resort to the approximation in (2), (6) and duly track the behavior of every node. The tightness to analytical results confirms the validity of the presented modeling approach.

Preliminary insights are offered by the green solid curve in Fig. 4, which reports the average AoII, expressed in seconds, of the RAN strategy. We explore transmission probabilities corresponding to an average time between messages sent by a vessel (T_p/τ) that range between 5 seconds and 3 minutes. These values are consistent with the minimum and maximum reporting intervals foreseen by AIS [4]. Recalling that high levels of AoII are indicative of a not up-to-date perception at the satellite, the plot clarifies how poor performance is attained when updates are sent too often or too sporadically. In the first case (leftmost part of the curve), the large number of ships in the satellite footprint are congesting the channel with too many transmissions, leading to collisions and packet losses. Notably, attempting to deliver more often – a solution that might work well for communications among small clusters of ships at sea as originally intended by the standard – results in a detrimental loss of performance. For instance, a transmission interval of 5 seconds leads in the configuration under study to an average AoII of more than 30 minutes, which may not be tolerable for many applications. On the other hand, the right handside of the plot confirms that the AoII degrades also when updates are sent seldom, simply due to lack of communication. Fig. 4 also reports results for the C-AW and S-AW strategies. These were obtained by applying standard numerical optimization tools to the AoII formulation derived in Sec. III to identify the transmission probabilities $\{\tau_{g,s}, \tau_{g,c}, \tau_{b,s}, \tau_{g,c}\}$ that minimize $\overline{\Omega}$. Clearly, the trends do not vary along the x-axis of the plot, which solely report the update probability τ of the RAN scheme. More interestingly, the use of a data-relevance driven approach triggers significant gains. For the S-AW policy, an average AoII of $\sim$17 seconds is attained, halving the result that the RAN approach can provide with an optimal transmission frequency. The result is obtained by favoring transmissions only when state changes occur, and by fine-tuning the access probability to the actual channel conditions. From this standpoint, it is worth to remark that the implementation of the S-AW strategy and its optimization through the provided analytical framework only requires the statistics of channel conditions and of the ships state change (which can reasonably be extracted) as well as of the number of nodes, which may be determined by the position of the vessel and considering some pre-loaded density values.

To delve further into these aspects, Fig. 5a shows the ratio of the average AoII attained using the C-AW or the S-AW policies to that of the RAN strategy. In this case, the RAN scheme operates with an average transmission frequency of either one message every 30 seconds per ship (top curves), or of one message every 10 seconds (bottom curves). All results are obtained by varying on the x-axis the average time

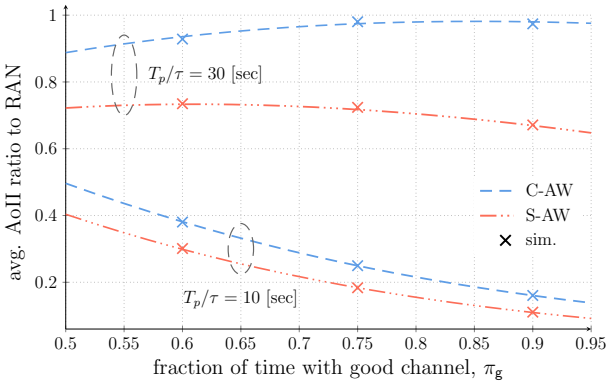


Fig. 6. Ratio of AoII with C-AW and S-AW to that of RAN, vs. fraction of time with good channel conditions, π_g. In all cases, $T_p/\gamma = 10$ seconds, and the average time between ship state changes is $T_p/\alpha = 5$ minutes.

between state changes of a vessel (i.e., T_p/α) from 30 seconds to 15 minutes. The plot shows how, the less frequently a ship experiences a state change, the more beneficial a data-relevance based approach is. Indeed, updates become more valuable in such cases, and a timely transmission helps dramatically compared to the RAN scheme, which may congest the channel by having vessels send messages that contain stale information. Even for $T_p/\tau = 30$ sec., i.e., close to optimal conditions for RAN as seen in Fig. 4, the S-AW policy improves by more than 40% when state changes are sporadic, and the AoII of the scheme is only $1/10$-th of what undergone with RAN when the latter sends messages with frequency $T_p/\tau = 10$ sec. These results are obtained by employing the optimal transmission probabilities shown in Fig 5b. When a state change is experienced, updates are sent with probability close to 1. A notable exception is found for very frequent changes and in case of good channel conditions (zoomed in portion of the plot), to avoid coggling the channel with too many transmissions. On the other hand, the optimal strategy accounts for potential losses of messages due to erasures or collisions, and foresees transmissions also when no state change is experienced ($\tau_{g,s}, \tau_{b,s} > 0$), although with much lower probability. The approach strikes thus a balance, avoiding congestion while keeping the possibility to inform the receiver by retransmitting updates, so to prevent long intervals of silence that would lead to a stale knowledge. Interestingly, the transmission probability is higher under bad channel conditions, to counteract the harsher erasure rate.

To conclude, we report in Fig. 6 the ratio of average AoII of C-AW and S-AW to that of RAN against the average fraction of time a vessel sees good channel conditions. For RAN, the cases $T_p/\tau \in \{10, 30\}$ sec. are considered, whereas for the C-AW and S-AW schemes the trends are again obtained by optimizing the transmission probabilities. Besides highlighting the attainable gains, the plot buttresses once more how the key enabler for reducing AoII and having better vessel tracking lies in the definition of transmission policies that tie the delivery of updates to relevant state changes. Indeed, especially for $T_p/\tau = 10$ seconds, while minor improvements can be gathered by adapting transmissions to current channel conditions (C-AW scheme), a clear gap is experienced with S-AW.

V. Conclusions

We studied different transmission strategies for vessel monitoring via LEO satellite, considering a benchmark scheme that foresees transmission of updates at regular intervals (inspired by the AIS system), and solutions that adapt the transmission probability to current channel conditions of the ship-to-satellite link and to changes in the vessel state. Via a Markovian analysis, we characterized in closed form the average AoII for all the solutions, and discussed their performance in a setting that is representative of AIS message reception via satellite. The results show how data-relevance based transmission strategies trigger fundamental improvements.

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