Age of Local Information for Fusion Freshness in Internet of Things

(Invited Paper)

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***Abstract*—In recent years, the applications of Internet of Things (IoT) have been extensively explored. Among these applications, information fusion based on probability theories or Artificial Intelligence (AI) plays a foundational role. However, to the best of our knowledge, few works consider the scheduling of the IoT nodes that collect redundant data to promise the freshness of the fused information. Age of Information (AoI) is a metric that characterizes the obsolescence of information. Although AoI works well in single-source updating systems, it is hardly applicable to a multi-source system setting such as IoT. In this paper, we propose a new metric called Age of Local Information (AoLI) to illustrate the obsolescence of data collected by each node of IoT used in fusion. We first simulate AoLI in an FCFS queue and show that the optimal arrival rate that minimizes the mean AoI does not necessarily result in a quicker information fusion. Instead, the arrival rate that minimizes the maximal AoI performs better. We then propose a scheduling policy called the Fusion Greedy policy to schedule the IoT nodes in a discrete manner under an FCFS queue of length 1. Through simulation, we demonstrate that the proposed policy outperforms traditional policies such as Whittle's index policy or the AoI Greedy policy.**

***Index Terms*—Internet of Things, Age of Local Information, Artificial Intelligence.**

I. Introduction

As the development of networking techniques such as 6G continues, the Internet of Things (IoT) has become one of the keys developments of the information revolution. The enormous data collected by IoT enables a higher level understanding of the environment and better decision-making, thus it is expected to provide many potential benefits to our daily lives. However, the possible billions of devices connected to the IoT create lots of redundant information and lay a heavy burden on communication. Therefore, scheduling the devices in the IoT is essential.

Information fusion plays a central role in the applications of IoT. There are several advantages of information fusion, namely: 1) more sensible and precise information; 2) higher robustness and reliability; and 3) better control performance. Traditional information fusion methods mostly rely on probability theories. However, due to the explosive development of Artificial Intelligence (AI), many new information fusion algorithms based on AI have been developed. These algorithms not only perform better on the traditional linear system information fusion tasks but are also applicable to more complex non-linear system information fusion as well as the higher level semantic interoperability [1]. Hijji, *et al.* [3] combined the 2D Convolution Neural Network (CNN) and 1D CNN to form a new neural network to fuse the information updated by the cars in the IoT to detect the potholes on the road. The pre-training method that enabling task immigration is widely used in deep neural networks. Wang, *et al.* [2] proposed a neural network (NN)-based information fusion algorithm, which is enhanced by pre-training, to improve the performance of the IoT. Although many information fusion methods have been proposed, as far as we know, characterizing the freshness of fused information of IoT system and local information of IoT nodes that collects redundant information (which is a common issue [4]) remains to be discovered.

The newly proposed metric, Age of Information (AoI) [5], which is defined as the time elapsed since the last generating time of the information, is now attracting research interest [6], [7]. However, AoI only characterizes the obsolescence of information in a single-source network, which makes it unable to handle multi-source information transmission and fusion tasks. Therefore, an alternative metric that can account for multi-source information updating and fusing in a IoT system has emerged. Nowadays, comparing to minimizing the raw AoI, people are more interested in the AoI induced from some actions. Note that in this aspect, the raw AoI could be viewed as the Age of Information on the successful transmission of packages. Query AoI (QAoI) [8] considered AoI on the query, which is an initiative user-driven action. The authors minimizes QAoI by controlling the waiting period between two queries. Effective AoI (EAoI) [9] further considered scheduling AoI proactively, which is the first work that introduce the idea of feedforward control to the AoI-based scheduler. On the other hand, Age-Upon-Decisions (AuD) [10] considered studied the AoI when a decision is made, whose action, on the opposite to QAoI, is performed on

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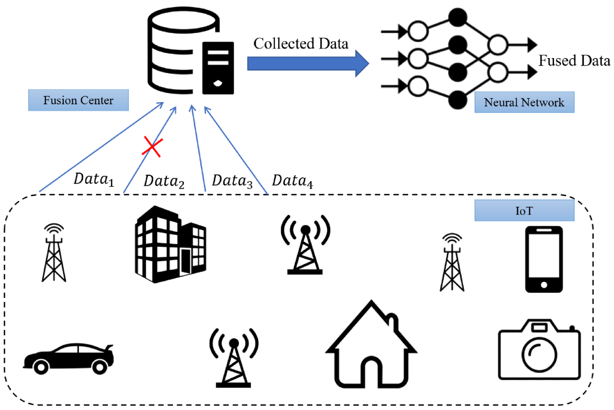

Fig. 1. The IoT nodes collect local information and transmit it to the fusion center, which performs information fusion through NN. The fusion center then broadcast the fused information.

the client instead of the user. The authors conclude that the periodic arrival usually performs better than the randomized one. Security is also an importance issue in communication of the IoT system. Recently, an AoI based metric concerning the security information transmission issue under eavesdropping was proposed [11]. The authors argued that by maximizing the AoI of the eavesdropper, the prescription of the information could be guaranteed. It should be noted that the metrics based on AoI could all be enhanced by a similar idea to protect the interested information by enlarging the corresponding metric of the eavesdropper.

In this paper, we propose a new metric called Age of Local Information (AoLI) to characterize the obsolescence of local information used for fusion. Note that since we schedules the nodes of an IoT system, some of the local information could be redundant. This is one of the main differences between AoLI and AoI. To optimize AoLI, we not only balance the information gathering and transmitting rate, which is similar to AoI, but also pursue a trade-off among all the information sources. In this sense, we define AoLI for each source in two situations. In the case where the local information of a source is used for calculating the fused information, then the corresponding AoLI is defined as the time elapsed since the generating time of its local information. On the other hand, if the information fusion has already been processed, AoLI is simply defined as the time elapsed since the broadcasting time of the latest fused information.

The work most relevant to the proposed AoLI is [10]. However, despite the similarities between our approach to AuD, there exist notable differences that should be mentioned. First, the action we choose to induce AoLI is based the information fusion, which sets restrictions on the information sources. On the other hand, the authors of AuD assume that the server make decisions following a Poisson process, which basically treats each information source independently.

In the following, we provide an example of AoLI along with its features. As illustrated in Fig. 1, the fusion center fuses the local information, which is updated by each IoT nodes, using some Neural Networks. Once the fused information is successfully calculated, the fusion center broadcasts it. It is worth noting that since we assume the redundancy of the local information, the fusing process can commence without waiting for the remaining local information.

In the ensuing discussion, we take an IoT system as an example and delve deep into some of the various cases that the system may encounter during its runtime. Subsequently, we demonstrate the aforementioned characteristics in minimizing AoLI. Form Fig. 1 we observe that the local information set is used to calculate the fused information. It can easily be deduced that if the distance between the nodes and the object is rather large, then the local information gathering process become slow, resulting in a large AoLI. On the other hand, if the information gathering is quick enough and the nodes transmit frequently but the fusion center process these packages slowly, the AoLI will still be large. In the above we show how AoLI can indicate the balance between the information gathering and the processing rate, which is similar to AoI. However, AoLI also indicates the trade-off among the information sources, which is of great importance in the scheduling of IoT systems. Still, let's take Fig. 1 as an example. Since the capacity of the IoT network is limited, if one node transmits its information extremely quickly, then the others may encounter poor network conditions, resulting in a delay in calculating the fused information. This delay enlarges the AoLI because there is not enough timely information available.

Since AoLI is specifically proposed for multi-source information updating systems, such as IoT system, here are some of the features of AoLI that may benefit IoT systems:

- Tolerance of network topology changes. Since many nodes of IoT are highly dynamic, network topology changes occur frequently. However, the definition of AoLI is uncorrelated with the network topology, which greatly enhances the robustness of the IoT scheduling policies based on AoLI. Additionally, the factors of network topologies are revealed in the evolution of AoLI, thus changes in these factors only demand modification to the scheduling algorithms.
- Distributed nature. The definition of AoLI is weekly correlated with the fusion center, so it is possible to schedule the IoT nodes in a distributed manner based on AoLI, which is preferred in large-scale systems.
- Enabling the scaling of IoT systems. An IoT system must be able to accommodate demands for the addition or reduction of nodes during operation. Fortunately, our definition of AoLI can be utilized in multi-scale IoT systems with varying numbers of nodes.

The rest of this paper is organized as follows. We first introduce our system model and give a formal definition of AoLI in section II. In section III, we discuss the relation between the maximal AoI and AoLI. Then, we propose methods to calculate the arrival rate that minimizes the maximal AoI. In section IV we propose a scheduling policy based on AoLI. In section V we show the simulation results. Finally, we conclude this paper in section VI.

II. System Model

In this paper, we consider an IoT system composed of N nodes, indexed by k, where $k \in \mathscr{N} \triangleq \{1, \cdots, N\}$, and one fusion center. The node k collects local information at time stamp $u_k(t)$, denoted by $I_k(t)$. Then, it transmits the $I_k(t)$ through a wireless network to the fusion center. For the simplicity of analysis, we use FCFS queue to model such information collection-transmission actions. Once the local information transmitted to the fusion center is sufficient to perform a fusion, and the fusion center execute the fusion action and broadcasts the fusion result to all the nodes. We define the most recent time instance of the fusion as $c(t)$. We also follow the assumption that $I_k(t)$ contains all the available local information of node k before $u_k(t)$ [5]. Thus AoI Δ_k of node k evolves as follows:

$$\Delta_k = t - u_k(t). \tag{1}$$

We also define the Age of Fused Information (AoFI) that illustrate the freshness of the fusion information as follows:

$$S(t) = t - c(t). \tag{2}$$

Now we are ready to define AoLI, which we denote by $S_k(t)$. AoLI envoves as follows: it increases linearly during the transmission of the local information and incurs a hop on the calculation of the fused information. The hopping of AoLI is quite different form that of raw AoI since we assume that the local information collected by each node is redundant and some of it may not be used for fusion. In the case where the local information of a node k, $I_k(t)$, is used for the calculation of the fused information, the AoLI of this node, $S_k(t)$, reduces to $t - u_k(t)$, where $u_k(t)$ is the generation time of the local information $I_k(t)$. On the other hand, the AoLI should infer the occurrence of the information fusion action. Thus, in the case where the local information of node $k^{'}$ is not used for the calculation of the fused information, the corresponding AoLI reduces to 0. As discussed above, we define the AoLI of node k at time t as follows:

$$S_k(t) = \begin{cases} t - u_k(t), & \text{if } I_k(t) \in \mathscr{A}(t), \\ t - c(t), & \text{otherwise}, \end{cases} \tag{3}$$

where $\mathscr{A}(t)$ denotes the set of the latest local information from each node after the last calculation of fused information at time t.

$$\mathscr{A}(t) \triangleq \{I_k(t) | t > c(t), k \in \mathscr{N}\}. \tag{4}$$

Note that during the calculation time instance that calculates the fused information, $\mathscr{A}(t)$ is the local information set that is used for the fusion.

In the following example, we will illustrate the differences between AoLI and AoI. Consider an obstacle that can only be sensed by two nodes, node 1 and node 2. Suppose node 1 suffers from poor network conditions and updates its information much slower than node 2. We use two preemptive queue of size 1 to model the information updating process of each node. By preemptive, we mean that if new local information arrives and encounters a full queue, then the newly collected information is preempted. We assume that the fused information could be calculated from the local information set $\mathscr{A}(t) = \{I_1(t), I_2(t)\}$. Then following our definition of AoLI, the AoLI of node 1 and node 2 are $S_1(t) = t - u_1(t)$ and $S_2(t) = t - u_2(t)$, respectively. To compare AoLI and AoI, we plot the changes in AoLI for node 1 and 2 in Fig. 2, and the changes in AoI in Fig. 3, respectively.

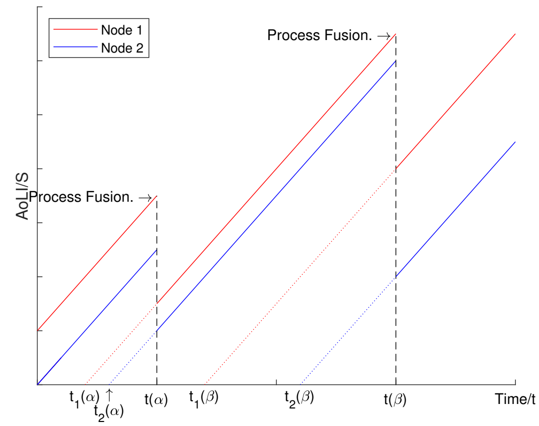

Fig. 2. The evolution of AoLI. At time instance $t(\alpha)$ and $t(\beta)$, the newly updated local information is enough to perform information fusion and AoLIs of node 1 and node 2 encounter a hop.

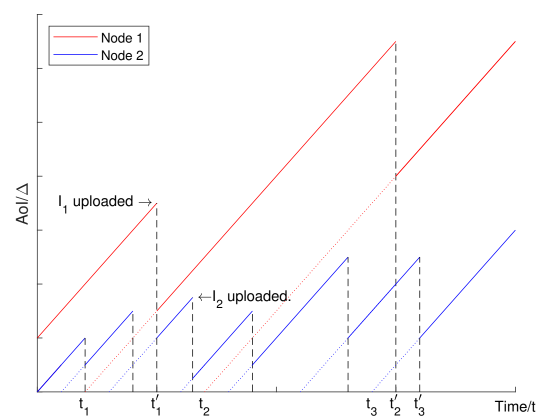

Fig. 3. The evolution of AoI. Different form AoLI, AoI is a single-source metric, thus AoI of node 1 and node 2 are uncorrelated with each other and incur hop on its own transmission success.

As shown in Fig. 3, the local information is sensed at the time instant without prime and is updated at the time instant with prime. Therefore, at time t_1', the information collected by node 1 at t_1 is updated to the fusion center node and the AoI of node 1 is reduced to $t_1' - t_1$. Conversely, as shown in Fig. 2, the fusion center node broadcasts the calculated fused information at time slot $t(\alpha)$, and the AoLIs of node 1 and node 2 are reduced to $t(\alpha) - t_1(\alpha)$ and $t(\beta) - t_2(\beta)$, respectively. Note that the AoI of node 2 is reduced to $t_3' - t_3$ at time instant t_3' in Fig. 3, as the information of node 2 is successfully updated. However, the AoLI at time t_3' remains the same as the information of node 1 between t_2 to t_3 is unavailable to the fusion center node, so it cannot perform information fusion. This example demonstrates that the behavior of AoI and AoLI can be significantly different. Such differences become more pronounced in more complicated system settings.

By comparing Fig. 2 and Fig. 3, we can see that some of the communication resources are wasted since the local information of node 2 $\{I_2(t), t_2(\alpha) < t < t_2(\beta)\}$ is transmitted to the fusion center node but ultimately discarded for the next calculation of the fused information performed at time instant $t(\beta)$. Thus, in this example, it is expected that by allocating more communication resources to node 1, the AoLI could be further reduced. On the other hand, if we reduce the allocation frequency of node 2, we could save energy wasted by the unnecessary transmission of local information collected by node 2.

III. Analysis Based on AoI

The optimization of AoLI, as defined in equation (3), is challenging. However, we have observed an inequality relationship between the value of AoLI and the maximal value of AoI given by the following expression:

$$S_k \leq \max_{i \in \mathscr{N}} \Delta_i, k \in \mathscr{N}, \tag{5}$$

where S_k denotes the AoLI of node k. Therefore, we can intuitively minimize AoLI by minimizing the maximal AoI. Note that the system setting that minimizes AoI does not necessarily minimize AoLI, which we demonstrate through simulation in the rest of this paper.

In the following, we focus on an IoT system where local information is updated through an M/M/1 queue. Each node $k, k \in \mathscr{N}$, enqueues the information I_k following a Poisson process of rate λ_k. The local information is served by the fusion center with the transmission time following an exponential distribution of parameter $1/\mu$. Additionally, We define the utilization factor of node k as $\rho_k \triangleq \lambda_k/\mu$. It can be easily seen that the optimal arrival rates λ_k that minimizes $\Delta_{\text{max}} \triangleq \max_{k \in \mathscr{N}} \Delta_k$ and $\Delta_{\text{sum}} \triangleq \sum_{k \in \mathscr{N}} \Delta_k$ are different. In latter section, we will simulate and show the differences in S_k under these two system settings. Through the simulation, we aim to demonstrate the effectiveness of minimizing the AoLI using the inequality (5).

The Stochastic Hybrid System (SHS) model is a widely-used model. it considers systems whose states are piece-wise continuous and introduces the discrete state to handle the discontinuous point. As suggested in [12], the SHS model can be easily applied to the AoI queuing systems and dramatically reduces the analysis complexity compared to traditional queuing theory methods. To build an SHS model, we first define the continuous part and the discrete part of the state, denoted by $\mathbf{x}(t)$ and q, respectively. Then, we write the state transition function of the continuous part conditioned on the discrete one, which is a simple continuous form of Markov Chain. However, the complexity of the system still exists, demonstrated by the possible intractability of the system state when considering the discrete part of the state and its impact on the continuous part of the state. To handle such complexity, we can introduce a test function whose expected value is tractable, allowing us to calculate some result of interest without fully parsing out the SHS model. specifically, in the application of AoI analysis in the SHS model, the continuous part of the state transition function is unrelated to the discrete part. Therefore, the test function could be calculated by solving the stationary distribution of the discrete part of the state and then calculating the expected value of the mean AoI. For more discussion on SHS model, please refer to [12] and [13].

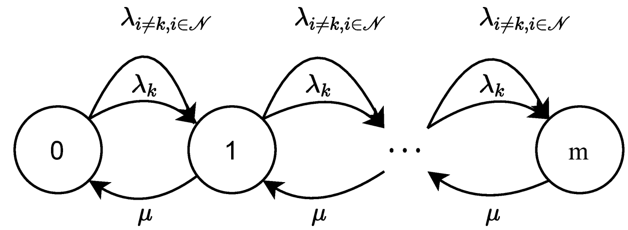

Fig. 4. The state transition diagram of the state q.

The simple definition of AoI makes it easier to define the states to characterize the evolution of AoI for each node k. Specifically, we define the discrete state $q \in \{1, \cdots, m\}, m \to \infty$ as the number of packages waiting in the queue and the continuous state $\boldsymbol{x}(t) \in \mathbb{R}^{m+1}, m \to \infty$ as the evolution of the age of some chosen node k. The state transition diagram of the discrete state q is shown in Fig. 4. On the other hand, $\boldsymbol{x}$ increases with slope 1 if the state q remains still, while it experiences a state hopping on the transition of the discrete state q. Assuming the ergodicity of the Markov chain shown in Fig. 4, we can calculate its stationary distribution, denoted by $\boldsymbol{\pi}$. Since the evolution of $\boldsymbol{x}(t)$ can be fully determined by $\boldsymbol{\pi}$, the stationary distribution of $\boldsymbol{x}(t)$ is also available to us. Then, according to [14][Theorem 2], the multi-source AoI is:

$$\Delta_k = \frac{1}{\mu}\left[\frac{1-\rho}{(\rho - \rho_{-k}\mathscr{R}_k)(1-\rho\mathscr{R}_k)} + \frac{1}{1-\rho} + \frac{\rho_{-k}}{\rho_k}\right], \tag{6}$$

where $\rho_k = \lambda_k/\mu$, $\rho = \sum_{k \in \mathscr{N}} \lambda_k/\mu$, $\rho_{-k} = \sum_{i, i \neq k, i \in \mathscr{N}} \lambda_i/\mu$, and $\mathscr{R}_k = \frac{1+\rho-\sqrt{(1+\rho)^2 - 4\rho_{-k}}}{2\rho_{-k}}$. Note that equation (6) allows us to calculate the optimal arrival rate that minimizes either the maximal AoI or the mean AoI.

IV. AoLI-based Scheduling Policy

In this section, we propose a scheduling policy based on AoLI that minimizes AoFI, ensuring that the fused information is fresher. Considering that most IoT devices are based on the digital chips, the proposed scheduling policy is in discrete form. Therefore, we consider an IoT consisting of N nodes and one fusion center. The transmission and fusion time are slotted, and each node can complete its task within one time slice. We further define $d_k(t) \in \{0, 1\}, k \in \mathscr{N}$, to denote the transmission decision at time slice t, and $s_k(t) \in \{0,1\}, k \in \mathcal{N}$, to indicate the transmission state, where

$$P(s_k = 1) = p_k, \tag{7}$$

where $p_k, k \in \mathcal{N}$, denotes the successful transmission rate. Then, we define $\gamma_k, k \in \mathcal{N}$, to indicate whether a transmission is succeed as follows:

$$\gamma_k(t) = d_k(t)s_k(t). \tag{8}$$

To calculate AoI under such system setting, we update them at the end of each time slice, which lead to the discrete form of AoI as follows [15]:

$$\Delta_k(t) = \begin{cases} \Delta_k(t-1)+1, & \text{if } \gamma_k(t) = 0, \\ 1, & \text{otherwise.} \end{cases} \tag{9}$$

The evolution of $c(t)$ in the discrete form can be deduced by sampling $c(t)$ at the end of each time-slice. Since the system we considering gathers information redundantly, we further assume that fusion can be processed when local information from $M, M < N$, nodes is successfully updated. As such, the evolution of $c(t)$ is as follows:

$$c(t) = \begin{cases} t, & \text{if } \sum_{k\in\mathcal{N}} \gamma_k(t) >= M, \\ c(t-1), & \text{otherwise.} \end{cases} \tag{10}$$

To this end, the discrete form of AoLI is as follows:

$$S_k(t) = \begin{cases} S_k(t-1)+1, & \text{if } f(t) = 0, \\ \Delta_k(t), & \text{if } f(t)\gamma_k(t) = 1, \\ 1, & \text{otherwise,} \end{cases} \tag{11}$$

where $f(t)$ indicate whether $c(t)$ equals t.

Considering the definition of AoLI as well as the assumption of redundant information gathering, the scheduling policy that minimizes AoLI is quite different from that which minimizes AoI. As proved by Kadota, *et. al* [15], the optimal scheduling policy that minimizes AoI of a symmetric system that updates information similarly is the Greedy policy, while the Whittle's index policy is a sub-optimal policy that minimizes AoI of an unsymmetrical system. However, in the following, we show through simulation that to obtain a fresher fused information, scheduling $\arg\min_{k\in\mathcal{N}} \Delta S_k$, which is defined as follows, is a better policy.

$$\Delta S_k \triangleq S_k - \Delta_k, \forall k \in \mathcal{N}. \tag{12}$$

We call the newly proposed policy Fusion Greedy policy. We further illustrate that ΔS_k denotes the relative network status of node k comparing to other nodes. This means that the larger the value ΔS_k is, the better network status of the corresponding node. Therefore, by scheduling the node with the minimum value of ΔS_k, we can allocate the network resources more efficiently than policies based on AoI. What's more subtle is that by scheduling the nodes with the smallest difference of AoLI and AoI, the nodes whose information is not used by the latest fused information are more likely to be scheduled next. This trend balances the information transmitting load of each node.

Note that the Fusion Greedy policy not only benefits from the advantages of AoLI described in the introduction section of this paper, but it is also a flexible lightweight scheduling policy that allows for real-time system modification and quick scheduling decision making.

V. Simulation

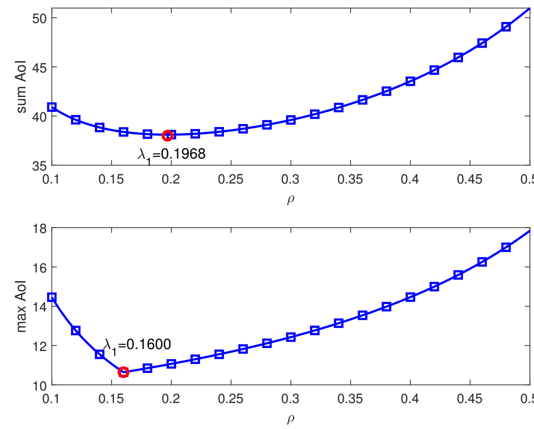

Fig. 5. The maximum AoI, Δ_{max}, and summation of AoI, Δ_{sum}, under different λ_1.

We first simulate an FCFS queue and confirm that the arrival rate that minimizes the maximal AoI performs better than the arrival rate which minimizes the mean AoI to obtain a fresher fused information. To this end, we consider a system consisting of four nodes and a fusion center. The information updating process of the nodes follows a Poisson distribution with rate $\lambda_k, k \in \{1,\cdots,4\}$, where $\sum_{k\in\{1,\cdots,4\}} \lambda_k = 0.8$, λ_1 varies from 0.1 to 0.5, and $\lambda_k, k \in \{2,3,4\}$ follow the ratio of 3:4:5. We further assume that the processing time, including information transmission and calculation, follows an exponential distribution with parameter 1. As shown in Fig. 5, the minimum Δ_{sum} occurs when $\lambda_1 = 0.1968$ while the minimum Δ_{sum} occurs when $\lambda_1 = 0.1968$. To further confirm that the AoLI is smaller under the system setting of $\lambda_1 = 0.1600$, we perform a 20000 times of queuing simulation and confirm that when $\lambda_1 = 0.16$, $S = 147$, whereas for the case $\lambda_1 = 0.20$, $S = 153$.

In the following, we will restrict the queuing length to 1 and simulate the scheduling policy that we have proposed earlier. Since the proposed policy is discrete, we assume that the successful transmission probability of the node 1 ranges from 0.5 to 0.9, while the other nodes have probabilities of $0.4, 0.6, 0.9$, respectively. We simulate the system under the following policies: AoI Greedy policy, Whittle's index policy and our Fusion Greedy policy for 20000 iterations. The schedulers choose one node to perform transmission at each iteration, and the fusion process is executed when three nodes successfully transmit, in other words, $M = 3$. The simulation result are shown in Fig. 6, from which it is clear tha our policy performs significantly better than the other two as p increases.

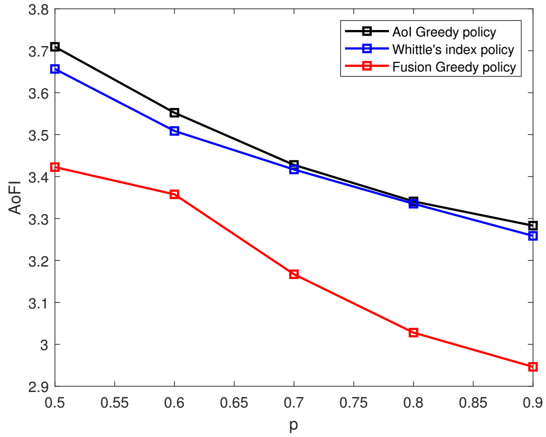

Fig. 6. The mean AoFI using three scheduling policies under different transmission success probabilities, where the proposed Fusion Greedy policy performs the best.

Considering that IoT typically consists of a large number of devices, we are interested in comparing the adaptability of the proposed policy to AoI-based policies at different system scales. Therefore, we perform another simulation of three policies in an IoT system with a varying number of nodes. The transmission success probability of each node is randomly chosen from the range 0.6 to 0.9, the simulation is also performed for 20000 iterations for each policy, one system scheduled at each iteration, and $M = 3$. The simulation results are illustrated in Fig. 7. From these results, we can see that the proposed policy fluctuates much milder than the ones based on AoI as the the system scale increases. Conversely, the system AoFI increases dramatically for the AoI-based policies as the IoT scale becomes larger. Thus, we conclude that the newly proposed policy is more adaptable to the scaling of IoT systems.

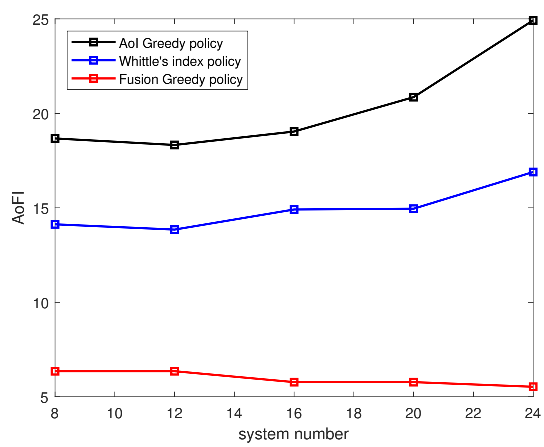

Fig. 7. The mean AoFI using three scheduling policies under different number of nodes, where the proposed Fusion Greedy policy adapt to the scaling of the system the best.

VI. Conclusion

In this paper, we have considered the problem of keeping the fused information in an IoT system as fresh as possible. We have proposed a new metric called the Age of Local Information (AoLI) and discussed the differences between AoLI and AoI. We have shown that in a FCFS queuing system, the optimal arrival rate of AoLI is not the one that minimizes the summation of the multi-source AoI. Instead, through simulation, we have shown that the system performs better under the arrival rate that minimizes the maximal AoI. Lastly, we have proposed a scheduling policy called the Fused Greedy policy to minimize AoLI. Through simulation, we have demonstrated that the proposed policy outperforms policies such as the Whittle's index policy or the AoI Greedy policy. Additionally, the proposed policy exhibits much greater adaptability to different system scales.

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