Abstract—“Age of Information” is an interesting metric that captures the freshness of information in the underlying applications. It is a combination of both packets inter-arrival time and packet transmission delay. In recent times, advanced real-time systems rely on this metric for delivering status updates as timely as possible. This paper aims to accomplish optimal transmission scheduling policy to maintain the information freshness of real-time updates in the industrial cyber-physical systems. Here the coexistence of both cyber and physical units and their individual requirements to provide the quality of service is one of the critical challenges to handle. A greedy scheduling policy called deadline-aware highest latency first has been proposed for this purpose. This paper also gives the analytical proof of its optimality, and finally, the claim is validated by comparing the performance of our algorithm with other scheduling policies by extensive simulations.

Index Terms— Age of Information, Information Freshness, Industrial Cyber-Physical System, Greedy Scheduling, Packet Deadline, Latency, Jitter.

I. INTRODUCTION

Age of Information (AoI) [1] is a newly proposed cross-layer metric to measure the freshness of information from the receiver perspective. It grows linearly with the time elapsed since the generation of the latest packet received. Unlike traditional packet delay, AoI ensures the regular delivery of time-varying updates with minimum end to end delay. This unique feature enables AoI to improve the quality of service (QoS) of the system from both communication and control point of view [2]. In recent times, time-critical information updates are gaining ardent importance with the growth of advanced technologies in a diverse field of real-time applications such as traffic, stock market or weather forecasts, object tracking, internet of things (IoT) based remote health monitoring, smart manufacturing using cyber-physical system (CPS), device-to-device (D2D) communications for autonomous vehicles, power management in smart grids and many more.

A. Background and Motivation

CPS is a closed-loop networked control system that integrates computation, communication, and control of physical processes over a common wireless network. Application of CPS in the industry (e.g., smart factory) consists of a remotely sited wireless sensor-actuator network (WSAN) connected to some centralized or distributed controller(s) through high-speed internet. Sensors are sensing the physical states of the plant and transmitting those real-time updates to the controller. Controllers are responsible for decision making, and they are remotely managing the underlying tasks by employing suitable actuators in action. Our work is motivated by the need of the CPS for circulating the time-sensitive information through the WSAN in order to estimate and control the plant state remotely. Failing this may lead to
some production loss or fatal accidents. But, constraints like limited bandwidth and power resources, interference in wireless channels, etc. making the scheduling decision more complicated and challenging.

B. Related Work

There is a variety of literature available that deal with minimum AoI scheduling problems for information freshness [3-11]. Paper [3] addresses optimal scheduling strategy for a multi-source, common channel wireless network with the objective of minimizing the overall information age for delivering the information as timely as possible. Whereas, paper [4] finds a decision policy that determines both the sampling times and transmission order of the sources for minimizing the total average peak age (TaPA) and the total average age (TaA) in a multi-source, common channel system. Scheduling problems for minimizing the average and peak AoI in wireless networks under general interference constraints and throughput constraints are considered in [5] and [6], respectively. Paper [7] optimizes age-of-information without throughput loss for a multi-server queue. It proved that preemptive Last Generated First Served (LGFS) policy provides age optimality for both infinite and finite buffer queues. However, the optimality of a newly proposed algorithm preemptive and non-preemptive Maximum Age Difference (MAD) has been investigated in [8] for multi-flow single server networks with flow diversity. Reference [9] formulates a Markov decision process (MDP) to find dynamic transmission scheduling schemes for a wireless broadcast network, with the purpose of minimizing the long-run average age. On the contrary, references [10-11] formulates a decision problem to find an optimum transmission scheduling policy to minimize the AoI of the destinations in a broadcast network. Works, done in [12-14], investigate scheduling algorithms to maximize the information freshness in terms of AoI in CPS, but they do not consider deadlines for packet transmissions. In contrast, [15-16] find scheduling policies to maintain the freshness of real-time updates in CPS, but they do not consider AoI as their freshness indicator.

C. Contribution

In this paper, we consider an industrial cyber-physical system (ICPS), engaged in monitoring and controlling a set of stochastic processes in a plant with the help of multiple centrally operated sensor-actuator pairs. Due to bandwidth limitation, multiple sensors are trying to transmit through a common shared channel. Now, these real-time updates have their own deadlines depending on the time-varying nature of the underlying processes. However, the age of information content present in any update increases linearly with time, and as a result, its freshness drops. Here, both the packet loss as well as outdated information degrade the communication and control performances of the overall system. Keeping these challenges in mind, this paper:

- **Relates AoI with the latency and hence, freshness of a sensor sample.**
- **Formulates a utility function considering the deadline and freshness of a sensor sample.**
- **Proposes an age-based, deadline-aware packet scheduling policy to maximize the expected utility of the system. This policy, in turn, jointly maximizes the QoS (in terms of AoI, latency, and jitter) for the real-time monitoring and control of the industrial wireless sensor-actuator network (IWSAN).**
- **Proves the optimality of the algorithm analytically and compares its results with other popular algorithms in this context.**

These fundamental contributions make our work unique from the existing literature.
D. Outline

The rest of the paper is organized as follows. In Section II, we describe the system model and its related mathematical expressions are formulated in Section III. Section IV presents our proposed scheduling algorithm and proves its optimality through mathematical analysis. In Section V, we present and discuss the results of our simulative study. And last but not least, Section VI concludes the importance of the paper. However, in this paper, the words like sensor sample, status update, and packet are used interchangeably.

II. SYSTEM MODEL

A. Basic Modelling

The system model, in this paper, consists of a symmetric IWSAN with M sensor-actuator pairs. Sensors and actuators are geographically distributed but wirelessly connected in a closed-loop through a centralized processor or controller, as shown in Fig. 1. Index for sensors and their corresponding actuators are represented with notation $i$, for $i = 1, 2, ..., M$.

Sensors are updating the controller from time to time about the status of some physical parameters of their interests inside a plant. The Controller then analyzes that information and sends instructions to the corresponding actuators with a goal to handle the necessary control actions in the best possible way. In this model, sensors are transmitting their packets through a TDMA shared (according to WirelessHART standard [17] for IWSAN), single hop, time-varying, unreliable channel. When this channel is transmitting reliably, it is considered to be in ‘ON’ state. This ‘ON’ probability of the channel is represented as $p_i = p \in [0, 1]$. In contrast, when the channel fails to transmit it is said to be ‘OFF’ with probability $(1-p_i)$. However, this status update task is limited by a finite time horizon $T$, and within this limit, each of the individual TDMA slots from time $[t-1, t]$ is denoted by $t$, for $t = 1, 2, ..., T$.

B. Functionality

At the beginning of any slot $t$, sensors ready with their packets (we will call them ‘active’ sensors later in this paper) competes for sharing their status with the controller. The controller schedules the transmission from one of the active sensors or decides to remain idle based on some designated scheduling policy $\pi$. After the sample from sensor $i$ reaches the controller, the controller generates appropriate control command by analyzing the information content present in that sample and reliably send them to the corresponding actuator $i$ by the end of the current slot. At the end of the successful processing of a sensor sample, the controller instantly and reliably sends feedback to the source sensor. So, starting from the sample collections by the sensors, scheduling decision making, analysis of the sample, control command generation and up to the reception of feedback, the whole processing of a sensor sample takes one slot time in total.
C. Age Evolution

Age of Information (AoI) is indicated as $h_{t,i}(k_i)$. Here $k_i$ is the index number of $k^{th}$ sample packet from sensor $i$. Starting from the generation of the latest sample received, the age of information increases linearly until the successful processing of the next sensor samples. This is shown in Fig 2. After the successful processing of a sensor sample, its AoI drops to 1. On the contrary, unprocessed 'active' sensors, sense the present status of the system periodically in each slot by replacing the old samples and participate in scheduling. Their ages keep on increasing by one slot, each time they fail to transmit their samples. Therefore, in other words, our definition of 'age of information' indicates the time passed after the collection of last successfully processed sensor sample containing the information about the plant’s state.

After receiving the control command, the actuator takes some time equivalent to next $c_i(k_i) \geq 0$ number of slots to finish the appropriate actuation task. During this period, no new actuation task is required to be invoked and only after that period the sensor resumes sensing. So, before age value $(c_i(k_i) + 1)$ is attained, sensor $i$ is said to be ‘Inactive.’ Inactive mode protects the resource-constrained network from unnecessary congestion and energy dissipation by avoiding redundant sensor updates. When the age of the sensor $i$ goes beyond the value $(c_i(k_i) + 1)$, this sensor becomes ‘Active’ and participates in scheduling until its newly sensed sample is being processed successfully. But, if the $k_i^{th}$ sample of the active sensor $i$ fails to get service within its stipulated deadline $D_i(k_i)$, then the packet from sensor $i$ is dropped and the $i^{th}$ flow-line (sensor-actuator pair) goes ‘Out of service’ permanently up to the end of $T$. This is, of course, not a desirable situation to occur. However, the underlying incomplete task of the broken flow-line is controlled (and eventually shut down, if applicable) by some default or preset control commands.

So, at any slot $t$, the age of the sample $k_i$ from sensor $i$ can be represented as follows,

$$h_{t,i}(k_i) = c_i(k_i - 1) + L_{t,i}(k_i) + P_i(k_i).$$

Fig. 2. Age evolution for sensor $i$. 

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| Table of notations for sample $k$ from sensor $i$ |
|-----------------------------------------------|
| $a_i(k_i)$ = First sample generation instant after activation. |
| $p_i(k_i)$ = Processing delay. |
| $c_i(k_i)$ = corresponding action execution time. |
| $L_i(k_i)$ = Latency before processing. |
| $LX_i(k_i)$ = Latency after processing. |
| $t$ = Discrete time in terms of slot numbers. |
| $h_i(k_i)$ = Age of information at the beginning of slot $t$. |
| $D_i(k_i)$ = Deadline of sample. |
Here, \( c_i(k_i - 1) \) is the time required to perform the control action based on the analysis of the previous sample from the same sensor. This component of age is useful and unavoidable. Rest, the sum of latency \( L_{t,i}(k_i) \) and processing time \( P(k_i) \) degrades the QoS of the sensor-actuator network by enhancing the end to end communication delay. In this model, \( P(k_i) \) is always considered as one slot time.

### III. MATHEMATICAL FORMULATIONS

From Fig 2, the total age \( AoI_i \) is obtained from the area covered by the age curve for sensor \( i \). It is expressed as follows,

\[
AoI_i = \sum_{t=1}^{T} AoI_{t,i} = \frac{1}{2} + \sum_{t=1}^{T} h_{t,i}(k_i).
\]  
(5)

By ignoring the constant term in (5), the average age becomes,

\[
\overline{AoI} \approx \frac{1}{TM} \sum_{t=1}^{T} \sum_{i=1}^{M} \{ h_{t,i}(k_i) \}
\approx \frac{1}{TM} \sum_{i=1}^{M} c_i(k_i - 1) + L_{t,i}(k_i) + P_i(k_i).
\]  
(6)

Next, neglecting the constant terms \( c_i(k_i - 1) \), and \( P_i(k_i) \), average latency (AL) is obtained as,

\[
AL = \frac{1}{TM} \sum_{t=1}^{T} \sum_{i=1}^{M} \{ L_{t,i}(k_i) \}.
\]  
(7)

RMS jitter in the actuation tasks is obtained as,

\[
JT = \frac{1}{TM} \sum_{t=1}^{T} \sum_{i=1}^{M} \{ L_{t,i}(k_i) + 1 \}^2.
\]  
(8)

From the existing literature, we are well aware that smaller the average age, higher the information freshness obtained. By analyzing (5-6), it can be said that minimizing the average age (\( \overline{AoI} \)) to maximize the information freshness is equivalent to minimizing the average latency (AL) for this system model. Moreover, packet drop leads to the breakdown of the corresponding flow-line. So, this work involves two challenges:

1. Minimization of the average latency of sensor samples.
2. Minimum packet drops.

By maximizing the average (expected) utility of the information content present in the active sensor samples of the system, both the above-mentioned challenges can be overcome.

The utility of the information content in a sample \( k_i \) from an active sensor \( i \) is expressed as,

\[
U_{t,i}(k_i) = f \left( F_{t,i}(k_i), X_{t,i}(k_i) \right)
\]

where, 
\[
X_{t,i}(k_i) = \mathbb{E}(L_{X_{t,i}(k_i)}).
\]  
(9)

\( F_{t,i}(k_i) \) is the freshness of information. It monotonically decreases with increasing latency \( L_{t,i}(k_i) \) of the sensor sample \( k_i \) that contains the information.
Latency is the number of time slots spent by an active sensor in the system before it is getting service. When latency is zero, the freshness of the information is maximum (\( F_{t,i}(k_i) = 1 \)). In this paper, \( F_{t,i}(k_i) \) is considered as \( \frac{1}{L_{t,i}(k_i) + P_i(k_i)} = \frac{1}{\text{state age}} \). As, \( P_i(k_i) = 1 \) in this system mode, therefore, \( F_{t,i}(k_i) = \frac{1}{L_{t,i}(k_i) + 1} \).

Laxity \( L_{X_{t,i}}(k_i) \) of an active sensor sample \( k_i \) is defined as the number of time slots left up to its deadline after the completion of the processing of that sample starting from the current instant. From Fig 2, laxity of \( k_i^{th} \) active sample at slot \( t \) is, \( L_{X_{t,i}}(k_i) = (D_i(k_i) - t) = (D_i(k_i) - L_{t,i}(k_i) - P_i(k_i)) \) slots time.

When a sample is not scheduled for transmission even after having \( L_{X_{t,i}}(k_i) = 0 \), then it is going to be dropped at the end of the current slot. This type of sample with zero laxity is called ‘Critical Sample.’ If more than one critical samples are present at a particular slot \( t \), only the critical sample with the highest utility value is considered to have a hard deadline. Other critical samples are being graced by delaying their deadlines by one more slot. As a result, their laxity becomes 1 and they turn out to be non-critical samples in the current slot. The same phenomena will take place to all the critical samples the channel is \( OFF \). This is called the ‘Conflict Avoidance’ mechanism. So, from this we can conclude that at most one critical sample can be present in the network at any time slot. However, an active sensor having the critical sample is called ‘critical sensor’ and other active sensors with non-critical samples are called as ‘non-critical sensors’.

Whenever a critical sample is dropped, its utility becomes 0 forever. However, any positive laxity of a sample does not affect its utility. So, the influence of laxity on utilization is captured in a variable denoted as \( X_{t,i}(k_i) \) and it can be expressed as follows,

\[
X_{t,i}(k_i) = \begin{cases} 
0 & \text{for } L_{X_{t,i}}(k_i) < 0 \\
1 & \text{for } L_{X_{t,i}}(k_i) \geq 0.
\end{cases}
\]  

(10)

\( U_{t,i}(k_i) \) is directly proportional to any real powers of \( F_{t,i}(k_i) \) and \( X_{t,i}(k_i) \). So, the utility can be expressed as,

\[
U_{t,i}(k_i) = k_F k_X F_{t,i}^\beta (k_i) X_{t,i}^\gamma (k_i) = k_F^\beta (k_i) X_{t,i}^\gamma (k_i).
\]  

(11)

In the above equation, \( k_F, k_X \) are proportionality constants of \( F_{t,i}(k_i) \) and \( X_{t,i}(k_i) \), respectively and \( k = k_F k_X \). \( \beta \) and \( \gamma \) are positive, real-valued indices.

Here, we introduce a special notion of ‘Priority’ (\( Prior_{t,i}(k_i) \)) of an sensor \( i \) at any time slot \( t \), based on the utility \( (U_{t,i}(k_i)) \) and laxity \( (L_{X_{t,i}}(k_i)) \) it’s sample \( k_i \) offers. It is defined as follows:

\[
Prior_{t,i}(k_i) = \begin{cases} 
\frac{1}{U_{t,i}(k_i) X_{t+i,1}(k_i)} & \text{for } X_{t+i,1}(k_i) = 1 \\
\infty & \text{for } X_{t+i,1}(k_i) = 0.
\end{cases}
\]  

(12)

If the sample \( k_i \) from the active sensor \( i \) is critical at \( t \), then its laxity \( L_{X_{t,i}}(k_i) = 0 \) and \( L_{X_{t+i,1}}(k_i) = (L_{X_{t,i}}(k_i) - 1) < 0 \), if not served in the present slot. So, \( X_{t+i,1}(k_i) = \infty (L_{X_{t+i,1}}(k_i)) = 0 \) and \( Prior_{t,i}(k_i) = \infty \) (by definition). On the other hand, if the sample from the active sensor \( i \) is non-critical, then \( L_{X_{t,i}}(k_i) > 0 \) and \( L_{X_{t+i,1}}(k_i) \geq 0 \). So, \( X_{t,i}(k_i) = X_{t+i,1}(k_i) = 1 \) and \( Prior_{t,i}(k_i) = \frac{1}{U_{t,i}(k_i)} = \frac{1}{L_{X_{t,i}}(k_i)} \).
\[
\frac{1}{k \rho^Y_x(k_i) X^Y_x(k_i)} = \frac{1}{k F^Y_x(k_i)}
\] (from (11) and (12)). Moreover, from the calculation of the priority for critical sensor considering the ‘conflict avoidance’ mechanism, we can conclude that a critical sensor has the highest priority among all the active sensors present at that particular slot \( t \).

Next, the expected weighted sum utility of information (EXWSUol) is calculated as,

\[
EXWSUol = \frac{k}{TM} E \left[ \sum_{t=1}^{T} \sum_{i=1}^{M} (\alpha_i U_{t,i}(k_i)|\bar{I}) \right].
\] (13)

Here, \( \bar{I} = [h_i(1), c(0), D(1)] \) is the initial condition vector. \( \alpha_i = \alpha > 0 \ \forall \ i \in M \) is the real-valued weight assigned to any sensor \( i \) in the WSAN. From now onwards, the initial condition and packet index will be omitted for notation simplicity.

Now, we know that among \( M \) sensors, only active sensors take part in the scheduling. Let, \( S_t \) be the set of all the active sensors at the beginning of slot \( t \). In order to maximize the utility of information, the objective function is considered as follows:

**Objective Function:** \( O_T^\pi = \max_{\pi \in \Pi} E[O_T], \) where, \( O_T^\pi = \frac{kM}{TM} \sum_{t=1}^{T} \sum_{i \in S_t} U_{t,i} \).

*Finally, this paper aims to find an optimal work conserving non-anticipative, offline, dynamic TDMA scheduling policy \( \pi \), from the set of all the admissible policies \( \Pi \), to maximize the objective function.*

**IV. OPTIMALITY OF SCHEDULING POLICY**

In this section, first, a greedy scheduling policy ‘Deadline aware Highest Latency First (HLF-D)’ is proposed. Then its global optimality is analyzed in Theorem-I.

**Definition:** (i) At any time slot, if no critical sample is present in the system, HLF-D, a greedy scheduling policy, schedules the transmission of an unprocessed sample from the active sensor with the highest latency. (ii) The presence of a critical sample ensures that none but the critical sample will get service. (iii)[Tie-Breaking Condition] All ties are being broken arbitrarily.

**Theorem-I:** For any symmetric IWSAN network with an unreliable time-shared channel from the sensor to the processor, among the class of admissible policies HLF-D attains the maximum expected weighted sum utility of information \( (O_T^\pi) \) for sensor samples with deadlines.

*Proof:* To prove the optimality of HLF-D scheduling policy, the value of the objective function obtained by HLF-D and any other admissible policy \( \pi \in \Pi \) are compared.

In the objective function, let, \( \sum_{i \in S_t} U_{t,i} = V_t \). If it can be proved that \( V_t^{HLF-D} \geq V_t^\pi \ \forall \ t \in T \), then it is sufficient to state that \( O_T^\pi = O_T^{HLF-D} \geq O_T^\pi \ \forall \ \pi \in \Pi \).

Now, let us denote the elements in \( S_t \) as \( x_a \) for \( a \) in the range \([1,M]\). So, \( S_t = \{x_a\}_t \) for \( a = 1 \ldots R^{(t)} \) be the set of active sensors at the beginning of slot \( t \). \( R^{(t)} \) is the number of elements present in the active set i.e. \( |S_t| = R^{(t)} \leq M \). \( S'_t = \{e_a\}_t \) for \( a' = 1 \ldots R^{(t)} \) is the modified set \( S_t \), arranged in decreasing order of priority of the constituents. However, the priority of samples from \( a^{th} \) and \( a'^{th} \) active sensors in the active sensor set \( S_t \) and modified active sensor set \( S'_t \) are denoted as \( \text{Pri}_{t,a} \) and \( \text{Pri}_{t,a'} \), respectively.
So, in the objective function, the sum of utility of the active sensor samples becomes 
\[ V_t = \sum_{i \in S_t} U_{t,i} = \sum_{x \in S_t} U_{t,x} = \sum_{a \in S^t} \sum_{i \in S^t} U_{t,a}. \]
Here, \( U_{t,a} \) and \( U_{t,a'} \) are the utilizations of samples from \( a^\text{th} \) and \( a'^\text{th} \) active sensors in sets \( S_t \) and \( S'_t \), respectively.

Let’s say, at any time slot \( t \), the active sensor from \( S'_t \), scheduled for transmission, is denoted by \( d^t \). If the channel is ‘ON’, the sample from the active sensor \( d^t \) is processed successfully during this slot. However, if any critical sample is present in slot \( t \), then this sample is going to be dropped at the end of this slot, if not scheduled for transmission. Active sensor from which critical sample is dropped is denoted by \( drop^t \). In the next slot \( t + 1 \), active set \( S_{t+1} = S'_t \setminus \{d^t, drop^t\} \cup N_{t+1} \) where \( N_{t+1} = \{y_n\}_{t+1} \) for \( n = 1 \ldots r^{(t+1)} \) is the set of newly active sensors at the beginning of slot \( t + 1 \). We put a 0 for the empty place of \( drop^t \) at the beginning of the set \( S_{t+1} \). This zero padding implicates that, according to our system model, the particular flowline \( drop^t \) will go out of service and its corresponding actuation task will be handled by some default command from the controller. However, this sensor will stay in the active set as a dummy element with a sample having utility = 0 and laxity < 0). But, this out-of-service sensor does not take part in scheduling. Therefore, the number of elements in \( S_{t+1} \) becomes \( R^{(t+1)} = [\max(0, (R^{(t)} - 1)) + r^{(t+1)}] \leq M \).

Now, if any active sensor with critical sample (utility > 0, laxity = 0 and priority = \( \infty \)) pops up in this slot \( t + 1 \), we place that sensor in \( S'_t \) before those dummy zeros followed by the active sensors with non-critical samples in the decreasing order of their priority.

To prove \( V_t^{HLF-D} \geq V_t^{\pi} \forall t \in T \), without loss of generality, we next try to prove that \( U_{t,a'}^{HLF-D} \geq U_{t,a'}^{\pi} \forall e_{a'} \in S'_t \) and \( t \in T \).

**Assumption:**

I. For comparing HLF-D and \( \pi \) policies, it is imperative that the channel condition and the number of newly active sensors at the beginning of each slot remain independent of the underlying scheduling policy and does not change during one slot.

II. In this proof sensor and sensor sample both the terms can be used interchangeably. This is because the samples are present within the sensor itself.

We are using the **Induction method** for this proof.

**Base case:** Initial conditions are the same for both the policies. So, the set of active sensors \( S_t \) is the same for both HLF-D and \( \pi \) at slot \( t = 1 \). This yields \( U_{1,a'}^{HLF-D} = U_{1,a'}^{\pi} = U_{1,a'} \forall e_{a'} \in S'_1 \).

**Inductive step:** For any time slot \( t \), it is assumed that, \( U_{t,a'}^{HLF-D} \geq U_{t,a'}^{\pi} \forall e_{a'} \in S'_t \). It is required to prove that, \( U_{t+1,a'}^{HLF-D} \geq U_{t+1,a'}^{\pi} \forall e_{a'} \in S'_{t+1} \).

At any slot \( t \), active sets obtained from two policies HLF-D and \( \pi \) are as follows:

\[
S_t^{HLF-D} = \{e_1, e_2, \ldots, e_i, \ldots, e_j, \ldots, e_k, \ldots, e_R(t)\}^{HLF-D}_t
\]
\[
S_t^{\pi} = \{e_1, e_2, \ldots, e_i, \ldots, e_j, \ldots, e_k, \ldots, e_R(t)\}^{\pi}_t.
\]
Now, one of the four distinct cases may happen:

1. Critical sensors are present in both $S_t^{\text{HLF-D}}$ and $S_t^\pi$.
2. Critical sensor is present only in $S_t^{\text{HLF-D}}$ but not in $S_t^\pi$.
3. Critical sensor is present only in $S_t^\pi$ but not in $S_t^{\text{HLF-D}}$.
4. No critical sensor is present in either $S_t^{\text{HLF-D}}$ or $S_t^\pi$.

According to HLF-D, the active sensor, having the highest priority, is scheduled for processing. This follows, $d_t^{(\text{HLF-D})} = \arg \max_{x_a \in \mathcal{S}_t^{\text{HLF-D}}} \{ \text{Pr}_t \} = \{ e_1 \}$. Whereas, in policy $\pi$ any element other than the active sensor with the highest priority is scheduled for processing. This gives, $d_t^{(\pi)} = \{ e_k \} \neq \arg \max_{x_a \in \mathcal{S}_t^{\pi}} \{ \text{Pr}_t \} = \{ e_1 \}$. Here, $1 < k \leq R(t)$. Therefore, it can be concluded that starting from the same initial condition, HLF-D always processes the critical sample or, in absence of any critical packet, serves the packet with the highest latency incurred so far. Same is not true for $\pi$. So, critical packets may get dropped in $\pi$ and the number of active sensors in $S_t^\pi$ may be less than that in $S_t^{\text{HLF-D}}$. For comparing HLF-D and $\pi$, the number of elements in $S_t^\pi$ is made the same as that in $S_t^{\text{HLF-D}}$ by adding dummy zeros at the beginning of $S_t^\pi$.

Now, we compare HLF-D and $\pi$ for the aforementioned four cases one by one.

**A. Case 1.** We know that the critical has the highest priority in an active set. So, in $S_t^{\text{HLF-D}}$, $\{ e_1 \}$ and $\{ e_1 \}^\pi$ are the sensors with critical, respectively. From earlier discussions, $\text{drop}^{(\text{HLF-D})} = \{ \emptyset \}$ and $d_t^{(\text{HLF-D})} = \{ e_1 \}$. So in HLF-D,

$$S_{t+1}^{\text{HLF-D}} = (S_t^{\text{HLF-D}} \setminus \{ e_1 \}) \cup N_{t+1}. \tag{15}$$

From (15), the relation between $S_{t+1}^{\text{HLF-D}}$ and $S_t^{\text{HLF-D}}$ can be obtained as:

$$x_{a_t}^{\text{HLF-D}} = e_{a+1}^{t+1} \text{ for } 1 \leq a = a' < R(t)$$

$$\{ y_n \}_{t+1} \text{ for } n = 1 \text{ to } R(t+1) \text{ and } \{ e_1 \} \text{ for } R(t) \leq a \leq R(t+1). \tag{16}$$

Here, all the sensors $\{ e_{a+1}^{t+1} \}$ for $1 \leq a = a' < R(t)$ are having non-critical samples at slot $t$ and $\{ e_1 \}$ for $n = 1 \text{ to } R(t+1)$ has just arrived at slot $t + 1$. So, the utilization of the elements in $S_{t+1}^{\text{HLF-D}}$ are,

$$U_{t+1,a}^{\text{HLF-D}} = U_{t+1,a+1}^{\text{HLF-D}} \text{ for } 1 \leq a = a' < R(t)$$

$$= 1 \text{ for } R(t) \leq a \leq R(t+1). \tag{17}$$

Here, $U_{t+1,a}^{\text{HLF-D}}$ implies utilization of $a'$ element from $S_t^{\text{HLF-D}}$ in the next slot $t + 1$.

On the other hand, $\text{drop}^{(\pi)} = \{ e_1 \}^\pi$ and $d_t^{(\pi)} = \{ e_1 \}^\pi$. $\{ e_1 \}^\pi$ are active sensors having samples with non-zero utility. So in $\pi$,

$$S_{t+1}^\pi = (S_t^\pi \setminus \{ e_1 \}) \cup N_{t+1}. \tag{18}$$
From (18), the relation between \( S_{t+1}^\pi \) and \( S_t^\pi \),

\[
\begin{align*}
\{ x_a \}_{t+1}^\pi &= 0 & \text{for } a = 1, \\
&= \{ e_{a'} \}_{t}^\pi & \text{for } 1 < a = a' < k, \\
&= \{ e_{a'+1} \}_{t}^\pi & \text{for } k \leq a = a' < R(t), \\
&= \{ y_n \}_{t+1}^\pi & \text{for } n = 1 \text{ to } r(t+1) \text{ and } R(t) \leq a \leq r(t+1). 
\end{align*}
\]

(19)

Other than \( \{ e_1 \}_{t}^\pi \) all elements in \( S_{t}^\pi \) are non-critical. So, the utility of the elements in \( S_{t+1}^\pi \) are,

\[
\begin{align*}
U_{t+1,a}^\pi &= 0 & \text{for } a = a' = 1, \\
&= U_{t+1,(a')_{t}}^\pi & \text{for } 1 < a = a' < k, \\
&= U_{t+1,(a'+1)_{t}}^\pi & \text{for } k \leq a = a' < R(t), \\
&= 1 & \text{for } n = 1 \text{ to } r(t+1) \text{ and } R(t) \leq a \leq r(t+1). 
\end{align*}
\]

(20)

Now comparing (17) and (20) it is observed that,

for \( a = a' = 1 \): \( U_{t+1,a}^{HLF-D} = U_{t+1,(a'+1)_{t}}^{HLF-D} > 0 \) and \( U_{t+1,a}^\pi = 0 \). So, \( U_{t+1,a}^{HLF-D} \geq U_{t+1,a}^\pi \).

for \( 1 < a = a' < k \): In this segment, all the sensors are non-critical in both \( S_{t}^{HLF-D} \) and \( S_{t}^\pi \) and \( Pri_{t,a'} > Pri_{t,a'+1} \). So, \( U_{t,a'} \leq U_{t,a'+1} \). Combining this with our initial assumption of the induction step, it is obtained that \( U_{t,a'+1}^{HLF-D} \geq U_{t,a'}^{HLF-D} \geq U_{t,a'}^\pi \). Now, we know that all the unprocessed sensors from the current slot are going to be present in the active set of the next slot with a latency increased by +1. So, freshness of their samples decreases which, in turn, reduces the utility (according to (11)). Hence, we can say that if \( U_{t,a'+1}^{HLF-D} \geq U_{t,a'}^\pi \), then \( U_{t+1,(a'+1)_{t}}^{HLF-D} \geq U_{t+1,(a')_{t}}^\pi \), as well. This proves, \( U_{t+1,a}^{HLF-D} \geq U_{t+1,a}^\pi \).

for \( k \leq a = a' < R(t) \): From the initial assumption we can say that \( U_{t,a'+1}^{HLF-D} \geq U_{t,a'+1}^\pi \). All the sensors are having non-critical samples in this segment too in both \( S_{t}^{HLF-D} \) and \( S_{t}^\pi \). So, similar to the previous segment, we can show \( U_{t+1,(a'+1)_{t}}^{HLF-D} \geq U_{t+1,(a')_{t}}^\pi \) or in other words, \( U_{t+1,a}^{HLF-D} \geq U_{t+1,a}^\pi \).

for \( R(t) \leq a \leq R(t+1) \): \( U_{t+1,a}^{HLF-D} = U_{t+1,a}^\pi = 1 \).

From the above comparisons, it can be concluded that \( U_{t+1,a}^{HLF-D} \geq U_{t+1,a}^\pi \) \( \forall x_a \in S_{t+1} \). Again, the four sub-cases, similar to the abovementioned cases (1-4), may occur in slot \( t + 1 \) depending on the presence of a critical sensor in any active set. They are analyzed case by case to complete the induction.

**A.1. Subcase 1.1:** Let \( \{ x_{l} \}_{t+1}^{HLF-D} \) and \( \{ x_{j} \}_{t+1}^{\pi} \) are having critical samples in \( S_{t+1}^{HLF-D} \) and \( S_{t+1}^{\pi} \), respectively. Here \( l \) and \( j \) both are smaller than \( R(t+1) \). So, the relation between \( S_{t+1}^{HLF-D} \) and \( S_{t+1}^{\pi} \) are as follows,

\[
S_{t+1}^{HLF-D} = \{ x_1, x_2, \ldots, x_{l-1}, x_l, x_{l+1}, \ldots, x_{R(t+1)} \}_{t+1}^{HLF-D}
\]
\[ S^{t+1}_{t+1}^{HLF-D} = \{ x_j, x_1, x_2 \ldots x_{l-1}, x_{l+1} \ldots x_{R(t+1)} \}^{HLF-D}_{t+1} \]
\[ = \{ e_1, e_2, e_3 \ldots e_{l+1} \ldots e_{R(t+1)} \}^{HLF-D}_{t+1}. \]  

This gives,

\[ \{ e_{\alpha'} \}^{HLF-D}_{t+1} = \{ x_j \}^{HLF-D}_{t+1} \quad \text{for } \alpha' = 1 \]
\[ = \{ x_{\alpha-1} \}^{HLF-D}_{t+1} \quad \text{for } 1 < \alpha = \alpha' \leq l \]
\[ = \{ x_{\alpha} \}^{HLF-D}_{t+1} \quad \text{for } l < \alpha = \alpha' \leq R^{(t+1)}. \]  

\[ U^{HLF-D}_{t+1, a'} = U^{HLF-D}_{t+1, l} \quad \text{for } \alpha' = 1 \]
\[ = U^{HLF-D}_{t+1, a-1} \quad \text{for } 1 < \alpha = \alpha' \leq l \]
\[ = U^{HLF-D}_{t+1, a} \quad \text{for } l < \alpha = \alpha' \leq R^{(t+1)}. \]  

Similarly in \( \pi \),

\[ S_{t+1}^{\pi} = \{ x_1, x_2 \ldots x_{j-1}, x_j, x_{j+1} \ldots x_{R(t+1)} \}^{\pi}_{t+1} \]
\[ S_{t+1}'''^{\pi} = \{ x_j, x_1, x_2 \ldots x_{j-1}, x_{j+1} \ldots x_{R(t+1)} \}^{\pi}_{t+1} \]
\[ = \{ e_1, e_2, e_3 \ldots e_{j+1} \ldots e_{R(t+1)} \}^{\pi}_{t+1}. \]  

From (24) we get,

\[ \{ e_{\alpha'} \}^{\pi}_{t+1} = \{ x_j \}^{\pi}_{t+1} \quad \text{for } \alpha' = 1 \]
\[ = \{ x_{\alpha-1} \}^{\pi}_{t+1} \quad \text{for } 1 < \alpha = \alpha' \leq j \]
\[ = \{ x_{\alpha} \}^{\pi}_{t+1} \quad \text{for } j < \alpha = \alpha' \leq R^{(t+1)}. \]  

\[ U_{t+1, a'}^{\pi} = U_{t+1, l}^{\pi} \quad \text{for } \alpha' = 1 \]
\[ = U_{t+1, a-1}^{\pi} \quad \text{for } 1 < \alpha = \alpha' \leq j \]
\[ = U_{t+1, a}^{\pi} \quad \text{for } j < \alpha = \alpha' \leq R^{(t+1)}. \]  

Now comparing (23) and (26),

\[ \text{for } \alpha' = 1 : \quad U_{t+1, a'}^{HLF-D} = U_{t+1, l}^{HLF-D} \text{ and } U_{t+1, a'}^{\pi} = U_{t+1, l}^{\pi}. \]

It is known that HLF-D and \( \pi \) both started from the same initial condition. After that, HLF-D always serves the critical sample or the sample having the highest latency (in the absence of any critical sensor). Other active samples with lower latency is inherited to the active set in the next slot. On the other hand, \( \pi \) serves a sample with lower latency or any sample other than the critical one, and this critical packet is
dropped. As a result, one of the following two cases may occur when critical samples are present in the active sets for both HLF-D and \( \pi \) in two successive time slots:

1. The critical sample, present in \( S_{t+1}^T \) at any slot \( t+1 \), is same as that present in \( S_{t+1}^{HLF-D} \). Hence, \( U_{t+1,i}^{HLF-D} = U_{t+1,j}^T \).

2. Different critical samples are present in \( S_{t+1}^T \) and \( S_{t+1}^{HLF-D} \). This can only happen when, in any prior slot, the non-critical sample having the highest latency is not served by \( \pi \) but, it is served by HLF-D. This leftover sample is inherited to the future slots and is present in \( S_{t+1}^T \) as the critical sample having the hard deadline. So, it is supposed to have higher latency (or, lower utilization) than that of the sample in the first element \( \{t_1\}_{HLF-D} \) in \( S_{t+1}^{HLF-D} \). Therefore, comparing the utilization of sensor samples we get that, \( U_{t+1,j}^{HLF-D} \geq U_{t+1,i}^{HLF-D} \geq U_{t+1,j}^T \).

These prove, \( U_{t+1,j}^T \leq U_{t+1,i}^{HLF-D} \) or, in other words, \( U_{t+1,a}^{HLF-D} \geq U_{t+1,a'}^\pi \) for \( a' = 1 \).

For \( a = a' > 1 \): if \( i \leq j \), from (23) and (26) it can be seen directly that \( U_{t+1,a}^{HLF-D} \geq U_{t+1,a'}^\pi \). Otherwise, we look back to the elements in previous sets \( S_{t}^{HLF-D} \) in (17) and \( S_{t}^\pi \) in (20) to replace values of \( U_{t+1,a}^{HLF-D} \) and \( U_{t+1,a'}^\pi \) in (23) and (26), respectively. From backtracking, it can be concluded that, \( U_{t+1,a}^{HLF-D} \geq U_{t+1,a'}^\pi \) for \( i > j \) if \( f i l k < k \). Next, we show that if \( i > j \) then, it naturally follows \( l < k \).

If the same critical sensor is present both in \( S_{t+1}^{HLF-D} \) and \( S_{t+1}^\pi \) and its position be \( i \) in \( S_{t+1}^{HLF-D} \), then in \( S_{t+1}^\pi \), it must be in the same position or after \( i \) (due to initial 0 padding). That means \( i \leq j \). But \( i > j \) means two completely different sensors are critical in \( S_{t+1}^{HLF-D} \) and \( S_{t+1}^\pi \). This can happen only when the element from \( S_{t+1}^\pi \) same as the \( l \)th sample in \( S_{t+1}^{HLF-D} \) is already served by \( \pi \) at the previous time slot \( t \) or any earlier slot. Let say, the \( k \)th sensor in \( S_{t+1}^\pi \) is same as the \( l \)th sensor in \( S_{t+1}^{HLF-D} \). Now, at any slot \( t \), the first element from \( S_{t}^{HLF-D} \) is being served. Other elements are shifted one position left and they are inherited to the active set \( S_{t+1}^{HLF-D} \) in the next slot. So, \( l \)th sensor in \( S_{t+1}^{HLF-D} \) was in \( (i + 1) \)th position in \( S_{t}^{HLF-D} \). Therefore, between \( S_{t}^\pi \) and \( S_{t}^{HLF-D} \), \( k \geq (i+1) \), or in other words, \( i < k \) always.

For the limited scope of discussion, in this paper, only one case and its one subcase have been analyzed thoroughly. Analysis for the other cases and their all possible subcases proceeds in the same manner and finally it can be concluded that if \( U_{t+1,a}^{HLF-D} \geq U_{t+1,a'}^\pi \) \( \forall i' \in S_{t+1}^\pi \) at any slot \( t \), in the next slot \( t+1 \) too, \( U_{t+1,i'}^{HLF-D} \geq U_{t+1,i'}^\pi \) \( \forall i' \in S_{t+1}^\pi \) (induction complete).

V. RESULTS AND DISCUSSION

This section simulates in MATLAB the performance of HLF-D in terms of EXWSUoI, \( \bar{A}_l \) and RMS jitter (EXWSUoI has the unit (No of time slots))\(^1\). Rest all the parameters are expressed in terms of the number of time slots) for symmetric IWSAN network and compare the results with those of Highest Latency First (HLF) policy [14] and other traditional algorithms viz. Earliest Deadline First (EDF) and Least Laxity First (LLF). All the algorithms as mentioned above including our proposed one, have the complexity of order \( O(n) \). Parameters used for all the simulations and their values are listed in Table I. Initial age is considered to be \( h_{i+1} = c_i(0) + D_i(1) \) slots.

Fig. 3 plots the comparison of EXWSUoI values varying with \( T \) for different algorithms. From this plot, it can be seen that the expected utilization of information is always maximum for HLF-D for any value of \( T \).
Fig. 4 compares the mean age of information, latency, and RMS jitter of the sensor-actuator network. It can be clearly seen that our proposed HLF-D algorithm provides the lowest values and for all of the preferred metrics than those of the other scheduling policies. HLF shows the worst performance for all the parameters in both Fig 3 and 4.

Fig. 3. Comparison of EXWSUol vs T for different algorithms.

Though a smaller value of average age should be maintained to keep the information fresh for accurate decision making in the cyber systems, reference [14] proves that minimizing the latency content, involved in the age, is more effective for the thoughtful trade-off between information freshness maximization and jitter minimization in CPSs. Moreover, ICPS is a time-critical real-time system. Here information exchange should be done as timely as possible to guarantee real-time responses. Whenever a packet misses its deadline, it is dropped, causing production loss, accidents, or some fatal consequences. Therefore, minimizing packet loss has the utmost importance, too, in addition to latency minimization.

| Parameters                                      | Symbol | Value Assigned |
|-------------------------------------------------|--------|----------------|
| Number of flow-line (sensor-actuator pair) [14], [18] | M      | 16             |
| The weight assigned to each sensor              | $\alpha_i = \alpha > 0$ $\forall i \in M$ | 1              |
| Time-shared transmission channel reliability    | $p_i = p$ $\forall i \in M$ | 0.8            |
| Time slot (According to WirelessHart standard [17]) | $t$    | 10 ms          |
| Initial useful age [18]                         | $c(0)$ | [1,25]         |
| Initial deadline [19]                           | $D(1)$ | [1,20]         |
| Real Indices                                    | $\beta > 0, \gamma > 0$ | 1              |
The algorithm HLF proposed in [14] provides optimality in terms of data freshness and network performance in ICPS only when the packet deadline is not being considered. Whereas, HLF-D maximizes the expected utility value of all the time-critical information in IWSAN. This can be done by minimizing the average latency of the sensor samples and attaining minimum packet drops. Moreover, this algorithm also minimizes the RMS jitter of the actuation tasks performed in the network. So, one may aptly conclude that HLF-D is the most suitable deadline-aware scheduling strategy for optimizing the freshness of information and QoS in ICPS.

VI. CONCLUSION

This paper analyzed the age-based information freshness in symmetric IWSAN application. One deadline-aware, dynamic priority-based greedy sensor scheduling algorithm ‘Deadline-aware highest latency first’ was proposed for that purpose. Its optimality has been proved in terms of the utility value of information content. Moreover, its effects on system performance in terms of mean age, latency, and RMS jitter were also compared with that of the highest latency first and other traditional scheduling algorithms by extensive simulations. From this paper, it can be concluded that to guarantee a real-time response and data freshness simultaneously, our proposed algorithm is the most effective packet scheduling scheme for CPSs in industry applications.

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