Modeling Value of Information in Remote Sensing from Correlated Sources

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***Abstract*—This paper investigates remote sensing networks and discusses different models to characterize the Value of Information (VoI), a metric that describes how informative the data transmitted by the sensors are. For each sensor, the VoI evaluations comprise the average node-specific Age of Information (AoI), the average cost spent for sending updates, and the AoI of neighbor nodes, assumed to be correlated sources of information and therefore benefiting the VoI of other sensors nearby. We discuss how this metric can be tracked through a two-dimensional Markov chain, but we also show how this representation can be simplified by including the impact of neighbor nodes within the transition probabilities, so as to obtain a simpler model that gives the same insight in terms of VoI evaluations.**

***Index Terms*—Age of Information; Internet of Things; Data acquisition; Networks; Modeling.**

I. Introduction

Age of information (AoI) has recently emerged as a useful performance metric for remote sensing applications in the Internet of Things (IoT) [1], [2]. For many scenarios of industrial, agricultural, or environmental monitoring and surveillance, as well as for medical applications, updates might be sporadic and of limited size [3]. Thus, more than guaranteeing high throughput or low delivery delay, it is critical to ensure that the information about the underlying physical processes monitored is up-to-date [4].

In a scenario where a source transmits data to a destination, AoI is defined as the time elapsed since the most recent successful update received, and hence it captures the freshness of information from the destination's standpoint [5]. This concept can be expanded to consider that, if updates come for free, it is straightforward to keep the AoI to low values, i.e., basically updating the information very frequently. However, if there are some costs associated with exchanging data, updates are not so frequent and the AoI increases. As a result, it can be argued whether the benefit of achieving low AoI (i.e., up-to-date information) is worth paying those costs [6], [7]. For the sake of simplicity, here we will use a weighted combination of the AoI (possibly from multiple sources, as will be discussed later) and a transmission cost term, which we will consider to be our "value of information" (VoI). In the literature, similar approaches are adopted also including other metrics, essentially conveying the same meaning of this combination, to further describe the benefits coming from an update compared to its cost, such as the stochastic decrease of uncertainty [8] or a multi-parameter combination including timeliness and relevance [9].

The generalization of this rationale to the case of multiple sensors coexisting in the same area opens some new challenges. A basic extension of the underlying model would imply to define and track the AoI/VoI for the specific sensors separately, which is however appropriate only if they are associated with different physical processes, independent of one another [10]. In this case, when considering a specific AoI/VoI, only an update from the corresponding sensor can bring "fresher" information to the destination.

However, in many IoT applications, multiple sensors actually track correlated underlying processes, sometimes even the same one [11], [12]. Since the general purpose of introducing AoI/VoI evaluations is to determine how often one should update [13], considering the AoI/VoI from multiple sources as totally unrelated would cause a storm of (often redundant) updates.

Our goal is instead to consider situations where correlation among sensors is explicitly kept into account to reduce unnecessary updates. For mission-critical and emergency monitoring, this would be particularly relevant to avoid network congestion in the precise moment an alert is to be raised, due to some recent updates suggesting a problem or malfunctioning [14], [15]. At the same time, for energy-constrained devices, limiting unnecessary exchanges of data can prolong the lifetime [16].

While we recognize the importance of an efficient AoI/VoI management under correlated sensed data (e.g., from sensors in spatial proximity or tracking interconnected quantities), our investigations in the present paper are not directed towards mathematical optimization approaches but rather to the involved modeling aspects. In more detail, we consider a VoI model for data coming from a specific sensor, comprising three ingredients: (i) the AoI of the data received from that sensor; (ii) the transmission cost of the sensor; and (iii) a further AoI-related term to account for some recent information coming from other correlated sources, i.e., the most up-to-date "neighbor sensor" that can benefit the AoI of the sensor under consideration, to some extent.

For this VoI concept, we propose two different models, both being discrete time Markov chains (MCs) [17], which are compared. First, we consider a detailed evolution of a two-dimensional state considering the sensor of interest and adding a further dimension, to describe whether the most recent update from one of the neighbor sensors can also be useful to some extent. We will show that this model admits a coherent evaluation especially in terms of when to update. However, a further simplification is possible, which is what described by the second MC model, where the updates coming from neighbor sensors are simply merged with the updates from the sensor of interests in the transition probabilities. While this is clearly an approximation, it is shown to be very good in terms of resulting evaluations especially for what concerns the original purpose of assessing the updating frequency. Thus, it emerges as a practical instrument to be implemented in low-cost IoT devices to enable a decentralized network control [7].

The rest of this paper is organized as follows. In Section II we discuss the related work. Section III presents our methodology and introduces the definition of the VoI, and also the two MC models. Numerical results are presented in Section IV to provide quantitative insight. Finally, Section V concludes the paper.

II. Related Work

Remote sensing systems with multiple quantities being monitored at the same time are an immediate generalization of standard AoI analyses [10], [11]. Also, considering correlation in the monitored metrics has recently received significant attention, since it allows for a more meaningful representation of many IoT systems. Most of the proposed investigations relates to how the presence of this correlation can be turned into a more performing management of the updates, in terms of scheduling efficiency or low energy consumption [12], [16].

In [18], spatial correlation of information in a field under monitoring is investigated from the perspective of determining the optimal spatial density of sensing points to achieve an adequate and timely coverage of the process, so the distribution of multiple sources is itself the parameter to derive. The existence of many sensors is instead explicitly addressed as an aspect to manage in [19], and is investigated from a queueing theory perspective with continuous time. At the same time, [20] goes further and investigates a proper scheduling of the sources within a similar scenario. In both these papers, there are multiple AoI values at the destination depending on one specific sensor only, without correlation. In [21], multiple sources are considered but they all monitor the same process (hence, their correlation makes them alternative to one another), their differences being instead in their energy consumption and reliability, that can be traded off for one another. Another paper considering multiple correlated sources is [22], where a joint allocation and scheduling problem is considered to minimize the AoI. However, the scenario is that of wireless cameras capturing different but possibly overlapping pictures, and the objective is a multi-view optimization that is decomposed into smaller problems.

From the perspective of scheduling IoT devices to minimize the average AoI, keeping into account a multiplicity of correlated sources and exploiting their correlation, the main reference is [5], where this problem, also considering different types of devices, is formulated as an infinite horizon average cost Markov decision process. The difference between all these papers and our present contribution is that we do not seek for an optimization exploiting the correlation of neighboring sources, but rather we discuss its quintessential characterization and we propose a low-complexity representation, which can in turn be exploited in simple IoT contexts to determine efficient updating patterns.

To this end, it is worth mentioning that we specifically focus on discrete time MC models, so our investigation can be seen as an extension of [17]. The use of such models allows for matrix-geometric approaches and is convenient in many scenarios, where a discrete time axis can be considered [23]. Also, this would make it immediate to merge these investigations with the special cases where the source or the channel follow an embedded MC [24]–[26].

Finally, the idea of VoI is often addressed as an expansion to the plain concept of AoI and, as discussed, is subject to different interpretations [6], [8], [9]. Our stance in the present paper is that VoI is introduced as an extension of the AoI and we will explicitly mean it to represent a linear combination of the information freshness of correlated data coming from different sensors and a cost term [23], even though different expressions can be used to this end, with similar meaning but more complex math.

III. Methodology

Consider a system with multiple sensors sending data to a single receiver/collection point. We can think of the different sensors as all monitoring correlated metrics of an underlying process of interest. This can be the result of spatial correlation, which would possibly expand to a specific geometric structure of the sensor placement, such as a lattice or a grid [18], [27], or a logical relationship among the underlying metrics [5], as would be the case for biometric sensors for the same individual - in this specific case, the relevance of health tracking metrics would be directly connected to the AoI of at least some of them, when not all [3].

We focus on a specific device i, and summarize the correlation of its tracked metric with other measurements from N different "neighbor sensors" in set $\mathcal{N}$ that can also be tracked. All the sensors in $\mathcal{N} \cup \{i\}$ adopt similar policies for sending updates, acting without any coordination but just being aware of their mutual correlation. The receiver is interested in getting information about the process status of sensor i but also somehow benefits whenever the information in the neighbors is fresh. For this analysis, we consider a discrete time axis divided into slots of the same duration called *epochs*; in each epoch, sources can either update or stay idle, and we assume that their transmissions are without collisions. So the age of information for source i is

$$\delta_i(t) = t - \max_{\tau_i^{(k)} \leq t} \{\tau_i^{(k)}\} \tag{1}$$

where $\{\tau_i^{(1)}, \tau_i^{(2)}, ..., \tau_i^{(n)}, ...\}$ are the epochs where the ith source sent an update. We remark that with this notation, the AoI assumes value 0 for all the epochs $t = \tau_i^{(k)}$ where an update is performed.

We consider the simplest possible operating model for the sources, i.e., they decide in a random fashion, and independently of one another, whether to send an update or stay idle during the current time slot, and this decision is made with identical and independent distributed (i.i.d.) probability p. Thus, the average AoI at the receiver's side for the current source can be computed as a direct consequence of its geometric distribution (starting from 0), i.e., [23]

$$\mathbb{E}[\delta_i] = \frac{1}{p} - 1 \tag{2}$$

If we choose $\mathbb{E}[\delta_i](p)$ as a metric to optimize, it is trivial to note that the function is minimized for $p^* = 1$. But this is unrealistic in a real scenario, since the sensing/transmission operations ought to be kept limited to avoid unnecessary expenditures and strain of the sensor. To account for this, we may include a cost term proportional to the transmission rate according to a parameter $c > 0$. In this case, we can define a penalty function

$$K_1(p) = \mathbb{E}[\delta_i] + cp = \frac{1}{p} - 1 + cp \tag{3}$$

where both terms combined into $K_1(p)$ (the expected AoI and the average transmission cost) are better when set to a low value. Thus, our goal may be seen as to find a penalty-minimizing update probability p^*, which is promptly found as $p^* = \sqrt{1/c}$. Even though the result is immediate, it properly accounts for the intuition that a higher cost decreases p^*. This implies that c can be seen either as an external parameter related to information update costs, e.g., in terms of energy consumed [28], or as a virtual tunable parameter that is used to regulate the frequency of updates in a distributed fashion [23].

This setting can be extended from a modeling standpoint by considering and exploiting the presence of multiple sources providing correlated informaton. In this case, we look for a possible further decrease in the transmission probability, other than what expressed by the cost, since a situation where fresh information coming from a neighbor sensor is strongly correlated may make it pointless to update for the sensor of interest too.

Thus, we extend this analysis by involving the N neighbors of the sensor of interest, which are assumed to follow the same rule of updating with probability p. Now, we consider that the processes monitored by N neighbors are correlated with that of the sensor of interest and if one of them sends an update this can be in some way also useful to the sensor of interest itself.

In order to quantify this usefulness, we decrease the AoI of the sensor of interest, which in (2) is introduced as a penalty (the lower, the better). We therefore insert a factor that measures the difference between the age of the sensor of interest and the age of the most up-to-date neighbor, whenever this is lower than the age of the sensor of interest. Otherwise, i.e., if the sensor of interest is more up-to-date than its entire neighborhood, there is no benefit achieved by exploiting the correlation. We obtain the following quantification that we regard as the VoI V_i of sensor i (as opposed to the AoI that is just based on the single sensor)

$$V_i = \mathbb{E}\big[\delta_i - \alpha(\delta_i - \min_{j\in\mathcal{N}} \delta_j) \cdot \mathbb{1}(\min_{j\in\mathcal{N}} \delta_j < \delta_i)\big] \tag{4}$$

where α is a hyper-parameter used to weigh the benefit that the most up-to-date neighbors has fresher information, and $\mathbb{1}(\cdot)$ denotes a characteristic function (equal to 1 if the Boolean condition is true, 0 if false).

Since we assume that all the sensors behave identically for what concerns their updating policy, symmetry reasons dictate that the sensor of interest is actually the one with the freshest information in $1/(N+1)$ of the cases, in which case the benefit of exploiting the correlated information is 0. In the remaining cases, i.e., a fraction of $N/(N+1)$, the neighbor with lowest AoI brings instead a decrease in the VoI of the sensor of interest. The value of such AoI is the minimum of N geometrically distributed variables, thus we can extend (4) to

$$V_i = \frac{1}{p} - \frac{\alpha N}{N+1}\Big(\frac{1}{p} - \frac{1}{1-(1-p)^N}\Big) - 1 \tag{5}$$

Even when the AoI is replaced by the VoI, the objective of a cost-effective management is to minimize a penalty function combining value and cost, i.e.,

$$\min K_2(p) = V_i + cp \tag{6}$$

which results in a minimizing transmission probability p^* that is promptly found as the solution of setting a first-order derivative to 0. This means that, for sufficiently high cost c, p^* is the value for which $\mathrm{d}V_i/\mathrm{d}p = -c$.

To expand the model from just an average value computation to a full-fledged statistical characterization, we can actually use a discrete time MC jointly tracking the AoI of the sensor of interest and its neighborhood, which would generalize to cases where the VoI does not follow from a linear combination of ages through weight α. Remarkably, since the AoI values can be seen as rewards of renewal processes, whose cycles relate to an update from either the sensor of interest or one of the neighbors, such a MC would precisely track the VoI according to our proposed definition.

A. *Complete MC model*

To model the usefulness of the neighbors we propose a *triangular* MC that works in the following way: $M+1$ states [1] are used to track the states where the sensor of interest i is the most up-to-date and then $M(M+1)/2$ states where at least one neighbor has fresher information than node i, in which case we simply track the AoI of the *most up-to-date neighbor*.

A graphical representation of this is shown in Fig. 1. Two sets of $M+1$ nodes and $M(M+1)/2$ nodes represent the respective cases where (i) the sensor of interest i is most up-to-date, in which case we track its AoI as the state; or, (ii) another neighbor sensor is, in which case we track the information of both AoI values of the node i and that neighbor. Thus, each state $k \in \mathcal{S}$, with $|\mathcal{S}| = (M+1)(M+2)/2$, of the MC is associated with either just value A_k, which represents the AoI for the node i at state k, or A_k and B_k, the latter being the AoI of the most up-to-date neighbor at state k, if lower than A_k.

Given the probability of updating p (assumed to be the same for all nodes) and the number of neighbors N, we can create the triangular MC depicted, with 3 possibles transitions: (i) the sensor of interest sends an update, whose probability is p; (ii) node i does not update, but at least one of its neighbors does, which happens with probability $(1-p)(1-(1-p)^N)$; or (iii) no one sends an update, and the transition probability for this event is $(1-p)^{N+1}$. Here, we can exploit the renewal properties of AoI that whenever a node (either the sensor of interest or a neighbor) performs an update, it necessarily becomes the most up-to-date, where if no sensor updates, the most up-to-date node remains the same of the previous epoch.

The VoI of sensor i can be computed after evaluating the steady-state probabilities π_k of the chain being in state k through

$$V_i = \sum_{k=0}^{\frac{(M+1)(M+2)}{2}} A_k \cdot \pi_k - \alpha \sum_{k=M+1}^{\frac{(M+1)(M+2)}{2}} (A_k - B_k) \cdot \pi_k \tag{7}$$

[1] The AoI ought to be unlimited, but for a tractable numerical evaluation, we set a maximum AoI value of M.

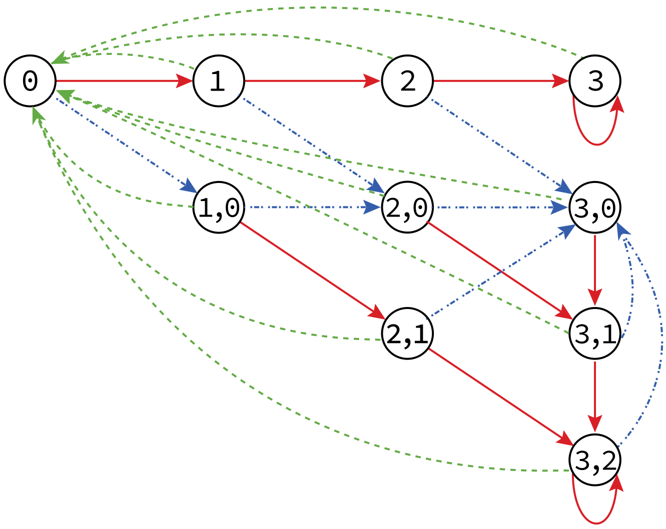

Fig. 1: Example of a complete MC model. Solid red arrows, blue dotted arrows, green dotted arrows mean updates from no node, a neighbor but not the sensor of interest, and the sensor of interest, respectively. States X in the top row imply that the sensor of interest is the most up-to-date with AoI X, while states X, Y denote the AoI values of the sensor of interest and the most up-to-date neighbor, respectively.

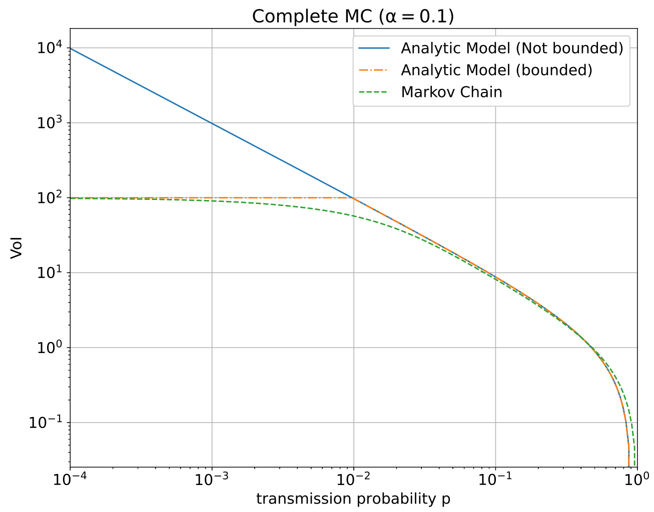

Fig. 2: Comparison between VoI computed with complete MC and the corresponding theoretical model with $\alpha = 0.1$

where the first summation considers the average AoI of node i for all the states, whereas the second one accounts for the cases where a neighbor is more up-to-date which decreases the VoI as per (4).

Aside from numerical limitation for solving the MC, this model is *exact* and allows to fully track the VoI model presented above. We also remark that, differently from the solution of (5) that only applies to the case of updates with i.i.d. probability p for all epochs and all sensors, the MC model can actually be extended to more elaborate scenarios where the update rule is optimized [8], [11], [20], [22].

B. Scalar state MC

We now propose a simplification to the previous MC. Instead of having a triangular structure with two-dimensional states, we use a scalar state MC where each node represents only an equivalent VoI of the node i. The assumption is that we merge transitions including an update, assumed to happen with probability t, regardless of whether it is coming from the sensor of interest or one of the neighbors, where the latter case is clearly weighted with a coefficient $q < 1$.

Within this model, we can consider only 2 transitions: the MC advances to the next state with probability $1 - t$ and returns to state 0 with probability t. The transition matrix $\mathbf{P}$ of this MC is

$$\mathbf{P} = \begin{bmatrix} t & 1-t & 0 & 0 & \dots \\ t & 0 & 1-t & 0 & \dots \\ t & 0 & 0 & 1-t & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \tag{8}$$

To take into account the usefulness of the neighbors we consider:

$$t = p + (1-p)(1-(1-p)^N)q \tag{9}$$

where p is the probability of update, N is the number of neighbors and q is the probability that the update of a neighbor is useful, in which case the VoI is reset to 0 even though the update does not come from sensor i. In this way, when at least one neighbor updates status, this updates becomes also useful for the sensor i with probability q as it was fully informative and reset its AoI.

Analogously to the previous complete MC, we can set an upper limit M to the AoI values tracked, and once evaluated the stationary distribution vector $\boldsymbol{\pi}$ it is possible to compute the VoI as

$$V_i = \sum_{k=0}^{M} k \cdot \pi_k \tag{10}$$

Note that $q = 0$ and hence $t = p$ leads back to the model present in (2).

The scalar state MC can be made very similar to the complete MC through a careful fine tuning of the parameter q as a function of α, so as to match the performance at least in the average sense. One can link the value of q and α given the number of neighbors N and the transmission probability p. By matching the average VoI of the two chains we obtain

$$\frac{1}{p} - \frac{\alpha N}{N+1}\left(\frac{1}{p} - \frac{1}{1-(1-p)^N}\right) - 1 = \frac{1}{p + (1-p)(1-(1-p)^N)q}$$

where the left side of the equality comes from (5) as the average VoI, while the right side derive from (3) as the average VoI for the scalar state MC. Then it is possible to solve the equation for α or q. With a few simple algebraic steps we arrive at

$$q(\alpha) = \frac{1}{Z_2(p,N)}\left(\frac{p}{1 - p \cdot Z_1(p,N) \cdot \alpha} - p\right) \tag{11}$$

where

$$Z_1(p,N) = \frac{N}{N+1}\left(\frac{1}{p} - \frac{1}{1-(1-p)^N}\right)$$

and

$$Z_2(p,N) = (1-p)(1-(1-p)^N) .$$

Both $Z_1(p,N)$ and $Z_2(p,N)$ are functions only of p and N and so once these two parameters are set, they act as constant terms of (11).

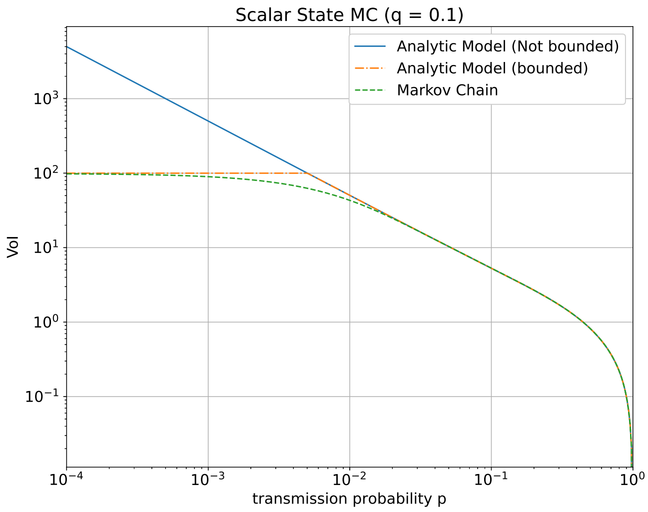

Fig. 3: Comparison between VoI computed with scalar state MC and the corresponding theoretical model with $q = 0.1$

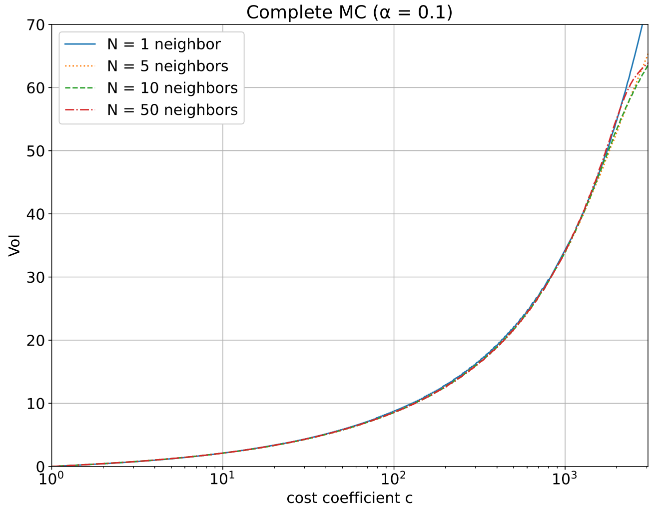

Fig. 5: VoI of the complete MC with $\alpha = 0.1$ vs. the cost coefficient c.

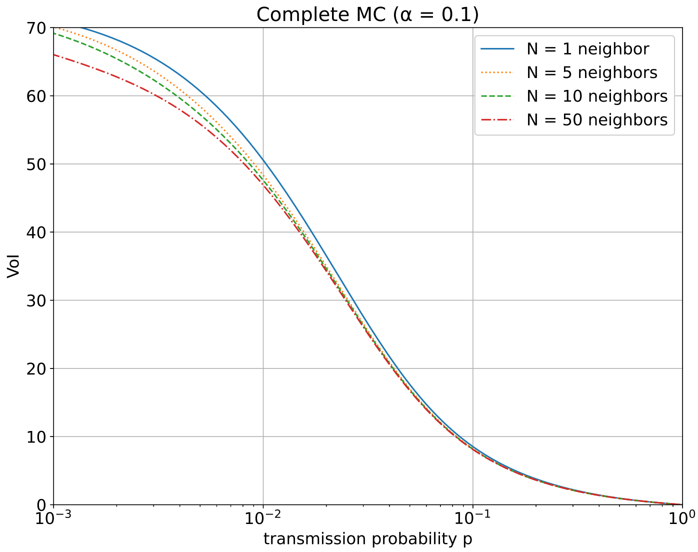

Fig. 4: VoI of the complete MC with $\alpha = 0.1$ vs. the transmission probability p.

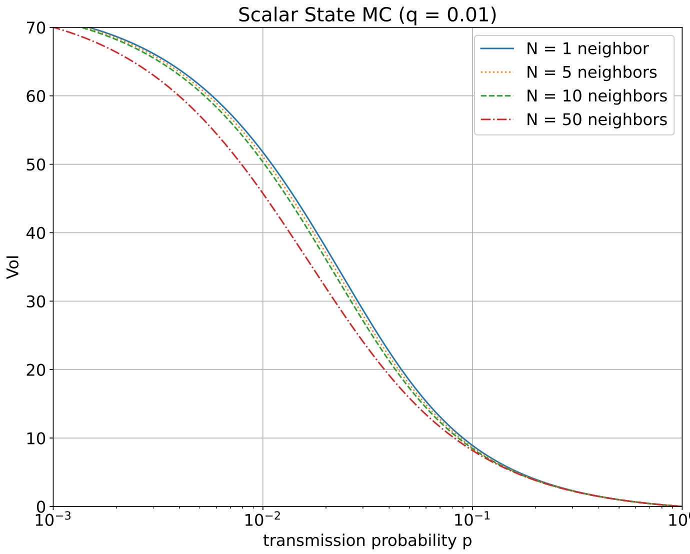

Fig. 6: VoI of the scalar state MC with $q = 0.01$ vs. the transmission probability p.

IV. Results

We now present some numerical results to give a quantitative insight of how the different models capture the underlying VoI and how suitable they are to perform some simple management of the involved parameters. In particular, we are interested in seeing whether setting a proper cost parameter c can tune the update probabilities of the sensors, also when correlation among multiple sensors is kept into account with $\alpha = 0.1$, which describes a limited but noticeable influence.

We first test if the two MCs correspond to the underlying theoretical model. To do this, we choose a set of parameters ($N = 10$, $q = 0.01$ and $\alpha = 0.1$) and we compute the VoI both theoretically through (5) and via the MCs as per (7) and (10). The value of $q = 0.01$ is chosen according to (11) for N=10 and $\alpha = 0.1$, with p chosen as numerically fitting most of the values of p^* in the region of interest.

The results are plotted in Figs. 2 and 3 for the complete and simplified MC, respectively. For both models, we can observe that the MC correspond to the theoretical model, up to a computational bound imposed by the maximum number of states of the MCs. To have a more robust comparison we plot together with the unbounded theoretical VoI a bounded version defined as

$$V_{i,bound}(p) = \max(V_i(p), M) \tag{12}$$

with M the maximum AoI used in the MCs.

A. Numerical Performance

In Figs. 4 and 5, we report the numerical results obtained for the complete (triangular) MC, showing the VoI versus the transmission probability p and how the VoI can be set according to the cost coefficient c. These results were obtained for $\alpha = 0.1$.

In Figs. 6 and 7 we plot the numerical results obtained for the simplified scalar state MC. More precisely, the figures show the VoI versus the transmission probability p and how VoI is set as a function of the cost coefficient c, respectively.

In both Figs. 5 and 7, we associate every value of c with the optimal transmission probability p^*, to further compute

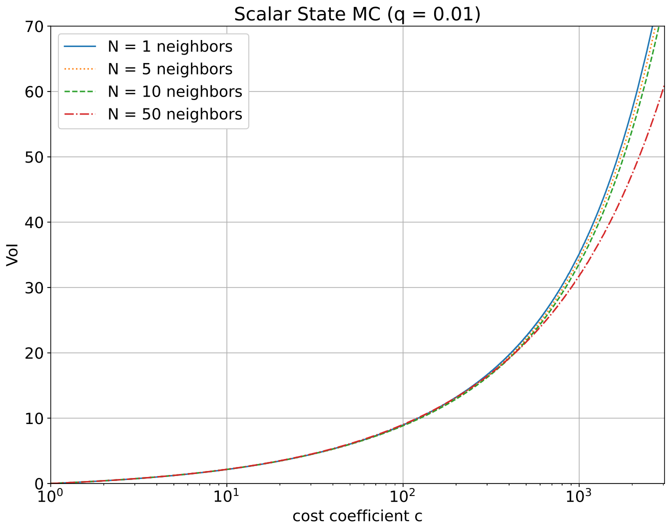

Fig. 7: VoI of the scalar state MC with $q = 0.01$ vs. the cost coefficient c.

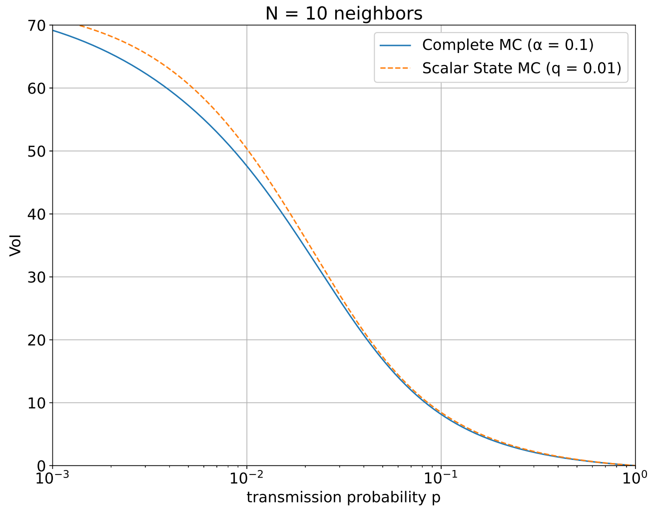

Fig. 9: Comparison between complete ($\alpha = 0.1$) and scalar state ($q = 0.01$) MCs with $N = 10$ neighbors, VoI vs. transmission probability p.

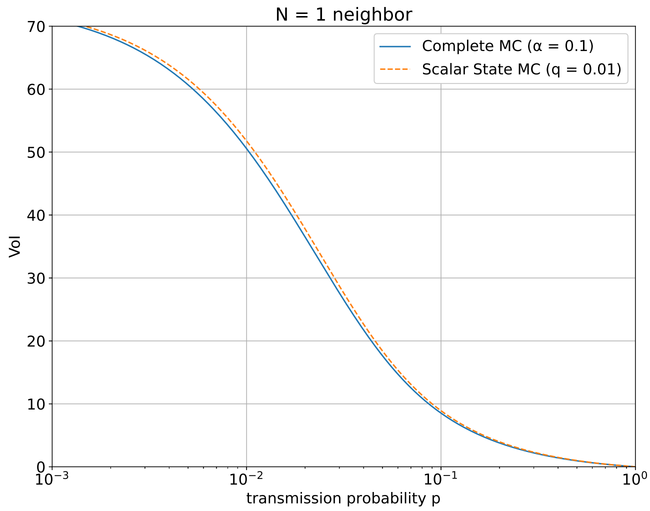

Fig. 8: Comparison between complete ($\alpha = 0.1$) and scalar state ($q = 0.01$) MCs with $N = 1$ neighbor, VoI vs. transmission probability p.

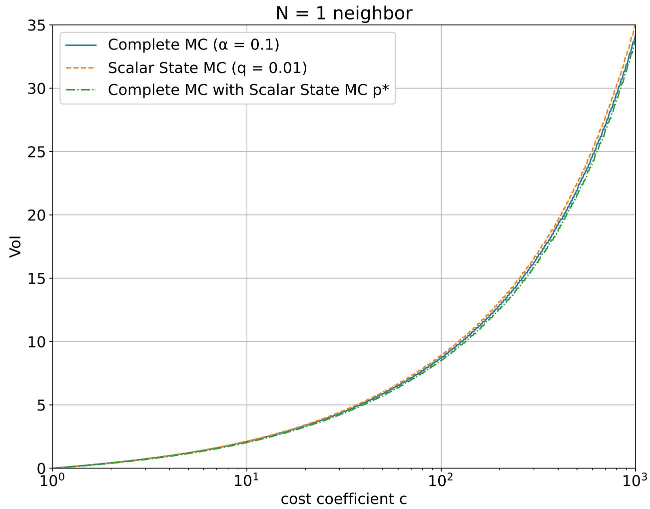

Fig. 10: Comparison between complete ($\alpha = 0.1$) and scalar state ($q = 0.01$) MCs with $N = 1$ neighbor, VoI vs. cost parameter c.

the VoI. To obtain this probability, we compute the derivative of the VoI in p (i.e., the curve in Figs. 4 and 6) and set it equal to $-c$, since the overall penalty is set from (6) as $K_2(p) = V_i + cp$.

From inspecting Fig. 4 we can also infer how the number of neighbors influences the VoI. More precisely, a higher number of neighbors tends to decrease the VoI. This is coherent with the intuitive idea that, the more nodes in the network, the more likely is that they help each other with the updates. This effect is more relevant for intermediate values of p, since for $p \simeq 1$ or $p \simeq 0$, the impact of correlated sensors on the updates is relatively limited.

Fig. 5 shows how the VoI changes, based on the cost factor c. Also in this case, coherently with intuition, for a small c we have a small VoI, while for a large c the VoI tends to increase. This reflects the fact that for small values of c the sensors pay a small price for each transmission and therefore are encouraged to transmit as much as possible. Similar conclusions can also be drawn for the simple MC analyzing Figs. 6 and 7.

Finally, we compare the results obtained by the two MCs. In Figs. 8 and 9, we show how the average VoI changes based on the transmission probability p, for the number N of neighbors set in the two figures to 1 and 10, respectively. We can observe that for $N = 1$ (Fig. 8), the two MCs obtain practically identical results, with the VoI values completely overlapping. The difference is more visible for higher N, especially considering the range between $p = 10^{-3}$ and $p = 10^{-1}$.

In Figs. 10 and 11, we compare the two models to highlight how similar they are in computing the VoI based on the cost coefficient c. Analogous to Figs. 5 and 7, we evaluate the VoI per each c, by considering the optimal transmission probability p^* for that specific point. The indirect setup of a VoI value according to c, through its direct imposition of p^*, i.e., by controlling the frequency of channel access in a distributed fashion, can be regarded as the main goal of our analysis. Thus, we can claim that even the simpler scalar state MC can be effective for a local implementation onboard the individual sensors.

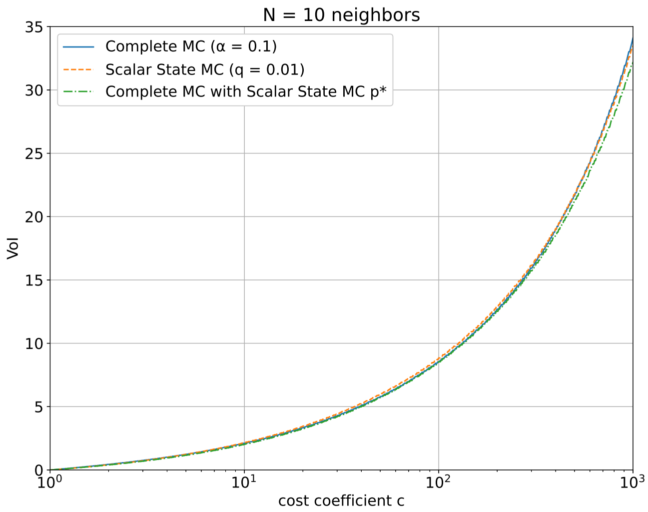

Fig. 11: Comparison between complete ($\alpha = 0.1$) and scalar state ($q = 0.01$) MCs with $N = 10$ neighbors, VoI vs. cost parameter c.

V. Conclusions

The assessment of freshness of information in resource-constrained networks is an important topic that can be addressed through analytical frameworks revolving around the VoI [4], [6], [9]. In this paper, we discussed a scenario with multiple sensors sending correlated information to a data collection point and we discussed how this can be captured by discrete time MCs with different degrees of complexity.

In particular, we presented a simple model where the impact of correlation is kept into account in the transition probabilities of a MC with scalar state representing a modified AoI including the freshness of multiple sources with different weights [5], [26]. Such a model is shown to be effective in characterizing basic updating policies with i.i.d. probabilities and can therefore be a suitable solution for large scale deployments of sensors with limited computational complexity and energy.

Future developments may involve the analysis, in the same spirit, of more advanced updating policies, still with possible simplifications in the system state, to see whether the simplified representation still allows for an efficient management, and the implementation of this rationale within specific applications for the IoT. Extensions to other related networking problems, which can be studied through MC-based approaches, such as the insertion of automatic repeat request (ARQ) in the transmission [15], [29] and/or measuring and optimizing power consumption of the sensors, especially for energy harvesting nodes [21], [28] can be subjects of future investigations.

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