Timely Monitoring of Events over a Finite Time Horizon for Smart Agriculture

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***Abstract*—Data freshness is extremely important in sensing scenarios with sporadic reporting, as typical, for example, of smart agriculture or forestry monitoring, to enact proper network control. Several papers are proposing metrics akin to age of information to quantify it, but they generally assume that status updates can be generated frequently, possibly at will. In this paper, we investigate how to track freshly and accurately a phenomenon that is bound to happen within a certain time window, but whose precise timing is not known in advance. The resulting evaluations offer insights for planning and managing random sporadic events in smart monitoring for agricultural applications.**

***Index Terms*—Age of Information; Smart agriculture; Status update; Modeling.**

I. Introduction

Due to the continuous growth of the worldwide population, traditional agriculture methods are becoming insufficient to meet the global needs for food, and an emerging demand for efficient, sustainable, and precise farming practices is on the rise. This can be achieved through the integration of smart sensing into agriculture [1], to enhance productivity and profitability, but also support broader goals of food security and environmental sustainability. Smart sensing technologies can provide real-time data on soil, weather, crop health, and pest activity, enabling them to make informed decisions that optimize resource use, increase crop yields, and reduce environmental impact [2].

However, sensing and monitoring operations in agricultural setups present a unique set of challenges, because events are often sporadic and unpredictable. Unlike industrial or urban settings, where data generation and events can be relatively continuous and follow typical patterns [3], agricultural landscapes experience a range of phenomena that occur irregularly. These can include sudden changes in weather, pest infestations, disease outbreaks, and variations in soil conditions, which makes it difficult to maintain persistent and effective monitoring, requiring sophisticated sensing technologies and strategies that can adapt to the irregular data patterns [4]–[6].

Sensors and monitoring systems must be highly responsive and capable of capturing relevant data as soon as they appear [7]. Only in this way robust data analysis and predictive modeling can be performed to anticipate potential issues before they become critical. Some authors such as [8] have argued about sensing of sporadic alarms, with a solution leveraging learning-based access selection and sampling frequency control. Also, [9] proposes a mutable sensor data analytics approach to maximize data freshness in the Internet of Underwater Things [10]. This utilizes blockchain and gradient descent learning to classify noise and irrelevant data in order to avoid transmitting them, thus reducing staleness for relevant data. Finally, [11] explores optimizing sensor data transmission schedules in smart agriculture and industry, where external sources provide non-controllable updates.

In this paper, we study the problem of timely and effective monitoring of events [12], which are only known from a statistical standpoint, i.e., through their probability density function, seen as a selection of optimal measurement instants over a finite time horizon. The primary objective is to capture that an event happened, minimizing the age of information (AoI) of the resulting measurement. This is performed, placing a priori the monitoring points over the time horizon, optimizing a proper compound objective.

Specifically, consider the example where two timing opportunities are available for sensing and updating the control management about the system state. This can result in three possible scenarios: (i) the event takes place before the first transmission instant t_1. Then, the value of AoI is updated after this first transmission and never changed; (ii) the event takes place between t_1 and t_2, which implies the same condition as before but with t_2 in lieu of t_1. Alternatively, the values of t_1 and t_2 are both too early for monitoring the event, in which case, after the event, the penalty grows undisturbed (but not unbounded, since the time horizon is finite).

Therefore, we formalize a minimization problem for AoI, depending on where we put the observation instants. We start from the approach of [13], where a single monitoring point was considered, by allowing for multiple observations. We expand and generalize from the cases where a closed form expression of the optimization was available since the probability density of the event is known and integrable, to a more general view where we consider a Gaussian distribution with different parameters. Numerical computations are still possible for these more complex scenarios with multiple monitoring points or intractable distributions. The findings reveal intriguing trends, including saturation and uniformity of monitoring times [14].

The rest of this paper is organized as follows. In Section II, we review related work. Section III presents the system model and analysis. Results for Gaussian distributed event times, with different choices of average and standard deviation are discussed in Section IV. Section V concludes the paper.

II. Related Work

The concept of age of information was first introduced by [12] and further developed by subsequent papers [15], [16]. The key idea behind this metric is to quantify the timeliness of information that is crucial in many real-time applications. Even though it is generally applied to scenarios such as vehicular networks or industrial IoT [8], [17], such a concept is also applicable to a plethora of scenarios, including those with a relatively slower dynamic evolution such as patient monitoring in e-health applications [18] and smart agriculture [2].

In particular, in this paper we consider a different approach to AoI, not focusing on *generation at will* as is usually done in most of the literature, but rather considering sporadic updates [19], [20]. However, we give a different take since we also include, as is sensible for an agriculture scenario where certain events are more predictable, albeit their exact instance is uncertain, that the monitoring system has a definite observation window [5], [14]. Within this interval, certain events of interest are happening, but at instants whose exact values are only known through prior statistics [13].

Such a scenario has a direct connection with many features that IoT-driven sensing is expected to bring in precision agriculture, including surveillance and prompt intervention to changed system conditions [21]. Integrating IoT devices in agricultural systems can trigger automatic responses, such as adjusting irrigation levels when moisture sensors detect drought conditions [4], [22], or enact pest control [23]. However, a timely proactive control is key in improving resource efficiency, directly benefiting crop health and productivity.

While enacting the specific control operation is left to the specific case under study, the general pattern that can be found in the literature of AoI applications to smart agriculture is that of minimizing information staleness to enable accurate control. For example, [24] considers an Unmanned Aerial Vehicle (UAV)-patrolled plantation and evaluates trajectory planning so as to minimize AoI for prompter intervention. A more general view of smart sensing ecosystems is also considered in [6] for integration with machine learning techniques. These two issues are combined in [25], where UAVs are used for data offloading and multi-agent reinforcement learning is employed, still with the same purpose of limiting AoI.

The analysis presented in the present paper can be related to other aspects of AoI, such as correlation among multiple sources [26], eventually leading to extensions of the AoI rationale, such as peak AoI [16], age of correlated information [27], age of task-oriented information [8], or age of incorrect information [28]. Even though our extension concerns, more than an extension of the AoI metric itself, its application within a different scenario, all these variations can be certainly considered as possible extensions for future work.

III. System Model

AoI is a metric used to quantify the freshness of information in a system that monitors events [7]. It is defined as the time elapsed since the last received update was generated at the source. Mathematically, at any given time t, the age of information $\Delta(t)$ can be expressed as a random process [15]:

$$\Delta(t) = t - u(t)$$

where $u(t)$ is the timestamp of the most recent update received before or at time t.

Inspired by this concept, we consider here a similar problem of timely *event detection and reporting*, as opposed to the plain reporting that takes the detection for granted [13]. This is done in the context of a finite horizon, where the event, e.g., a change in the weather condition or a monitored object is passing by, is bound to happen.

We normalize this observation window to be the real interval $[0, 1]$. Over this interval, a sensor can monitor the event at a specific interval and send an update about it to a remote observer [6]. We denote the timing of the event as x and the chosen monitoring/transmission instants as $t_1, t_2, \ldots, t_N$. We assume the communication exchange to be fully reliable, since channel erasures can be properly taken into account. Even though an extension with channel erasures, collisions, and/or delays would be immediate along the lines of [5], [21], [29], [30].

Ideally, AoI is contained if x is as close as possible to one of the t_js, but happens before it [17]. We distinguish the sensing instants t_j between those happening before x, in which case they go too soon and miss the event, or those performed after the event, i.e., $t_j > x$, in which case they detect the event but after a certain time. Notice that in this spirit, all transmissions following the first that catches the event just reiterate the same value.

The overall contribution of the analytical framework can be summarized through the following points.

- **Objective:** Minimize the expected AoI for an event that follows a known between [0, 1].
- **Variables:** The N monitoring points $t_1, t_2, \ldots, t_N$, where $0 \leq t_1 < t_2 < \ldots < t_N \leq 1$.
- **Constraints:** The monitoring points must be placed within the normalized time horizon $[0, 1]$.

As a general sample of the possible alternatives, we can consider different distributions, all derived from a Gaussian distribution truncated to the interval $[0, 1]$. We will look at Gaussian distributions with different values of mean and standard deviation. In general, the truncated Gaussian distributions to an interval [a, b] having mean μ and standard deviation σ follow the formula

$$f(x; \mu, \sigma, a, b) = \begin{cases} \dfrac{\frac{1}{\sigma}\phi\left(\frac{x-\mu}{\sigma}\right)}{\Phi\left(\frac{b-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right)} & \text{for } a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

where:

$$\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$$

is the probability density function (PDF) of the standard normal distribution, and

$$\Phi(z) = \int_{-\infty}^{z} \phi(t)\, dt$$

is the cumulative density function (CDF) of the standard normal distribution.

For example, the Gaussian distribution with mean $\mu = 0.5$ and variance $\sigma^2 = 1$, truncated to the interval $[0, 1]$, the probability density function (PDF) is

$$f(x) = \begin{cases} \dfrac{\frac{1}{\sqrt{2\pi}} e^{-\frac{(x-0.5)^2}{2}}}{\Phi(0.5) - \Phi(-0.5)} & \text{for } 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

The choice of the Gaussian distribution is motivated by several factors. Many environmental and agricultural variables, such as temperature, precipitation, and crop yields, often follow a distribution that can closely resemble or be inferred from a normal distribution because they result from the aggregation of many small, independent factors [22], [31]. As such, though not suitable for all situations, the Gaussian distribution serves as a natural and intuitive starting choice for modeling these variables in the context of agricultural monitoring.

Furthermore, the Gaussian distribution is particularly useful in the Bayesian framework for statistical modeling [32]. Its conjugate nature with respect to itself allows for straightforward updates of the probability distribution as new data becomes available. By using the Gaussian distribution as a prior, we can iteratively refine our estimates and predictions through Bayesian inference, effectively adapting our probability distribution to new information in a mathematically coherent manner. This iterative updating process improves the model's accuracy over time, providing a robust tool for monitoring and managing agricultural events.

For now, assume we have only one monitoring point. Thus, the total penalty depending on the position of an event and a monitoring point is:

$$P(t, x) = \begin{cases} \dfrac{(t-x)^2}{2} & \text{if } t > x \\ \dfrac{(1-x)^2}{2} & \text{if } a > x > t \end{cases}$$

We aim to compute the integral:

$$I = \int_0^{t_1} f(x) \cdot \frac{(t_1 - x)^2}{2} \, dx$$

Substituting $f(x)$ into the integral, we get:

$$I = \int_0^{t_1} \frac{\frac{1}{\sqrt{2\pi}} e^{-\frac{(x-0.5)^2}{2}}}{\Phi(0.5) - \Phi(-0.5)} \cdot \frac{(t_1 - x)^2}{2} \, dx$$

This simplifies to:

$$I = \frac{1}{\sqrt{2\pi}\left(\Phi(0.5) - \Phi(-0.5)\right)} \int_0^{t_1} e^{-\frac{(x-0.5)^2}{2}} \cdot \frac{(t_1 - x)^2}{2} \, dx$$

$$\int_0^{t_1} e^{-\frac{(x-0.5)^2}{2}} \cdot \frac{(t_1 - x)^2}{2} \, dx$$

Solving this integral by hand is unfeasible, so the optimization was done with the help of numerical simulation.[1]

[1]The simulation code can be found at https://github.com/maksimlk/ieee_2024_MetroAgriFor_PyProbDistOptimizer.

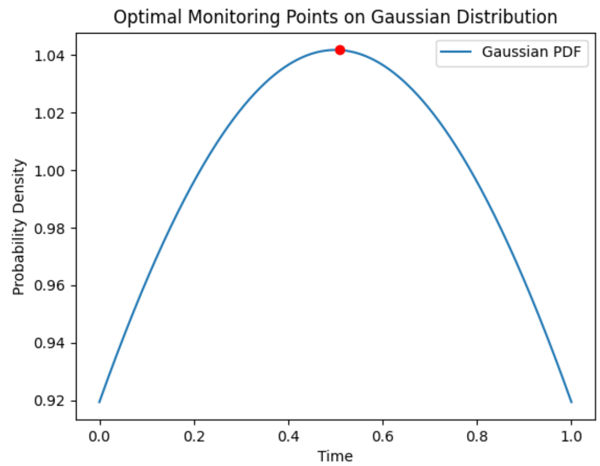

Fig. 1. Gaussian distribution $\mathcal{N}(0.5, 1)$ with 1 monitoring point

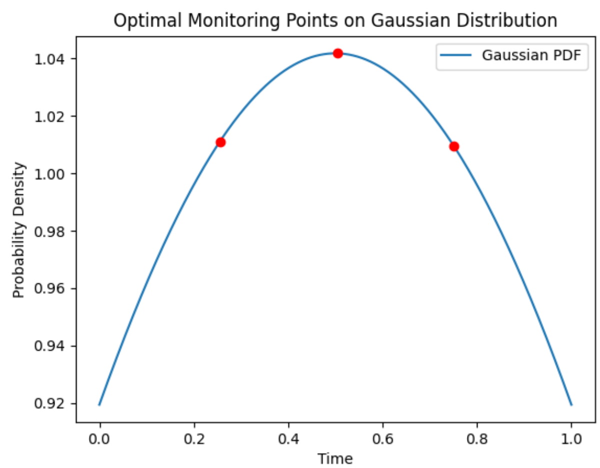

Fig. 2. Gaussian distribution $\mathcal{N}(0.5, 1)$ with 2 monitoring points

Similarly, although the formulas are more cumbersome, we can obtain the same integration formulas for multiple points, which again requires numerical integration.

IV. Numerical Results: Gaussian Distribution

We evaluate the case when the event positioning in time follows a truncated Gaussian PDF, with mean 0.5 and variance 1 truncated within the range $[0, 1]$. The results are shown in Figs. 1–3 for 1, 3, and 10 monitoring points. These results suggest that we aim to place monitoring points symmetrically around the mean, dividing the CDF into equal parts, which is a consequence of the symmetric shape of the prior distribution of the event.

In Figs. 4–6, we instead report analogous results for a Gaussian distribution with mean 0 and variance 1 truncated on the range $[0, 1]$. We observe that breaking the symmetry of the distribution generally leads to less intuitive values. For example, in the case of 3 transmission opportunities (Fig. 5),

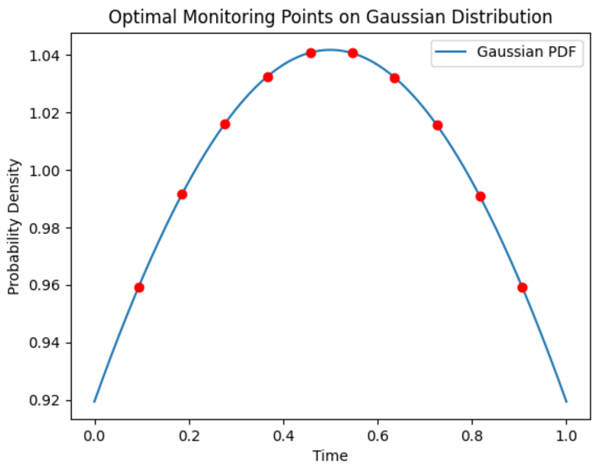

Fig. 3. Gaussian distribution $\mathcal{N}(0.5, 1)$ with 3 monitoring points

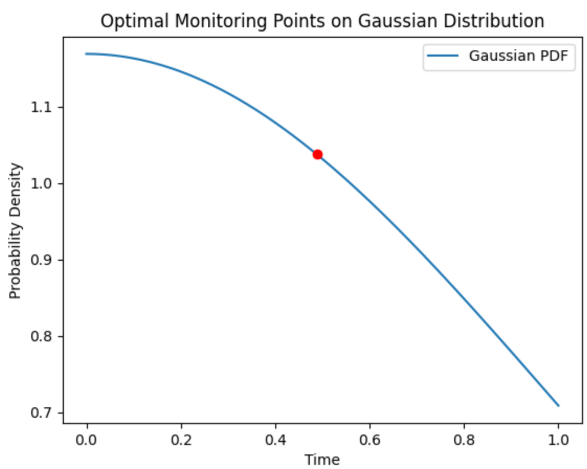

Fig. 4. Gaussian distribution $\mathcal{N}(0, 1)$ with 1 monitoring point

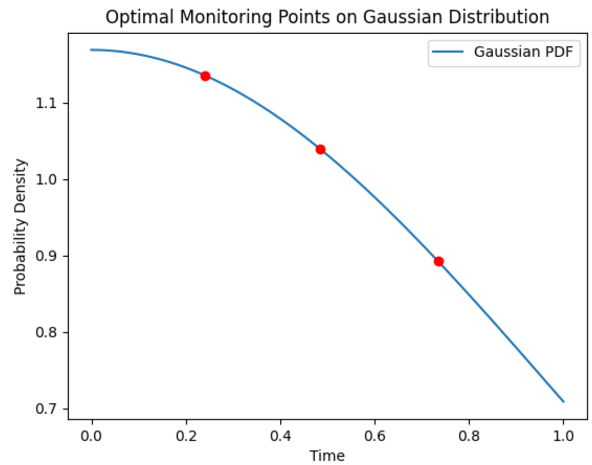

Fig. 5. Gaussian distribution $\mathcal{N}(0, 1)$ with 2 monitoring points

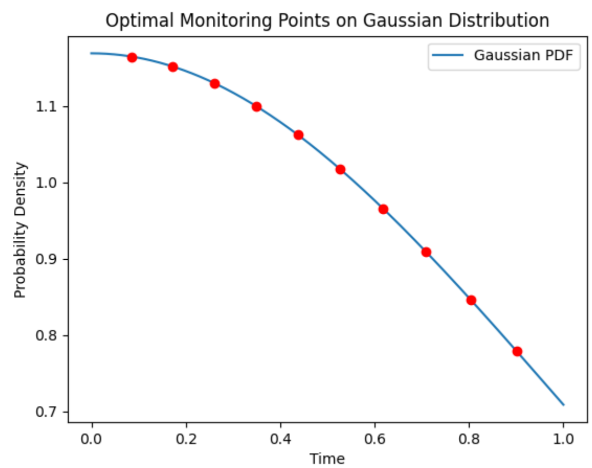

Fig. 6. Gaussian distribution $\mathcal{N}(0, 1)$ with 3 monitoring points

the precise values of the monitoring points are $t_1 = 0.2409$, $t_2 = 0.4839$, $t_3 = 0.7348$. This is a consequence of a distribution that is heavily non-symmetric, a result that is in line with the finding of [13].

We can also explore what happens if the variance of the Gaussian distribution is changed. For example, Figs. 7–9 consider a Gaussian distribution with zero average and a standard deviation equal to 0.2, once again for 1, 3, and 10 monitoring points. The optimal monitoring points are found to be $t_1 = 0.126$, $t_2 = 0.271$, $t_3 = 0.481$. These points are skewed towards the beginning of the observation window, reflecting that the PDFy is concentrated closer to 0.

On the other hand, if we increase the standard deviation to 2, which is reported in Figs. 10–12, our optimal monitoring points become $t_1 = 0.246$, $t_2 = 0.495$, $t_3 = 0.746$, indicating a broader spread of the distribution and an almost equally-spaced sampling of the interval, due to the PDF becoming more similar to a uniform distribution.

By using a similar approach and conducting numerical simulations on more complex distributions related to specific agricultural events, we can determine the best locations for monitoring points based on a particular penalty function. This helps us optimize the efficiency of our monitoring systems.

V. Conclusions

Smart agriculture can bring significant improvements in crop quality and yield, thanks to the use of IoT devices, sensors, and data-driven systems [11], [25]. Technologies such as LoRa offer the opportunity to monitor critical factors like soil moisture, crop health, and environmental conditions in real time. This can lead to enhance irrigation process and pest control, so as to improve yields and reduces waste [4].

Thus, monitoring alone is not enough, and a tighter control is required for real-time management, so as to obtain more efficient decision-making and immediate responses to the aforementioned issues. Selecting optimal monitoring points

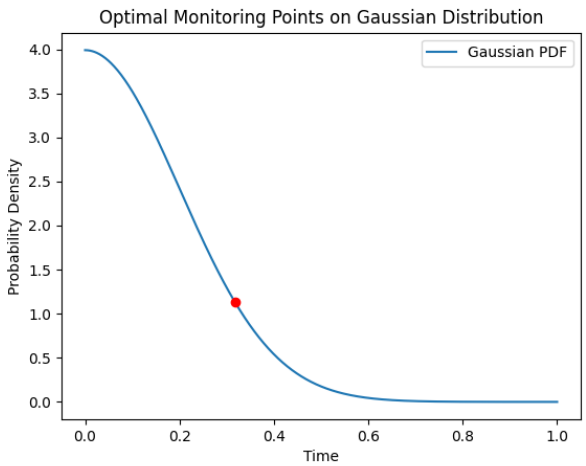

Fig. 7. Truncated Gaussian distribution $\mathcal{N}(0, 0.2)$ with 1 monitoring point

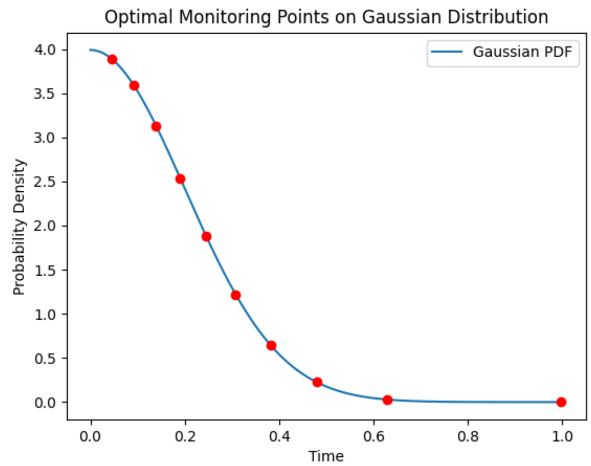

Fig. 9. Truncated Gaussian distribution $\mathcal{N}(0, 0.2)$ with 10 monitoring point

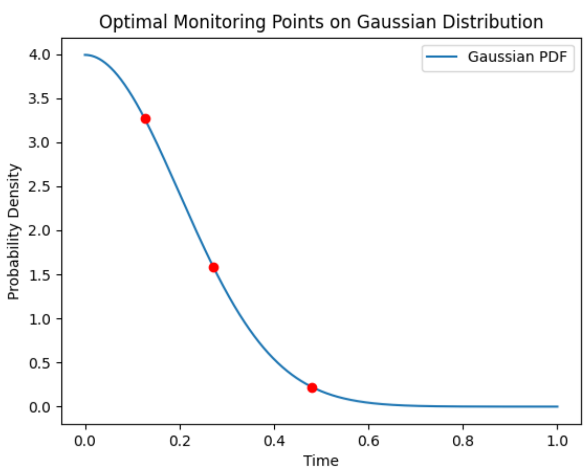

Fig. 8. Truncated Gaussian distribution $\mathcal{N}(0, 0.2)$ with 3 monitoring points

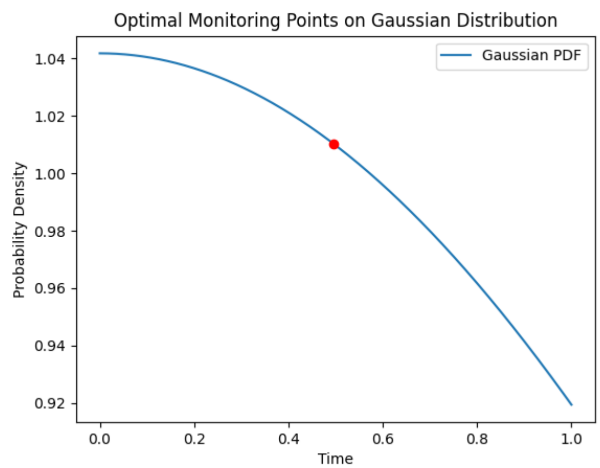

Fig. 10. Truncated Gaussian distribution $\mathcal{N}(0, 2)$ with 1 monitoring point

can lead to significant energy efficiency gains and a host of other benefits in agricultural practices. The ideas and models explored in this paper open up exciting opportunities for creating applications that utilize probability distributions of monitored events to strategically place monitoring points. Future research should focus on integrating advanced AI models for predictive analytics, which could enhance predictive decision-making [6], [25].

Other crucial areas for improvement include scalability, energy efficiency, and secure data-sharing [15], [33]. These are all promising directions for future work, as they can strengthen the resilience and adaptability of smart agriculture systems.

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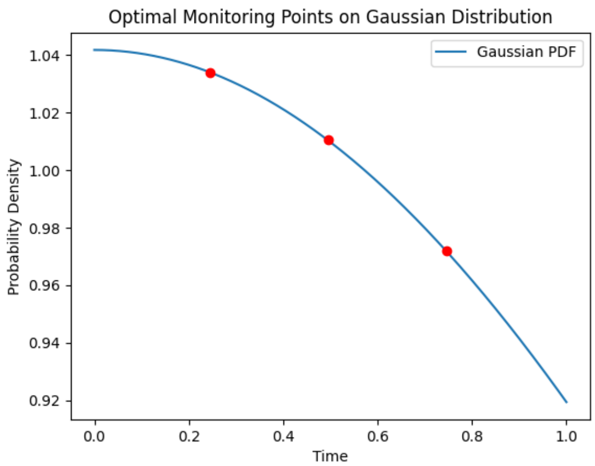

Fig. 11. Truncated Gaussian distribution $\mathcal{N}(0, 2)$ with 3 monitoring points

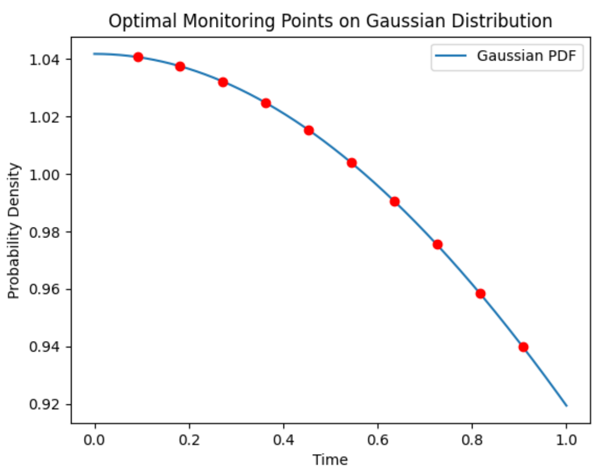

Fig. 12. Truncated Gaussian distribution $\mathcal{N}(0, 2)$ with 10 monitoring points

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