AGE OF INFORMATION IN NETWORK CODED INTERNET OF THINGS

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ABSTRACT

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The unique nature of the Internet of things (IoT), with potentially millions of interconnected devices featuring varying data rates, power levels, bandwidth, and range specifications, demands different performance metrics compared to traditional communication systems. In conventional wireless communication like cellular networks, performance markers such as data rate and spectral efficiency are paramount. However, in energy-constrained real-time IoT applications with low data rates, the timeliness of information, measured as age of information (AoI), takes center stage. AoI represents the time elapsed since the last packet update originated at its source and has garnered significant research attention. In this regard, This thesis provides an overview of AoI's role in designing and optimizing IoT applications, including AoI-based optimization, scheduling for IoT networks, application of learning methods in large-scale IoT systems, real-life applications and experimental results, together with a synopsis of potential future applications and research challenges, is provided in this thesis. Additionally, the timeliness in delivering updates within a multi-source multi-hop IoT networks via multicast transmissions with or without employing network coding is considered in this thesis. The effect of network coding on the average AoI is investigated employing a completely probabilistic model in a two-stage transmission scheme. The theoretical findings demonstrate that network coding has great potential to improve data freshness in multi-source multi-hop IoT networks, which closely represent the spine of real-life scenarios, and extensive simulation results corroborate the theoretical findings.

ÖZET

AĞ KODLU NESNELERİN İNTERNETİNDE BİLGİ YAŞI

Nesnelerin interneti (IoT) alanının benzersiz doğası, potansiyel olarak milyonlarca birbirine bağlı cihazın farklı veri hızları, güç seviyeleri, bant genişlikleri ve menzil özelliklerine sahip olduğundan dolayı geleneksel iletişim sistemlerinden farklı performans ölçütlerini gerektirir. Hücresel ağlar gibi geleneksel kablosuz iletişimde veri hızı ve spektral verim gibi performans ölçütleri belirleyicidir. Ancak düşük veri hızına sahip enerji açısından sınırlı gerçek zamanlı IoT uygulamalarında bilgi yaşı (AoI) önem kazanmıştır. AoI, son paket güncellemesinin kaynağında oluşturulduğu andan bu yana geçen süreyi temsil eder ve literatürde kullanımı artmaktadır. Bu bağlamda, bu tez, IoT uygulamalarının tasarımını ve optimizasyonunu şekillendiren AoI'nın rolünün genel bir bakışını sunmaktadır. AoI tabanlı optimizasyon, IoT ağları için zamanlama, büyük ölçekli IoT sistemlerinde öğrenme yöntemlerinin uygulanması, gerçek dünya uygulamaları ve deneysel sonuçlar da dahil olmak üzere bir dizi konuyu ele almaktadır. Ayrıca, bu tezde, çoklu kaynaklı çoklu atlamalı IoT ağlarında güncellemelerin zamanında iletilmesi konusu ele alınmaktadır. Ağ kodlama kullanmanın ortalama AoI üzerindeki etkisi tamamen olasılıksal bir model kullanılarak iki aşamalı iletim şeması araştırılmıştır. Teorik bulgular, ağ kodlamanın çoklu kaynaklı çoklu atlamalı IoT ağlarında veri tazeliğini artırma potansiyeline sahip olduğunu göstermektedir. Son olarak, geniş kapsamlı simülasyon sonuçları teorik bulguları desteklemektedir.

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LIST OF SYMBOLS

E	Encoded message
f_i	Encoding coefficient
$f(\cdot)$	Probability density function
$F(\cdot)$	Cumulative distribution function
l	Number of bits for the packets at each information source
M	Information message
N_r	Number of monitors
N_s	Number of servers
N_t	Number of sources
p_{ij}	Transmission success probability from the i-th source to the j-th server
q_{jk}	Transmission success probability from the j-th server to the k-th monitor
R	Transmission rate
s_j	Number of packets at the j-th server
t_τ	Transmission times for uncoded strategy
t_τ^{NC}	Transmission times for network coded strategy
λ	Mean of exponential distribution
$\prod$	Product operator
$\sum$	Summation operator

LIST OF ACRONYMS/ABBREVIATIONS

ACK	Acknowledgement
ADRA	Age-dependent Random Access
AF	Amplify and Forward
AmI	Ambient Intelligence
AoCI	Age of Changed Information
AoD	Age of Data
AoI	Age of Information
AoP	Age of Processing
AP	Access Point
ARQ	Automatic Repeat Request
AuD	Age upon Decisions
AUV	Autonomous Underwater Vehicle
CC	Chase Combining
CDF	Cumulative Distribution Function
CoI	Coage of Information
CoI	Information Cofreshness
CR-IoT	Cognitive Radio-based IoT
CSMA	Carrier Sense Multiple Access
D2D	Device-to-Device
DCAAs	Dynamic Channel Access Attacks
DF	Decode and Forward
DRDPG	Deep Recurrent Deterministic Policy Gradient
DRL	Deep Reinforcement Learning
EH	Energy Harvesting
FCFS	First-Come–First-Served
FIFO	First-In-First-Out
GATS	Grant Assignment and Transmission Scheduling
GIoT	Green IoT

GPD	Generalized Pareto Distribution
HAP	Hybrid Access Point
HD	Half-Duplex
IFE-DGCS	Information Freshness-Guaranteed and Energy-Efficient Data Generation Control System
IIoT	Industrial IoT
IoT	Internet of Things
IUDA	Information Update Delivery and Acquisition
KKT	Karush-Kuhn-Tucker
LGFS	Last-Generated First-Served
LP	Linear Programming
LZW	Lempel–Ziv–Welch
MC	Markov Chain
MDP	Markov Decision Process
MEC	Mobile-Edge Computing
MTDs	Machine-Type Devices
NACK	Negative Acknowledgement
NBU	New-Better-Than-Used
NE	Nash Equilibrium
OPG	Ordinary Potential Game
PDF	Probability Density Function
PPP	Poisson Point Process
PSO	Particle Swarm Optimization
QoS	Quality of Service
RMAB	Restless Multi-Armed Bandits
S-IoT	Satellite-Based IoT
STI	Spatially Temporally Correlated Mutual Information
TARQ	Truncated Automatic Repeat Request
TD3	Twin-Delayed Deep Deterministic
UAVs	Unmanned Aerial Vehicles
UC	Uncoded

VNF	Virtual Network Function
WET	Wireless Energy Transfer
WN	Wireless Node
WNCS	Wireless Networked Control System

1. INTRODUCTION

In today's world, the Internet of things (IoT), which refers to the interconnection of physical objects through sensors and wireless communication, has been instrumental in delivering significant advancements that enhance our quality of life. The number of internet-connected IoT devices is projected to exceed 83 billion by 2024, a substantial increase from the 35 billion recorded in 2020 [1]. Presently, IoT finds its primary applications in diverse fields such as agriculture, healthcare, transportation, industry, energy, smart homes, smart cities, and wearable devices, with new application domains expected to emerge in the near future. This widespread adoption owes much to advancements in sensor technology, efficient energy harvesting, wireless energy transfer, and innovations in low-power wireless communication. Furthermore, the ability to monitor real-time data, analyze information collected from sensors, and develop optimal systems has fueled the growing demand for IoT applications.

In many wireless communication standards, such as 4G and 5G, performance metrics like throughput, outage probability, bit error rate, packet error rate, and spectral efficiency take precedence. However, in the context of IoT applications, particularly those involving numerous devices transmitting data at fixed or relatively lower rates than traditional communication systems, the freshness of information emerges as a critical performance metric. To address this need, the concept of age of information (AoI) was introduced as a measure of data freshness, quantifying the time elapsed since the most recent status update was generated.

For time-sensitive applications like remote surgery or real-time monitoring of critical parameters in healthcare, the need for extremely fresh and accurate data is paramount to ensure patient safety. Similarly, in time-critical IoT networks, AoI constraints are essential to maintain the quality of service (QoS). For instance, in forest fire detection using IoT networks, temperature-measuring devices scattered across landscapes play a vital role. Unmanned aerial vehicles (UAVs) may be used to collect and transmit data from these sensors to identify fires promptly. In such scenarios, the freshness of temperature data is critical, necessitating network designs that keep AoI levels in check, accounting for factors such as sensor count, UAVs, flight paths, and more. Moreover, energy constraints in many IoT sensors, which operate on harvested energy, further emphasize the importance of data freshness. Several parameters, including scheduling strategies, sampling frequencies, packet sizes, and network hops, impact AoI performance.

Given the growing diversity of IoT applications and the increasing relevance of AoI as a design and optimization metric in next-generation wireless networks, this thesis aims to provide a comprehensive survey of contemporary research on AoI in IoT networks. While existing literature includes IoT surveys and surveys on AoI applications, this chapter distinguishes itself by offering an updated overview of AoI in IoT networks, considering factors such as energy constraints, network architectures, packet formatting, scheduling strategies, and a wide range of IoT applications. The chapter also explores optimization methods and design strategies, encompassing both traditional optimization formulations and solutions, as well as innovative approaches based on machine learning techniques. Additionally, the thesis will draw from the insights provided in relevant articles to further enrich the understanding of AoI in IoT networks, considering aspects such as multi-hop networks, multi-source scenarios, and the potential benefits of network coding.

The specific contributions can be summarized as follows:

- The thesis provides a comprehensive survey of contemporary works in the field of AoI in IoT networks. It offers a broad view of the factors influencing network performance, including energy constraints, network architectures, packet formatting, pre-processing and scheduling strategies.
- The derivations of average AoIs are provided for multi-source and multi-server first stage of transmissions where the transmissions are not coded.
- The derivations of average AoIs are provided for multi-server and multi-monitor

second stage of transmissions. The comparison of AoIs with and without network coding is given. For both of the transmission stages, probabilistic open expressions are given instead of closed AoI expressions due to the complexity of the network model.

- Extensive numerical experiments are conducted and are shown to corroborate the theoretical findings which demonstrate significant AoI gains offered by network coding.

The rest of the thesis is organized as follows. AoI, the applications of AoI and various AoI performance metrics commonly used in the literature have been discussed in Chapter 2. Chapter 3 provides an overview of contemporary research in the growing field of AoI in IoT networks. It covers factors affecting network performance, IoT application domains, optimization methods, including traditional approaches and machine learning-based design strategies. The impact of network coding in multi-source and multi-hop IoT networks on AoI performance is duscussed in Chapter 4. Probability-based theoretical calculations are provided for both network coded and uncoded strategies to assess the average AoI performance. Furthermore, detailed simulation results have been presented, which are consistent with the theoretical calculations. Finally, Chapter 5 concludes the thesis by summarizing the results and giving future work plans.

2. AGE OF INFORMATION

In the information age, 5G and beyond communications are anticipated to support billions of data-generating devices such as mobile phones, cars, drones and industrial robots. According to the Ericsson Mobility Report published in November 2022 [2], the number of 5G subscriptions is expected to reach 1 billion by the end of 2022 and 5 billion by the end of 2028, accounting for 55 percent of all mobile subscriptions. With this unprecedented growth, time-sensitive applications such as real-time surveillance, monitoring machine conditions for predictive maintenance and autonomous driving as well as IoT-enabled devices such as industrial robots, fitness trackers, and household appliances will increase in importance and continuously gather new data. Thus, they rely greatly on the timely supply of information, i.e. the data freshness. A central unit in a factory, for instance, may use artificial intelligence to analyze the collected data from the scattered sensors and take immediate action to optimize the production line. Such time-sensitive optimization issues necessitate seamless device-to-device connections, i.e., accurate and up-to-date data. Due to the rise of new high-rate, resource-intensive applications such as virtual reality, augmented reality, and gaming, data freshness is necessary not just for IoT-enabled devices but also for mobile users.

AoI, a novel performance measure proposed in [3] to measure the timeliness and freshness of data packets in a network, has emerged as an important metric and attracted significant research interest. AoI at a receiver is defined as the elapsed time since the source created the last received information update packet [3]. AoI can be quantified as the elapsed time between the current timestamp and the creation time of the most recent received status update packet at the destination such that

$$\Delta(t) = t - u(t). \tag{2.1}$$

AoI model can be considered as shown in Figure 2.1. When the generation of update packets is complete, the timestamp $u(t)$ is saved, where this first step corresponds to points A or C in Figure 2.1. After generation, the source transmits the data through the channel. The destination node receives the transmitted signal. When the incoming packet is successfully received, the AoI decreases, which corresponds to points B or D. If the sent packet is lost or incorrectly decoded, then the AoI will continue to increase.

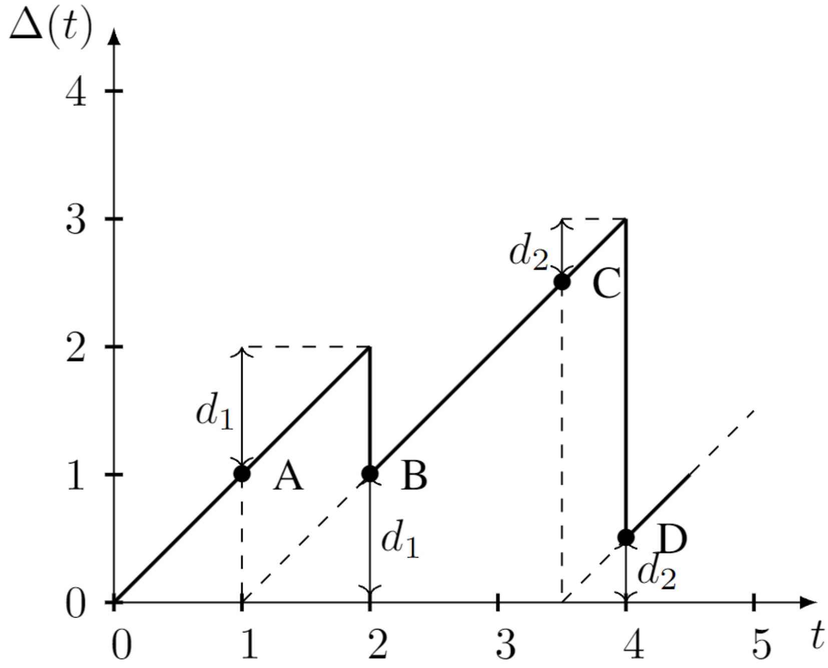

Figure 2.1. An example graph for the age of information at a receiver.

In addition to the conventional AoI function, it's worth delving further into the topic of non-linear AoI functions and their implications in the literature, particularly in the context of optimization and system design. These non-linear AoI functions introduce a more nuanced perspective on the timeliness of information updates, offering a versatile tool for tailoring communication systems to specific requirements.

Non-linear AoI functions, as exemplified in [4], depart from the conventional linear approach and can exhibit a wide range of behaviors, including exponential-like and logarithmic-like patterns. The fundamental idea behind using such functions is to capture the intricate dynamics of information freshness, which may not always conform to linear models. In this sense, generalized non-linear form of objective function is

$$J(t) = \alpha^{-1}(e^{\alpha t} - 1), \quad \alpha \neq 0 \tag{2.2}$$

where α is tuning parameter to determine which type of cost function is selected. For scenarios where rapid information updates are critical, choosing a positive α value can lead to an exponential-like pursuit of freshness. On the other hand, when stability and diminishing returns are more relevant, negative α values favor logarithmic-like behaviors.

In the AoI literature, average and peak AoI are frequently used metrics. The average AoI measures the mean age of the entire system in a given time range, hence it accounts for the general freshness of packets circulating in the network. In works such as [5, 6], the time average of AoI are found. In continuous system model, average AoI is calculated by time average of the AoI function which is expressed as

$$\varDelta_A = \frac{1}{T} \lim_{T\to\infty} \int_0^T \varDelta(t)dt. \tag{2.3}$$

On the other hand, peak AoI stands for the maximum AoI in the system in a given time range, therefore it highlights the most obsolete data flow. Peak AoI is especially important for applications with strict data freshness requirements such as real-time surveillance, autonomous driving and remote surgery. In [7–9], peak AoI related optimization problems are solved for different scenarios. For small $\epsilon > 0$, peak AoI can be formulated by the sample average of the peak values of the AoI which is mathematically expressed as

$$\varDelta_P = \lim_{T\to\infty} \frac{\sum_{t=0}^{T} \varDelta(t) 1\{\varDelta(t+\epsilon) \leq \varDelta(t)\}}{\sum_{t=0}^{T} 1\{\varDelta(t+\epsilon) \leq \varDelta(t)\}} \tag{2.4}$$

where $1\{\cdot\}$ is indicator function.

In addition to continuous system, average and peak AoI in discrete models can be expressed as

$$\begin{aligned} \varDelta_A &= \frac{1}{N} \lim_{N\to\infty} \sum_{i=1}^{N} \varDelta(i), \\ \varDelta_P &= \lim_{N\to\infty} \frac{\sum_{i=1}^{N} \varDelta(i) 1\{\varDelta(i+1) \leq \varDelta(i)\}}{\sum_{i=1}^{N} 1\{\varDelta(i+1) \leq \varDelta(i)\}}, \end{aligned} \tag{2.5}$$

respectively.

It has been shown in [10] that updating a destination about a remote system in a timely manner is not the same as maximizing the utilization of the communication system or ensuring that generated status updates are received with the least amount of delay. This is due to the fact that utilization can be maximized by having the source send updates as quickly as possible, which would result in the destination receiving delayed statuses due to the backlog of messages in the studied communication system. In this case, the stream of status updates can experience less delay if the rate of updates is decreased. Alternately, decreasing the update rate may result in the destination having status information that is unnecessarily out of date due to a lack of updates as mentioned in [11]. Consequently, the optimization/minimization of AoI in wireless networks has become an important issue.

AoI demonstrates notable proficiency to capture the data freshness in the realm of the real-time or time-sensitive communication systems, encompassing all of the potential use cases shown in Figure 3.3. In these domains, the significance of promptly accessible information cannot be overstated, as it underpins the informed decision-making, the system performance optimization, and the provision of dependable services. Quantifying and refining the AoI enables these systems to achieve increased efficiency, reduced latency and enhanced overall performance.

Following its inception in 2011 [3], the AoI has garnered increased recognition after 2015 for a variety of reasons. Initially, the widespread deployment of IoT devices and the exponential growth of data generation across diverse domains engendered an escalated demand for real-time information. Industries encompassing transportation, healthcare, and smart grids necessitated the low-latency data in order to streamline operations and facilitate informed decision-making processes. Furthermore, the advent of 5G networking technologies [12] expedited and fortified the data transmission, thereby enabling the rapid proliferation of various IoT systems in everyday life. Consequently, the real-time measurement and optimization of the AoI have gained even more prominence, particularly in the time-sensitive IoT applications.

The accuracy of output decisions, which determines the performance of IoT-enabled applications, is directly proportional to the freshness of the aggregated data measurements of the IoT devices at the destination nodes [13]. Different from [14] which considers recent works on AoI, IoT is the main setup that the idea of AoI came out. Therefore, we consider AoI in the context of not only for cellular IoT as in [15] but also for general.

In IoT networks, data rate considerations have taken a back seat due to several factors, including the limited resources and energy constraints of IoT devices. As a result, AoI has become a more important performance metric in IoT networks. Therefore, an overview of contemporary research in the growing field of AoI in IoT networks should be investigated.

3. AGE OF INFORMATION IN INTERNET OF THINGS

3.1. Introduction

The IoT, which is the connection of physical items to the internet via sensors and wireless links, delivers life-improving solutions and improves our quality of life. It is estimated that by 2024 there will be 83 billion internet-connected IoT devices, up from 35 billion in 2020 [1]. As shown in Figure 3.1, currently the primary application areas of IoT can be identified as agriculture, health, transportation, industry, energy, smart home, smart city, and wearable objects but new application domains are also expected to emerge in the near future. Improvements in the sensor technology, energy harvesting device efficiencies, advancements in wireless energy transfer (WET), and research on low-power wireless communication all have a significant impact on this anticipated widespread adoption. In addition, monitoring the status of items, analyzing the data obtained from sensors, and developing optimal systems enhance the evergrowing demand for IoT applications.

In many wireless communication standards such as 4G and 5G, throughput, outage probability, bit error rate, packet error rate and spectral efficiency are the key performance indicators. In contrast, freshness of information is a more important performance metric the context of IoT applications due to the presence of multitude of devices most of which are required to transmit at a fixed rate or at variable but relatively lower rates than most conventional communication applications. In this regard, AoI has been proposed in [3] as a new performance measure commonly used in the literature to assess the freshness of information. AoI is defined as the elapsed time since the source node generated the most recent received status update and is quantified as the time difference between the current timestamp and the generated timestamp of the most recent received status update.

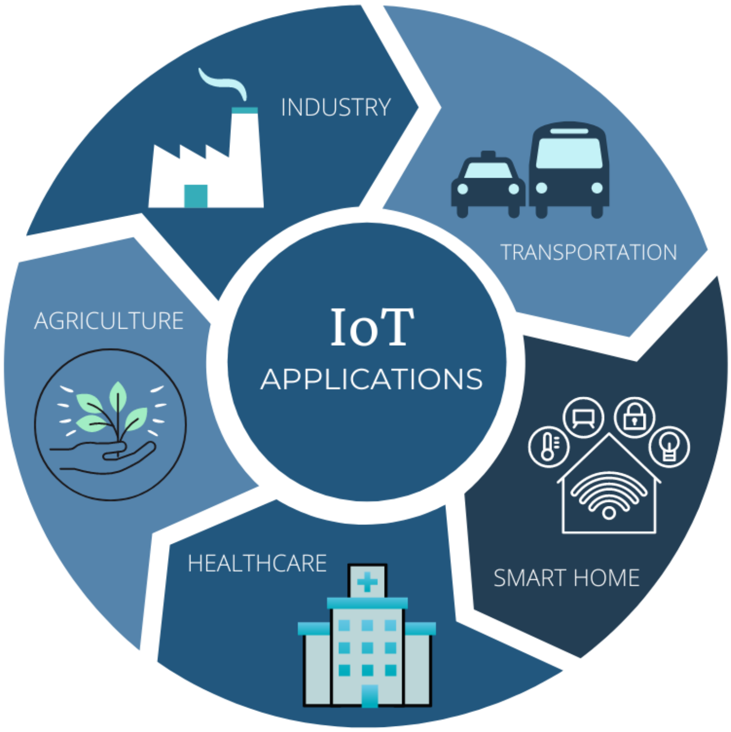

Figure 3.1. Application domains of IoT.

In time-sensitive applications such as remote surgery, for instance, the information displayed on the monitor from sensors such as temperature, blood pressure and heart rhythm must be extremely fresh and accurate. In order to avoid any risk on the human life, medical-IoT applications should be guaranteed to have real-time haptic feedback [16]. Furthermore, in time-critical IoT networks, AoI may be constrained to ensure QoS. For instance, in order to detect the forest fires before they spread, it may be essential to construct an IoT network with temperature-measuring devices which are randomly dispersed around the landscape [17]. UAVs can be used to collect and transmit data produced by these sensors. For a destination node, to identify a fire before it grows out of control, the temperature data supplied from sensors to the destination must be fresh. Therefore, the network should be constructed to maintain the AoI below a certain level, taking into account elements such as the number of sensors, number of UAVs, UAV flight path, etc. In numerous IoT applications, the sensors are battery-free since they harvest the energy required to operate [18]. Energy constraint makes it harder for sensors to frequently collect data and therefore making information freshness essential once again. In addition to the energy constraints other parameters such as the scheduling strategy, sampling frequency of the sensor, periodic and non-periodic packet sizes, pre-processing effects and the number of network hops also affect the AoI performance.

Observing the growing trend in the both the number and diversity of IoT applications in next generation wireless world and the potential role of AoI as a relevant design and optimization metric in them, this thesis presents a comprehensive overview of contemporary research works on AoI in IoT networks. Notice the literature is already rich in IoT surveys and there also have been a number of surveys on the application of AoI such as those given in [14] [15], [19]. [14], being the first ever survey on AoI presents an overview for AoI in low-latency cyber-physical systems where the emphasis is more on the use of different AoI metrics and less on specific applications such as IoT. Moreover, only works published up to and including 2020 have been considered whereas most of the advances especially in the IoT domain has taken place since then. AoI in cellular IoT has been reviewed in [15] where the challenges of achieving real-time updates over wireless fading channels are explored and a survey of optimization methods is presented with a novel prediction-based scheme. A recent survey of AoI in IoT networks is given in [19] where the main focus has been the large-scale networks specifically in the context of ambient intelligence (AmI) and IoT systems. Among many factors which have an impact of AoI, the emphasis has mostly been on the queuing policies, scheduling and multiple access strategies. Within this background, this chapter aims to provide an overview of contemporary works in this important and growing field within a broader view on not only the factors affecting the network performance such as the energy constraints, network architectures (single vs. multiple source, single vs. multiple hops, etc.), packet formatting, pre-processing, scheduling strategies, but also the range of IoT applications where AoI may be applicable. We also present optimization methods and design strategies for various IoT network structures which include both the traditional optimization formulations and solutions and also the design approaches based on machine learning techniques.

The rest of this paper is organized as follows: Section 3.2 presents the overall architecture of the various IoT networks and their components. The significance of the AoI in IoT is highlighted in Section 3.3 by considering AoI analysis and AoI aware design in IoT. There are different parameters which need to be optimized leading to joint optimization problems in IoT networks such as AoI-energy trade-off, AoI optimization for multi-hop networks, AoI optimization under correlated information and the effect of pre-processing which are investigated in Section 3.4. Learning-based AoI optimization and learning-based trajectory optimization for data collection to minimize AoI are discussed in Section 3.5. Section 3.6 discusses both sampling optimization and scheduling optimization considering different setups, for instance, decentralized IoT networks. Experimental and application-based works are discussed in Section 3.7. Section 3.8 presents the modified definitions of AoI, such as age of changed information and age of processing, which we collectively refer them as AoX. Open problems and final remarks are given in Sections 3.9.

3.2. Internet of Things

IoT is a system in which physical objects can collect data using smart sensors and transmit the gathered information to another device or the cloud via a wireless network. Identification, sensing, communication, computation, services and semantics are the six fundamental elements for IoT functionality as described in [20]. Even though there are numerous IoT applications, this chapter focuses on the most commonly used ones in the literature: satellite-based IoT (S-IoT), Industrial IoT (IIoT), cellular IoT, UAV-assisted IoT, green IoT (GIoT), ultra-dense IoT, massive IoT, cognitive radio-based IoT (CR-IoT) which are illustrated in Figure 3.2.

In addition to the previously mentioned IoT network types, the importance of the time-sensitive IoT networks, which caters to the data delivery needs of individuals, businesses and public institutions within a specified time duration with the required reliability, should be emphasized. Majority of the use cases, which include but not limited to industrial control for manufacturing jet engines, remote control in mining, remote bus driving, augmented reality, and smart harbor, etc., can be classified as shown in Figure 3.3. In addition, numerous real-world examples may well be provided such as i) multimedia IoT networks collecting data from sensors located at traffic lights, vehicles, and traffic cameras in order to perform vehicle accident prediction in near-real time (e.g., within 30 ms) [21, 22], ii) distributed measurement systems for time, mission, or safety-critical data traffic for Industry 4.0 [23, 24], iii) web front-ends of distributed systems which have quite common temporal requirements across different domains [25], and iv) healthcare event predictions and warnings for timely intervention [26, 27]. According to [28], the current Wi-Fi equipment cannot meet the stringent latency and reliability requirements of time-sensitive Industry 4.0 applications. Consequently, next-generation Wi-Fi technologies and how they can be leveraged to enable various time-sensitive Industry 4.0 use cases, including wireless industrial automation control, remote rendering in extended reality applications, and cooperative simultaneous localization and mapping using autonomous mobile robots in a manufacturing plant, have been presented in the same work. The significance of time-sensitive IoT applications cannot be overstated.

Figure 3.2. Types of IoT systems.

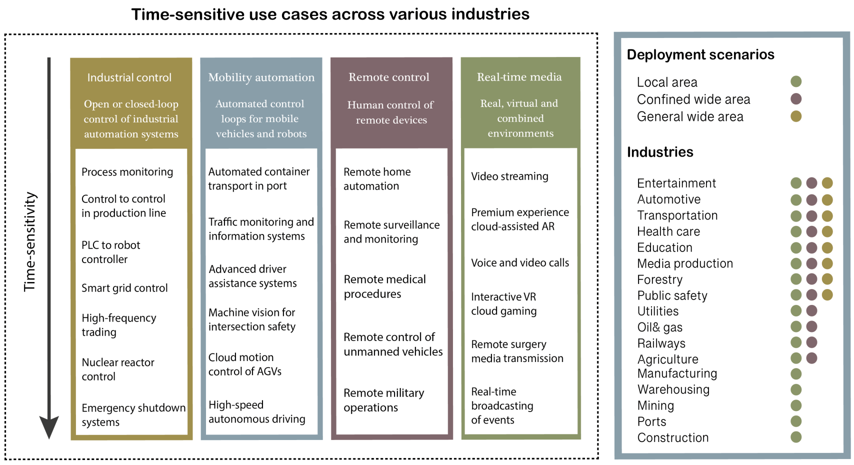

Figure 3.3. Examples of use cases enabled by time-sensitive IoT.

In some IoT applications, the sensors are dispersed throughout a vast geographical area that can encompass forests, oceans and even aircrafts. In such systems, a network with a broader coverage area is required as opposed to local networks. Owing to their pervasive coverage, satellites could be a viable option from this perspective. In order to connect the sensors of a flying item to the Internet, for example, we must construct a S-IoT network, which is commonly referenced in literature such as [29]. On the other hand, local IoT applications can be integrated into S-IoT networks. The S-IoT network is comprised of machine-type devices (MTDs), satellites, an IoT gateway, and a control panel according to [1]. MTDs transmit sensor data to a nearby IoT satellite. In some cases, a group of MTDs send their data to a local IoT gateway that is in communication with the satellite. After satellites transmit data gathered from MTDs to a central satellite, the central one collects and transmits data to the control panel. Moreover, when information is to be transferred from the control panel to MTDs, data is sent from the control panel to the central satellite, from the central one to others, and from satellites to MTDs directly via the IoT gateway.

The evolution of the industry has necessitated monitoring the condition of machines and their components and optimizing the production line in order to maximize productivity. Changes in temperature, humidity, pressure, location, or vibration, for instance, may have a direct impact on the production line, making sensor-based machine management essential. In this sense, IIoT is frequently used to differentiate such applications from general IoT and this concept is considered in a large number of IoT applications such as the one given in [30]. In [31], a three-tier IIoT system architecture is shown, consisting of an edge, platform, and enterprise tier. The edge tier collects data from edge nodes and transfers it to the edge gateway. Edge gateways transmit data to the service platform, which manages data analysis and operations. The third step, the enterprise layer, provides end-user interfaces.

The fact that end devices are energy-constrained and there may be no direct LOS between the IoT device and the IoT gateway is one of the greatest obstacles in IoT networks. In many IoT applications, sensors are battery-free and feature energy-harvesting tags. In such situations, one or more relays are utilized to improve communication between the end device and the IoT gateway. Relays are advantageous not just due to the energy constraints of the end devices, but also to minimize base station overload. In a cellular IoT network, for example, clustered IoT end devices transfer data to a relay, which forwards it to the IoT gateway. The authors of [32] categorized relays according to their functionalities: amplify and forward (AF), decode and forward (FD), and compress and forward (CF). The IoT device's signal is amplified and sent through an AF-type relay. In a DF-type relay, the received signal is decoded before the message is re-encoded and transmitted. A CF-type relay compresses decoded messages, then re-encodes and sends the compressed messages. It should be noted that CF-type relays require a longer processing time than DF-type relays, which has a direct impact on the freshness of information provided by IoT devices. In [33] and [34], the freshness of information in relay-based IoT applications is evaluated. In addition, as the number of relays in a multi-hop IoT network increases, the freshness of the information is diminished as explained in [35]. In [36], the freshness of information in multi-hop wireless networks is optimized.

Relays can be fixed or mobile. For instance, gateways can be used as fixed relay in a cellular IoT network, whereas drones can be used as a mobile relay. In UAV-aided IoT networks, UAVs are usually employed as relays thanks to their high mobility. UAVs follow a path and collect data from sensors and transfer the collected data to a central monitor. From this perspective, data collection and trajectory optimization for UAVs are investigated to increase information freshness in some works such as [37].

GIoT, referring to the reduction of the greenhouse effect by decreasing energy consumption and boosting the efficiency of IoT applications, is investigated in [38]. Ultra-dense type IoT networks, which are considered in [39], are defined in [40] as the number of cells exceeding the number of active users and denseness is measured as more than 10^3 cells/km^2. Massive IoT, defined in [41] as a large number of interconnected items that produce machine-to-machine (M2M) communication, is investigated in works such as [42].

Cognitive radio technology enables devices to dynamically detect available radio frequencies in the surrounding environment and use them for communication. As the number of IoT devices continues to increase, it is becoming difficult and expensive to assign a spectrum band to each device. The authors of [43] state that spectrum sensing and spectrum sharing may be integrated into IoT networks using the CR-IoT system discussed in many studies such as [44].

3.3. AoI in IoT

As discussed earlier, AoI is a commonly encountered and widely used performance metric in IoT networks, particularly in the time-sensitive applications. In this regard, while an overwhelming majority of the literature is dedicated to works involving AoI optimization, there also works dealing with AoI differently. For instance, some research works focus on the impact of system parameters on AoI which requires the theoretical analysis and derivation of closed-form expressions for it, while some others consider AoI as an additional constraint (instead of having as an objective function) within the system design. In this section we present an overview of works which fall into these two categories before presenting works dealing with AoI optimization in the next section.

3.3.1. Performance Analysis for AoI in IoT Networks

In the literature, several research works have focused on conducting theoretical analyses and deriving closed-form expressions for AoI. These investigations aim to showcase and quantify the influence of various system parameters on the freshness of data within IoT networks. In [45], the interaction between device-to-device (D2D) communications and real-time monitoring systems in a cellular IoT network is analyzed, with the locations of IoT devices treated as a bipolar Poisson point process (PPP). The authors characterize the performance of D2D communications based on the average network throughput, whereas the performance of real-time applications is measured by the AoI, given that IoT devices employ a distance-proportional fractional power control scheme when sending status updates to their serving base stations (BSs). In this approach, IoT devices located beyond a specified distance from BSs cannot provide status updates to the serving BS. The work characterizes the spatial moments of the temporal mean AoI of a given status update link, as its transmission success rate is a function of the interference field observed by its receiver. Thus, [45] provides effective design principles for future huge IoT networks that jointly support D2D and cellular real-time applications.

In [46], a random access-based IoT network with periodic status updates is considered, in which IoT devices broadcast their updates to an access point utilizing state-dependent slotted Aloha access. An analytical approach is proposed for deriving the average and peak AoIs and system throughput and the ideal update interval for IoT devices are examined based on the minimization of the average AoI.

The uplink of an IoT network in which a number of sensors broadcast update packets to a BS has been examined in [47]. By establishing a discrete time Markov Chain (MC), the authors examine the effects of the packet arrival rate, number of sensors in the network, and queue length of each node in order to forecast the AoI levels and packet loss probabilities in the network. According to results, the AoI is proportional to the queue length, the number of nodes, and the system's arrival rate.

In [48], a dense IoT monitoring network is presented in which IoT devices broadcast updates to their respective receivers over noisy channels employing a carrier sense multiple access (CSMA) scheme. According to various feedback instances, such as perfect feedback, no feedback and different policies, such as entering an inactive state or continuing to transmit, closed-form expressions of the average AoI of devices are provided. The authors of this paper demonstrate that preemption in service always reduces the average AoI of a device relative to when preemption is not present. To evaluate the asymptotic performance of a system with an infinite number of devices, a mean-field approximation approach is utilized, and the impacts of system characteristics on the average AoI are characterized.

The authors in [49] propose a mobile-edge computing (MEC)-assisted IoT system in which UAVs serve as MEC servers. Using a Markov chain, performance of data collection in terms of packet loss rate and data amount is evaluated. The computation frequency of a UAV is designed to account for energy and AoI constraints where IoT devices adopt first-come–first-served (FCFS) principle and M/M/1 queuing.

3.3.2. Design Issues under AoI Constraints

In time-sensitive IoT applications, AoI may not always be considered as the primary objective function of a minimization problem but instead used as an upper-bound constraint to ensure data freshness. This subsection is devoted to the review of works which falls under this category. To start with, for example, the optimal arrival rate is analyzed under average and peak AoI constraints in [50] where the optimal arrival rate is demonstrated to converge to the half of the service rate. To prevent congestion and delay in IoT networks, edge caching is an effective way to store data close to nodes in case of a requirement. However, the cached data must be kept fresh so that outdated data is not transmitted to network devices. A model-driven cache management system that is implemented by a cache-enabled edge proxy to reduce the amount of exchanged messages and meet AoI criteria is proposed in [51] to retain the freshness of cached data without causing congestion due to updates.

The objective of [52] is to minimize the time average cost of sampling and transmitting status updates over wireless channels with average AoI constraints. Solving a Lyapunov optimization problem, the authors provide an optimal method in terms of time average cost, which is proven by simulations, for deciding whether to sample a new packet, transmit the old packet, or keep silent.

An information freshness-guaranteed and energy-efficient data generation control system (IFE-DGCS) is designed in [53]. During the design phase, the probability of energy outages is minimized while the AoI is maintained below a specified threshold. The optimization problem is formulated by a constrained Markov decision process (MDP) and the optimal stochastic policy is derived by linear programming (LP). The comparison to typical energy-oriented systems reveals that a comparable energy outage probability behavior is achieved while ensuring a significantly reduced AoI in the network. Similar to [53], the authors of [54] investigate an IoT network aimed for joint optimization of AoI and energy efficiency, in which sensors transmit information updates to a central node situated on a mobile platform in an agricultural field. Using a modified nearest neighbor method and a data clustering strategy, an ideal trajectory for the mobile platform is proposed in order to improve the overall energy efficiency while maintaining the target AoI level and outage probability.

In [55] a scenario in which wireless sensors continuously collect and send environmental data to a centralized controller node is examined. As a goal, the mean, variance, and higher-order statistics of the network's energy consumption are minimized, subject to constraints on the probability of AoI threshold violations. Using results from the extreme value theory, the extreme AoI staleness is characterized and a distributed power allocation strategy is proposed.

Similar to [50], in [56], the violation likelihoods of AoI and peak AoI in IoT systems are described when a sensor transmits updates to a monitor assuming M/M/1 and M/D/1 queues with a first-come–first-served policy. In the same work, closed-form expressions are provided for peak AoI distribution in the network and violation probability for any AoI constraint. In addition, the optimal generation rate of the status update that leads to the lowest probability of violation is given.

The authors in [57] design and analyze an age-oriented random access for massive IoT networks by developing a new age-dependent random access (ADRA) protocol with a stationary threshold. In this protocol, each IoT device can only access the channel with a specific probability if its instantaneous AoI exceeds a pre-defined threshold. The authors then examine the proposed protocol's average AoI. Another random access scheme in which AoI has been considered can be found in [58]. The authors evaluate the average AoI of an uplink IoT monitoring network by considering a SIC-aided age-independent random access (AIRA-SIC) scheme, where the access point performs SIC with the intention of recovering collisions of multiple packets that are simultaneously transmitted by different devices in a slotted ALOHA manner. Based on the AoI levels of the devices, the authors demonstrate through simulations that the proposed AIRA-SIC outperforms the ADRA presented in [57].

In [59], AoI is considered in industrial IoT systems owing to its utility in the control and communication co-design to improve control performance in the event of a communication interruption which is illustrated in Figure 3.4. The authors create a control cost metric and consider average AoI under the assumption that packet loss occurs in a network with finite retransmission durations. The authors also establish that the optimal joint horizon cost is bounded by a linear function of AoI by merging energy consumption and control cost into a joint cost.

Joint optimization of the average cost of sampling and status update transmission subject to average AoI is considered in [60], where transmission errors may occur and a scheduling policy must determine whether a user must sample a new packet or resample in order to repeat a failed transmission. One of the analyzed scheduling strategies is dynamic, while the other two are stationary and random. Simulations demonstrate the significance of broadcasting an older packet in order to reduce the total average cost.

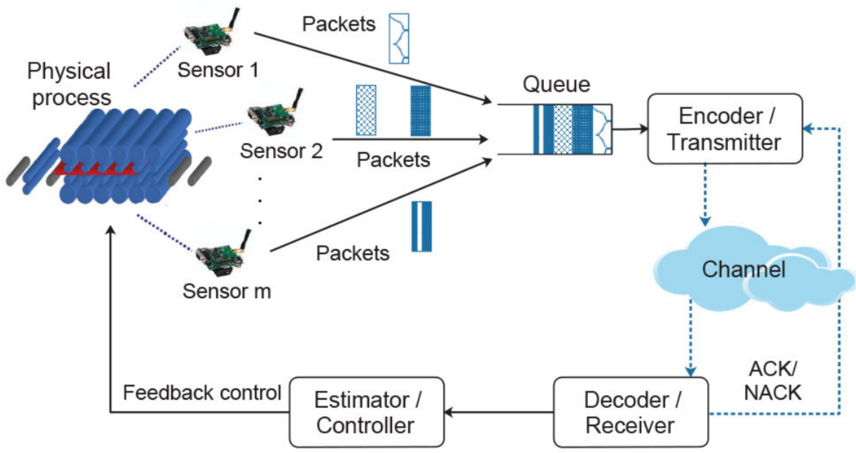

Figure 3.4. An example of system architecture for IIoT [59], © 2020 IEEE.

Unmanned surface vehicles are considered in [61] in the content of coordinated monitoring of the marine environment. AoI is used to characterize the effects of packet loss and transmission delay on the state estimate error of the maritime IoT system, as transmission performance such as packet loss and sensor data freshness play an essential role in the estimation of the system. To alleviate the impact of limited resources and path loss in the examined case, a mother ship-assisted cooperative transmission system is utilized. Then the position of the mothership, the channel allocation, and the transmit power are jointly optimized.

3.4. AoI Optimization in IoT

Optimizing AoI in IoT networks is critical because it affects the freshness and reliability of data. Minimizing AoI ensures up-to-date information for real-time applications, making IoT networks more responsive and effective. Therefore, the majority of the works in AoI literature is dedicated to the AoI optimization problems. In this section, we try to review works on AoI optimization where the different use case scenarios are formulated within a contrained optimization framework. In this regard, the initial focus is given to the AoI-energy tradeoff, followed by an exploration of the complexities involved when multiple information sources contribute to a single status update. Optimization in the context of correlated data is then discussed, along with considerations for multi-hop and relaying networks. Lastly, the impact of pre-processing on AoI is evaluated. Notice that AoI optimization is a wide area of research spanning a large body of applications and involving many different metrics and solution methodologies. An exciting and growing line of work is the solution of large scale AoI optimization problems using machine learning/deep learning methods. It is also worth mentioning that scheduling and sampling strategies used in the IoT networks have a huge impact on any AoI optimization routine. For clarity of presentation we omit these two important areas in this section and refer the reader to the two subsequent sections, namely sections 3.5 and 3.6, for the reviews of learning-based methods and scheduling/sampling issues for AoI optimization, respectively.

3.4.1. Joint Optimization of AoI and Energy Efficiency

AoI-energy tradeoff constitutes a key challenge in contemporary IoT networks, which represents a balancing act of maintaining minimal AoI while simultaneously regulating the energy consumption for sustainable operation. Especially in terrestrial IoT and S-IoT networks, incentive schemes and retransmission mechanisms are investigated with various optimization approaches such as particle swarm optimization and dynamic power control strategy.

In [62], a multi-node wireless powered communication network is considered in which IoT devices harvest energy from various selfish wireless nodes (WNs) and then use this energy to transmit real-time status updates to a hybrid access point (HAP). To combat the WNs' selfishness, energy-incentive scheme and price-incentive plan are proposed. AoI-energy utility-based optimization problem is established and closed-form expressions are derived to find the optimal solution for the first problem. Then, a Stackelberg game is built to maximize the AoI-price utility function and semi-closed-form expressions are derived to determine the optimal solution for the latter task. Superiority of the proposed systems are demonstrated numerically comparing to the benchmark scheme in terms of network utility. Furthermore, the effect of the distance between WNs and IoT devices, as well as the distance between HAP and IoT devices are also investigated.

In [63], an IoT monitoring system is investigated, in which an IoT device observes a physical process and delivers arbitrarily generated status updates to its associated access point (AP) via a wireless error-prone channel, which results in packet loss for status updates. The authors employ the truncated automatic repeat request (TARQ) mechanism because it is presumed that there is no feedback from the AP to the IoT device. The TARQ system requires IoT devices to repeatedly transmit status updates until a new physical process is detected or the maximum transmission time limit is achieved. After deriving closed-form expressions of the average AoI, the average peak AoI, and the average energy consumption, the average AoI is minimized by jointly optimizing the transmit power of the IoT device and maximum allowable transmission times under a constraint on the average transmit power. Simulations reveal that the employed TARQ system outperforms the conventional ARQ scheme.

A NOMA-based S-IoT network is considered in [64] in which satellites send status updates to numerous user equipments (UEs). Minimization of AoI under the long-term and short-term constraints of power and throughput is formulated. To solve the optimization problem, the authors turn it into a series of online power allocation problems using Lyapunov optimization methods. The particle swarm optimization (PSO) algorithm is proposed to find the optimal solution with linear computational complexity. The proposed algorithm outperforms the benchmark schemes in terms of AoI performance.

In [65], the dynamic power control policy for IoT networks is investigated in order to minimize the average AoI in the presence of stochastic status update arrivals. The authors assume that BS knows the age of information of the status update only when source nodes successfully transmit the packet and that BS is unaware of instantaneous channel power gains. The AoI optimal dynamic power control problem is formulated as a partially observable Markov decision process (POMDP) with continuous action space.

To reduce the weighted average AoI at the BS, the authors propose a deep recurrent deterministic policy gradient (DRDPG) based power control (DRPC) method, which outperforms the baseline approaches.

3.4.2. AoI Optimization with Multiple Sources

In order to generate a single status update, the majority of contemporary IoT systems consider the status data from a single sensor. Nonetheless, practical IoT networks may require several physical observations from many IoT sensors. This description refers to an IoT system that contains correlated devices or various information sources. Due to the fact that a status update is not generated until all multiple information has been successfully received, AoI should be evaluated for each physical observation independently in such scenarios. Moreover, multi-hop and multi-source network model is a model that defines data transmission in networks involving multiple sources and multiple hops. In this model, data packets are delivered to the destination by being carried by multiple intermediate nodes or routers. The multi-source and multi-hop network model, consisting of m independent sources, n intermediate servers, and x monitors, is shown in Figure 3.5.

The independent sources, I_1, I_2, ... , I_m, make real-time observations from the environment. These independent observations are transmitted to monitors through servers, which are referred to as S_1, S_2, ... , S_n. The probability of successful transmission from the ith source to the jth server is represented by p_{ij}. Similarly, the probability of successful transmission from the jth server to the kth monitor is represented by q_{jk}. It is generally assumed that the waiting time for a packet to be processed at a server or monitor follows an exponential distribution. Additionally, it is assumed that if an error occurs during packet transmission, NACK is sent to the sender.

The authors in [66] investigates discrete-time queueing model in multisource IoT systems with Bernoulli information packet arrivals and discrete phase-type service time distribution for all sources. For three distinct queueing disciplines, namely nonpreemptive bufferless, preemptive bufferless and nonpreemptive single buffer with replacement, the authors determine numerically the exact per-source distributions of AoI and peak AoI. The correctness of the proposed model is tested and the optimal selection of Bernoulli parameters for two IoT sources is analyzed using a numerical example.

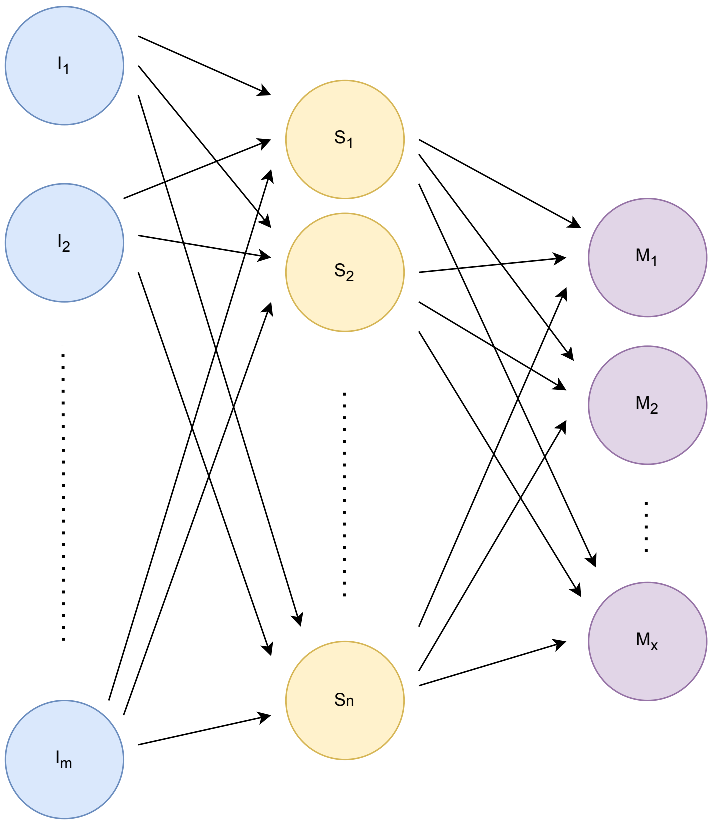

Figure 3.5. An example of network model with multiple information source.

The scenario in which multi-packet must be received successfully in order to generate a status update is considered in [67]. Learning-based strategies are examine in restless multi-armed bandits (RMAB) and a Whittle index-based scheduling policy is also presented in order to build an effective scheduling method. A new transmission policy based on erasure codes for lossy networks is proposed in order to enhance the performance of scheduling policies. In terms of AoI performance, the proposed method is found to be superior to existing baseline policies such as the naive Whittle index policy and the greedy policy regarding both lossless and lossy networks.

A similar network architecture is also studied in [68], and the authors design two optimization problems: AoI-aware multi-source information update issue (AoI-MSIU) and AoIR-aware multi-source information update problem (AoIR-MSIU). After establishing that the optimization problem is NP-hard, an efficient greedy algorithm with a guaranteed approximation ratio is proposed for the first case. For the latter case, a polynomial-time optimal maximum weight bipartite matching solution on an auxiliary graph is proposed. Simulation results of the superior performances of the proposed methods are presented.

Similarly, scheduling of IoT devices is investigated in [69] to jointly decrease the average AoI and total energy consumption in a scenario where multiple information packets are necessary for a single status update. The authors analyze two types of IoT devices: status updates of Type-I devices arrive randomly, while status updates of Type-II devices can be generated with a sampling cost upon BS's request. This problem is formulated as an infinite-horizon, average-cost MDP and show that, even if all devices are Type-II, the optimal scheduling policy is threshold-based with regard to the AoI. Simulations reveal that the proposed policy is more accurate than the myopic baseline policy.

3.4.3. AoI Optimization for Correlated Data

On the other hand, By extracting the correlated information from data, the energy consumption of IoT end devices can be decreased given certain AoI constraints, taking into account the massive data generated from thousands of IoT sensors. In [70], the authors propose a status updating policy that optimizes the sampling frequency of IoT devices and evaluate the effectiveness of the proposed policy using real data. The objective in [71] is to reduce the transmit power of sensors according to the peak AoI constraint and probabilistic constraint on queuing latency in Industrial IoT networks. The authors formulate the tail behavior of the latency as a generalized Pareto distribution (GPD) in order to address the power allocation problem via Lyapunov optimization. A combination of local model selection and federated learning is proposed, in which each sensor utilizes its own data to train the GDP model. It is concluded that the correlation-aware method presented for selecting local models in federated learning outperforms the standard methods. In addition, the authors in [72] examine the influence of the heterogeneous traffic pattern of IoT devices on AoI performance and energy efficiency in heterogeneous CR-IoT networks. After deriving the closed-form expressions for energy and AoI, an optimal transmit power optimization algorithm is proposed to maximize energy efficiency by utilizing diverse traffic patterns of IoT devices under a predefined AoI threshold constraint. Finally, benefits of the suggested approach are demonstrated numerically.

3.4.4. AoI Optimization in Multi-Hop Networks

There may be no direct link between the IoT end device and the destination node; therefore, some intermediate nodes may be utilized to route packets in multi-hop IoT networks. For this reason, AoI optimization under various constraints and rules is attracting attention in multi-hop IoT networks. In the literature, AoI optimization is considered under interference-free and general interference constraints. On the other hand, S-IoT has been particularly explored due to the significant propagation delays in multi-hop transmission.

AoI minimization under general interference constraints with R source-destination pairs is investigated in [36] where there is a graph between the R source nodes and the R destination nodes. Figure 3.6 illustrates the corresponding age propagation over nodes with $R = \{r_1, r_2\}$ as a network snapshot. Simple stationary policies based on a stationary probability distribution for link activation are derived. AoI, which is a function of link activation rates, is demonstrated as a convex function for a single source-destination pair. Then the optimal policy is obtained. For an R source-destination pair, the optimal policy is obtained by considering all source-destination pairs as independent single source-destination pairs. Unlike [36], in [35] interference-free multi-hop IoT networks are considered for a single source-destination pair. When packet transmission times are exponentially distributed and preemption is allowed, the authors prove that a preemptive last-generated first-served (LGFS) policy improves AoI performance more than any other causal approach. However, the authors indicate that preemptive LGFS policy may be far from optimal when modeling one of the new-better-than-used (NBU) distributions. In addition, the scenario that preemption is prohibited and packet transmission times are arbitrarily distributed is analyzed.

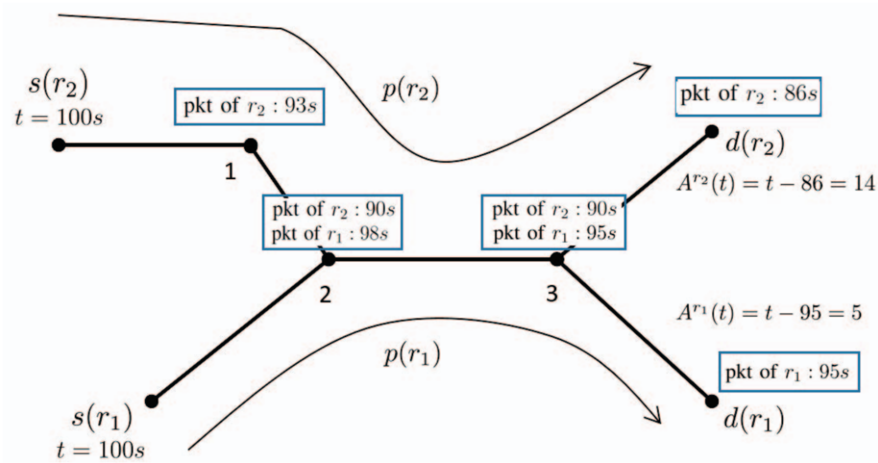

Figure 3.6. An example of multi-hop network [36], © 2017 IEEE.

Satellite-based multi-hop IoT networks are constrained by nontrivial propagation delay due to the long communication distances. Therefore, traditional automatic repeat request (ARQ) strategies have low efficiency and it is important to decide whether retransmission is beneficial for AoI or not. In [73], both simple hybrid-ARQ (HARQ) and incremental redundancy HARQ (IR-HARQ) transmission schemes are adopted and the age-optimal redundancy allocation problems under the reliability constraint are investigated. The authors first derive explicit expressions of the optimal codeword, then find the threshold of the propagation delay for beneficial retransmissions. On the other hand, a network code HARQ (NC-HARQ) transmission protocol is proposed for S-IoT in [29]. The authors derive the closed form expressions for average AoI of the proposed NC-HARQ transmission protocol by establishing a four states Markov chain. Finally, it is shown by simulation that the NC-HARQ protocol outperforms several state-of-the-art HARQ schemes in terms of average AoI. Moreover, non-ARQ, classical ARQ, truncated ARQ, and truncated hybrid ARQ with chase combining (HARQ-CC) schemes are investigated in [74] regarding the average AoI and energy consumption efficiency under fixed redundancy constraint. The authors derive the closed form expression for the average AoI and the average energy cost of each considered scheme by using the renewal processes theory. ARQ schemes are compared in terms of average AoI and average energy cost under different network parameters such as code length and SNR. The truncated HARQ-CC is shown to achieve the best average AoI and the moderate average energy cost compared to other schemes.

3.4.5. AoI Optimization in Relay Networks

Due to the energy constraints on IoT end devices, relay is a widely used element in IoT networks. However, this affects the freshness of information depending the operation performed. In [34], AoI is considered as a QoS metric in relay-based IoT networks where IoT gadgets provide a variety of services, including CCTV monitoring and video applications. Utilizing AoI, object location and service relevance measures, the authors cluster IoT objects and propose an algorithm to improve network mobility performance.

Decode-and-forward (DF) type relaying in an intelligent IoT monitoring system in which relay modes can be either half-duplex (HD) or full-duplex (FD) is considered in [33]. Minimization of AoI for two distinct relaying modes in the context of finite block length is examined. To minimize average AoI, the average AoI with optimal block lengths in two phases is approximated for the HD-DF type relaying, whereas for FD-DF type relaying, an iterative algorithm is proposed. Finally, the efficacy of the proposed methods is validated numerically.

3.4.6. Effect of Preprocessing on AoI Optimization

In context-aware real-time IoT applications, the raw data should be preprocessed to optimize the use of wireless spectrum and to provide end users with context-aware services. Computing-enabled IoT networks represent these applications in the literature. In this context, researchers have investigated packet combination, packet length optimization, and compression techniques to enhance AoI performance. Additionally, there is a growing focus on jointly optimizing preprocessing and re-transmission policies, particularly in dense IoT monitoring scenarios.

Peak AoI is considered in [75] as a freshness metric in computing-enabled IoT networks with numerous sensors. Closed-form expressions for the average PAoI are obtained, then computation and transmission are characterized as tandem queues. To minimize the average PAoI, a derivative-free approach that determines the optimal frequency of status updates is employed.

Instead of broadcasting separately, the sink node can recreate a single transmission packet by merging packets from many IoT sensors. This allows for the elimination of unnecessary information, such as headers, and the improvement of transmission efficiency. This system is considered in [76] for two distinct data gathering modes, namely periodic request and proactive request. After deriving the AoI, the authors propose a low-complexity scheduling algorithm to minimize instant AoI and numerically demonstrate the efficiency of the packet combination for minimizing AoI.

In [30], a wireless networked control system (WNCS) is considered in I-IoT networks in which the transmission packet length is adaptively adjusted to optimize reliability and AoI performance. A novel WNCS is proposed and a decision problem is formulated. The optimal variable-length packet-transmission policy for cost minimization is then presented and a sufficient and necessary condition for the existence of the optimal policy is derived.

In [39], a computing-enabled dense IoT monitoring system with CSMA scheme is considered, in which a large number of IoT devices may preprocess the raw sensor data. Two policies are considered: the preprocess-then-sense (PtS) policy and the preprocess-while-sensing (PwS) policy. For the former approach, each IoT device begins sensing the channel when preprocessing is complete, whereas for the later policy, preprocessing and sensing are performed simultaneously. The authors derive closed-form expressions of the average AoI for both policies and propose a mean-field approximation framework for the large population regime. Employing extensive simulations, the accuracy of the proposed approximation is demonstrated under policy PtS.

In [77], the joint design of the preprocessing and transmission is considered to minimize the weighted total of the average AoI and energy consumption of the IoT device. Due to the nonuniform durations of transmission and computation, the problem is formulated as an infinite-horizon, average-cost, semi-Markov decision process (SMDP). The authors then transform the problem into a discrete-time Markov decision process and show that a policy based on thresholds is the optimal solution. In conclusion, simulations reveal that preprocessing is successful for high AoI regimes and that the proposed approach outperforms two baseline policies.

In [78], time-consuming and computationally intensive preprocessing effect is considered in edge-assisted IoT devices with energy harvesting tags in order to minimize the average AoI within an energy cost budget. Due to the stochastic nature of the energy harvesting process and the energy budget constraint, the authors propose a Lyapunov-based average AoI minimization (LAoIM) algorithm to approximate an optimal solution and also deduce how distant the approximate solution is from the optimal one. Extensive simulations show that the proposed algorithm outperforms existing schemes. The authors in [79] assume that there is no energy budget constraint and aim to minimize average AoI and total energy consumption by proposing a joint preprocessing and transmission policy. The problem is formulated as an average cost SMDP before transforming it into a discrete-time MDP. The optimal solution is proven to be threshold-based policy. A low-complexity relative policy iteration algorithm is proposed for determining the optimal policy of the SMDP. The authors conclude by simulations that the proposed policy outperforms two baseline policies.

The authors in [80] investigate a novel online compression technique that eliminates the tradeoff between AoI and compression ratio by considering an instantly decodable variant. Using both predefined and dynamically generated dictionaries at the source nodes, techniques for enhancing AoI and compression performance are proposed. Using real-world datasets, it is demonstrated that the proposed method improves AoI (by up to a factor of 2.3) and compression ratio (by up to an order of magnitude) in comparison to DEFLATE and Lempel–Ziv–Welch (LZW).

3.5. Learning Based Methods for AoI Optimization

In dense IoT networks, the number of IoT end devices is high. Therefore, most of the problems such as scheduling and path optimization are NP-hard and non-convex. Finding globally optimal solutions is difficult. In recent years, machine learning algorithms have been widely used to optimize such problems such as deep Q-network and deep reinforcement learning (DRL). In this section, we will present works that use machine learning algorithms to optimize AoI in IoT networks. In the first subsection, works considering reinforcement learning for AoI optimization are examined, while in the second subsection, works considering AoI as a cost metric and perform trajectory optimization with learning-based methods are examined for the data collection models.

3.5.1. AoI Optimization with Reinforcement Learning

The authors in [81] address dynamic status update problem to balance the information freshness experienced by users and energy consumed by the sensor in caching-enabled real-time IoT networks. In order to solve this problem, a MDP is formulated and a model-free reinforcement learning algorithm is proposed. Finally, the convergence of the proposed algorithm and its efficacy are demonstrated by simulations comparing to the zero-wait baseline policy.

In [82], a multi-device computing-enabled IoT system with a common destination is considered. In this system, an IoT end device can either offload the computation of the status update to the destination node or send the computed status update to the destination. To minimize the average weighted sum of AoI and energy consumption, the design of offloading and scheduling policies is considered jointly. The optimization problem as a bilevel discrete-time MDP is formulated and the optimal solution is approximated by relative value iteration. The authors develop a DRL policy to reduce the dimensionality caused by the expansion of the system's scale; simulation results show that the proposed DRL policy is close to optimal.

Table 3.1. Comparison of learning-based AoI optimization works.

Paper	**Proposed Method**	**Algorithm**	**Objective**
[81]	Model free RL	Zero-wait baseline policy	AoI-energy consumption in caching-enabled IoT
[82]	DRL	MDP policy	Offloading in multi-device computing-enabled IoT
[83]	RL	Greedy policy	VNF scheduling
[84]	Distributed RL	Deep Q-network, Uniform sampling policy	AoI and sampling policy
[85]	DRL	5 baseline policies	AoI and energy consumption
[86]	Q-learning	Several baseline policies	AoI and energy consumption
[87]	Deep Q-network with Tabular R-learning	5 fundamental DRL algorithms and policies	AoI and energy consumption
[88]	Low-complexity online algorithm	Greedy policy, Max-Ratio policy	Under noisy channel
[89]	DRL	-	Autonomous maintenance
[90]	RL	-	Under dynamic channel access attacks

Virtual network functions (VNFs) provide service providers with the flexibility to deliver a particular network service. However, VNF scheduling is an NP-hard problem, and traditional methods for finding an optimal solution are too complex. Recently, deep reinforcement learning has emerged as a viable solution for such problems. In [83], both single agent RL and multi-agent DRL are utilized to optimize VNF cost and AoI in terms of network resources under QoS constraints in delay-sensitive Industrial IoT. Simulation results indicate that a single-agent solution is superior to a greedy algorithm in terms of AoI and network cost. In addition, the authors state that a multi-agent DRL design in which agents cooperate significantly reduces the average cost despite requiring more iterations.

In [84], minimizing the weighted sum of AoI and total energy consumption of IoT devices is aimed in real-time IoT systems. In the considered model, each IoT device samples the physical observation at a cost of some energy under nonlinear real-time dynamics and transmits data to a BS. However, wireless resource limitations compel BS to select a subset of IoT devices for transmission, resulting in an increase in the monitoring time for physical observations. From this perspective, it is essential to jointly optimize the device selection procedure at the BS and sampling policy of each IoT device to reduce total energy consumption and AoI. The authors propose distributed reinforcement learning for the AoI and sampling policy optimization, in which end devices discover optimal sampling frequency in collaboration. Using simulations on real pollution data, it is demonstrated that the proposed strategy outperforms a conventional deep Q network method and a uniform sampling policy in terms of the weighted sum of AoI and energy consumption.

The primary objective of [85] is to identify the best status update control mechanism on the edge node in order to reduce the average long-term cost of AoI and energy consumption. In this model, energy harvesting sensors measure a physical observation and transmit the data to a wireless edge node that serves as a gateway between sensors and users. Due to storage limitations, the edge node only stores the majority of received data. The edge node either sends a request to sensors to update its status or transmits the data already stored in the storage. Therefore, the edge node control mechanism faces a trade-off between energy consumption and AoI. The authors propose a deep reinforcement learning algorithm to find the optimal control policy without knowledge of the sensor's energy levels. The authors in [86] also consider that when the status is updated, edge nodes are aware of the battery levels of the sensors. The problem is modeled as a MDP, and a Q-learning algorithm to minimize the average AoI is proposed. Simulations show that a threshold-based policy is optimal and the proposed reinforcement learning algorithm significantly reduces the average cost compared to several baseline methods.

A similar network model is considered in [87]. where a MDP is formulated and a dueling deep R-network based dynamic status update algorithm is designed by combining a deep Q-network with tabular R-learning. The effectiveness of the proposed algorithm is validated by comparing it to five fundamental deep reinforcement learning algorithms and policies.

The authors of [88] examine a scenario in which edge nodes sample the status using multiple packets and transmit it to the destination node over a noisy channel. Low-complexity online algorithms are proposed and simulation results demonstrate that the Lyapunov drift policy outperforms the Greedy policy and the max-ratio policy.

In [89], the autonomous maintenance problem in IoT networks is formulated as a partially observable MDP. The authors numerically show that the utilized deep reinforcement learning algorithm is effective for training intelligent agents to determine whether or not maintenance is required.

The authors in [90] aim to minimize AoI in multi-channel IoT networks under dynamic channel access attacks (DCAAs). The distributed channel access problem is then formulated, and a reinforcement learning algorithm is implemented based on the theoretical outcomes of game theory. A utility maximization problem for each sensor node's average AoI is formulated under DCAAs with probabilistic ACK feedback. The problem is then converted to two ordinary potential game (OPG) models, and a distributed learning algorithm is proposed to reach Nash equilibrium (NE). Lastly, the efficacy of the proposed algorithm is validated by simulating with various variables. Table 3.1 shows a simple summary of learning-based approaches for AoI optimization.

3.5.2. AoI-based Trajectory Optimization for Data Collection

Owing to their adaptability and low deployment cost, UAVs are expected to play a crucial role in the collection of data from widely dispersed ground sensors over vast areas. In general, UAV-assisted IoT networks are considered, in which battery-limited UAVs are expected to collect physical observations captured by ground sensors and wirelessly transmit data to a monitoring station. Due to the energy constraints of ground nodes, a sensor is unable to transmit its physical observations unless a UAV is in close proximity to its region. Figure 3.7 illustrates the significance of the UAV's flight path. In order to minimize the weighted sum of AoI, [91] considers the joint optimization of scheduling policy on ground nodes and flight trajectory of the UAV under battery constraints. The problem is formulated as a MDP with finite state and action spaces and a finite horizon. Due to the high dimensionality of the state space, an age-optimal policy-finding algorithm based on DRL is proposed. Different from [91], pre-trained deep neural network is used to accelerate the learning process in [37].

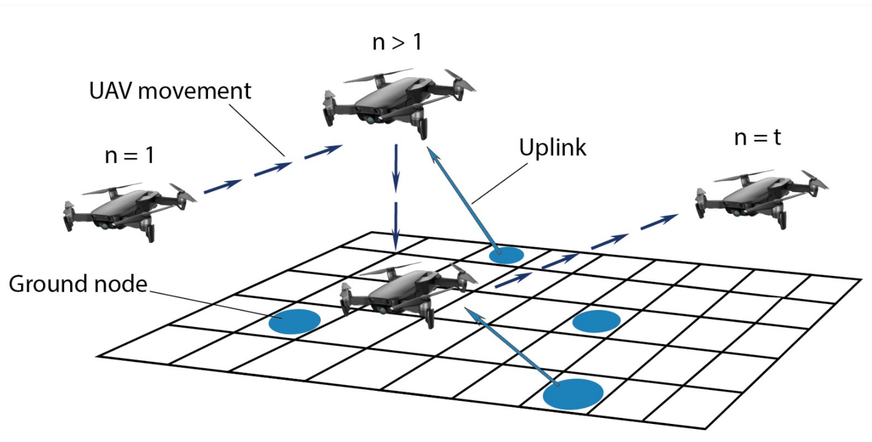

Figure 3.7. An example of UAV data collection model.

In [92], the flight trajectory of an energy-constrained UAV is optimized using a deep reinforcement learning method to decrease the average AoI at ground sensor nodes (SNs) while maintaining the lowest possible packet drop rate. A sample-and-replace policy refers to SNs that sample observations with a defined or random frequency and cache the sampled packet updates. The researchers define the data gathering problem as an MDP with finite state and action spaces and a finite horizon. Simulations demonstrate that the proposed technique outperforms the benchmark greedy strategy.

The same network architecture for UAV-assisted data collection and path planning is considered in IoT networks [93]. A dynamic programming approach is presented to optimize the UAV path planning and data acquisition problem by jointly considering the average AoI, sensor energy consumption, and sampling mode selection. Simulations reveal that the proposed method is competitive compared to the traditional flying time-optimal strategy.

In [94], a UAV-assisted wireless powered IoT system is explored, where it is assumed that the time required for sensors' energy harvesting (EH) from UAVs is nonlinear due to the nonlinear behavior of the EH circuit. The authors jointly optimize the UAV's trajectory, harvesting time, and data collection procedure at each sensor in order to minimize the average AoI of the data collected from all sensors. This nonconvex problem is divided into two subproblems: a combined energy transfer and time allocation for data acquisition problem and a UAV path planning problem. After showing the convexity of the first problem, Karush-Kuhn-Tucker (KKT) conditions are employed to identify the optimal solution, which serves as an input for the second subproblem. Simulation results reveal that DP outperforms ant colony heuristic algorithms in the solution of the defined problem.

The goal of [95] is to minimize the weighted sum of average AoI, energy required from UAVs and transmission energy at sensors and to this end, UAV flight speed, altitude of UAV and bandwidth allocation policy for data collection are jointly considered. The problem is modeled as a MDP. Twin-delayed deep deterministic (TD3) policy gradient-based UAV path planning algorithm is proposed via deep neural network. Simulations demonstrate that the proposed technique outperforms the deep Q-network and actor–critic-based algorithms. The authors in [96] assume that UAVs can update the sampling policy of IoT devices. On the other hand, UAV stores all past IoT device experience. A new algorithm is presented for lifetime reinforcement learning that utilizes these accumulated experiences. Simulations reveal that the proposed algorithm can converge more quickly than a baseline gradient algorithm. Table 3.2 summarizes the methods which are used for trajectory optimization in UAV-assisted IoT networks.

Table 3.2. Methods to optimize UAVs trajectory.

Deep Reinforcement Learning	[91], [92]
Dynamic Programming	[93], [94]
Gradient-based Neural Network	[37], [95]
Lifetime Reinforcement Learning	[96]

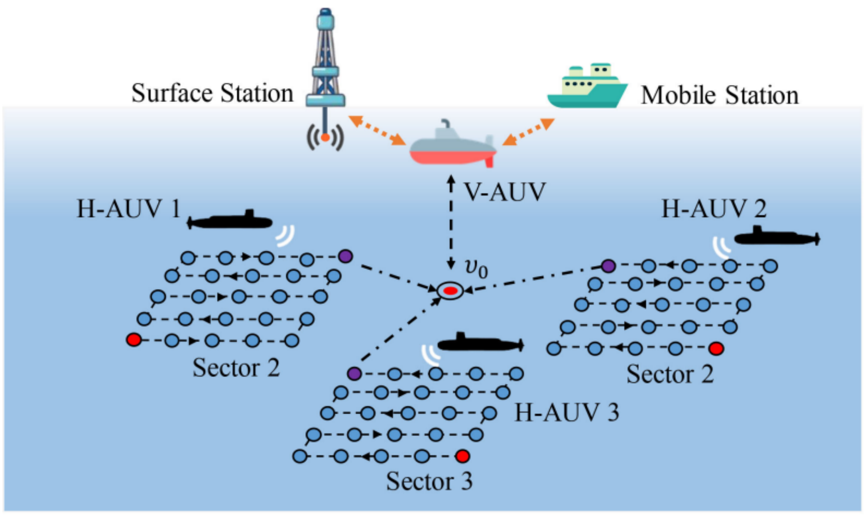

Figure 3.8. An example of AUV-assisted data collection model [97], © 2021 IEEE.

Different from the previous studies, data collecting in the ocean using autonomous underwater vehicles (AUVs), which is modelled in Figure 3.8 and proposed in [97]. Due to the vast area and large-scale deployment cost of sensor nodes in the Internet of underwater things (IoUT), heterogeneous multi-AUV-assisted underwater data collection is modeled to optimize the peak AoI under time-varying underwater environment, energy and mobility constraints of AUV. In addition, the process of information exchange is modeled using the limited service M/G/1 vacation queueing model. The authors also provide a low-complexity adaptive algorithm for adjusting the upper limit of the queueing length. Simulations demonstrate that the proposed strategy is superior to conventional methods for minimizing peak AoI.

3.6. Scheduling and Sampling Issues for AoI in IoT

One of the important research areas on AoI is designing schedulers to minimize AoI for information sources in a given network. The network may consist of a single-link, multi-link and may be cellular or a multi-hop network. Sophisticated design of a scheduler to minimize AoI is crucial as it must address the requirements on AoI metric depending on the criteria of the applications. To this end, we consider the works addressing the scheduling problem in IoT networks in this section.

3.6.1. Scheduling Optimization

Scheduling plays a crucial role in AoI optimization, determining when and how data updates are transmitted. Effective scheduling algorithms are required to reduce information staleness and optimize network performance while considering dynamic network conditions, varying data arrival patterns, energy constraints, and diverse application needs.

The authors of [98] consider a scenario in which several terminals share a single channel for transmitting or receiving status update packets. The scheduling is modeled as a restless multi-armed bandit problem inspiring from and exploiting the Whittle's index policy to incorporate stochastic packet arrivals, a decentralized status updating technique is proposed that provides universally near-optimal AoI performance.

To enable devices to share limited communication resources, [99] proposes centralized and distributed resource allocation techniques. The transmissions are intended to be completed in a timely manner, with AoI capturing the measurement of timeliness. Adopting nonlinear aging functions that are reliant on device type and message content, as opposed to the majority of previous works, implies the inherent heterogeneity of the network. Trying to achieve a high data rate in the network may result in congestion, hence diminishing the update's freshness at the monitoring device. On the other hand, a low data rate probably results in degraded freshness due to the increasing arrival periods between status updates. In [100], a novel transport layer protocol is proposed to handle such a trade-off. The aforementioned protocol adjusts the update data rate to reduce the average AoI of updates at the monitor. In [101], a dynamic IoT network is considered and a distributed scheduling technique is proposed to optimize the AoI in the network. Unlike majority of the previous works, the authors in [102] focus on devices where typically support monitoring applications. Due to the computational limitations of such devices, simple first-in-first-out (FIFO) queueing discipline is presumed. Consideration is given to the problem of optimal status update generation when a source consisting of a FIFO queue serves two applications, one of which is sensitive to AoI and the other of which is not.

In [103], a UAV-assisted IoT network is considered where, IoT devices periodically sample a stochastic process and transmit updates to a base station. Due to their limited powers, IoT devices may require intermediary nodes to forward update packets to BS. Considering this fact, UAVs with virtual queues are deployed as intermediary nodes between IoT devices and the BS in order to transmit information updates over unreliable channels. In the absence of channel conditions, the optimal online scheduling method is examined with the purpose of minimizing the expected weighted sum AoI for IoT devices. In a similar work [104], various scheduling policies for AoI minimization in two-hop UAV-relayed IoT networks are presented and compared. Maximum AoI first (MAF) policy for sampling of IoT devices at UAV (hop 1) and maximum AoI difference (MAD) policy for updating sampled packets from UAV to the BS (hop 2) outperform the others in terms of scaling to larger networks.

3.6.2. Impact of Varying Packet Size on Scheduling

Due to the dynamic nature of real-world physical processes, the sizes of status updates are typically not constant, resulting in varying sizes and consequently varying numbers of transmission slots for distinct updates. Therefore, there is a need for AoI optimization that take such facts into consideration. In [105], multi-time slot transmissions with non-uniform sizes of the status updates are considered as in a realistic scenario and the problem of joint device scheduling and status sampling is investigated with the objective of minimizing the average AoI at the destination. Similarly, an AoI-aware scheduling scheme for sensors is proposed to send status updates to cloud data center-based caches in [106].

In [107], heterogeneous sampling behaviors among source nodes with varying sample size and transmission slots are considered, and theoretical results for AoI are obtained. In addition, a near-optimal scheduling algorithm with low-complexity is proposed to minimize the AoI.

The impact of stochastic arrivals on the peak AoI of NOMA-based IoT networks is investigated in [108] where the authors propose a method for determining the queue service rate and derive the analytical expression for the distribution of peak AoI. In this scheme, NOMA outperforms OMA standard in terms of network average peak AoI.

The multicast transmission of an access point to multiple IoT devices is examined in [109], where a deadline is enforced for the service time of each multicast status update, and the update is dropped when the deadline is reached. The authors evaluate the timeliness of status updates in this multicast scheme and show that enforcing deadlines reduces the network's average and peak AoI.

3.6.3. Sampling Optimization

Sampling rate in IoT is crucial for AoI optimization, reducing AoI with higher rates due to more frequent updates. However, this comes with increased sensor energy consumption, affecting overall efficiency. Striking the right balance between AoI reduction and energy usage is vital for sustainable IoT deployment. Optimization of sampling techniques, such as sleep mode selection and retransmission enhancements, is actively investigated to enhance data collection efficiency while conserving energy resources especially in Industrial IoT networks. Optimization problems under energy constraints, RF-powered wireless energy transfer, and signaling overhead are also considered.

A typical industrial IoT application where multiple sensors monitor time-varying physical processes and send the information packets to a central BS through unreliable channels is given in [110]. Contrast to other approaches, each sensor may switch to sleep mode to save energy. For the setup, the authors formulate an AoI penalty minimization problem to schedule sensors' transmissions. After establishing a theoretically necessary condition for AoI penalty to converge to a finite value, a maximum weight based scheduling strategy is developed and its optimality is proved for symmetric networks with error-free channels.

The primary goal of [111] is to covertly collect data from sensors in order to evade enemies. Retransmission is employed on the transmitter side to improve AoI in the event of a failed packet transmission, hence increasing the likelihood of adversary detection. A time-restricted retransmission policy is proposed to exploit the AoI security trade-off, as longer retransmission durations enhance the system's susceptibility.

In [112], the authors consider the joint status sampling and updating problem in which IoT devices sample a physical process with a sampling cost and deliver the samples to a particular destination with an updating cost. The objective is to minimize the average AoI subject to an average energy cost constraint at each device. An online learning method that may be implemented locally on each IoT device and converges almost surely is proposed. Similar research can be found in [113], which investigates the optimal online sampling strategy that minimizes the average AoI when the source node is considered to be powered by wireless energy transfer from the destination. The difference between age-optimal and throughput-optimal approaches is derived analytically.

In [114], an RF-powered source sends status updates to a destination node and the main goal is to minimize the average AoI at the destination subject to time and energy costs of generating status updates at the source.

Since blockchain is a promising technology for ensuring the transparency, reliability and traceability of networked information exchange, its usage has extended beyond cryptocurrencies. In [115], the sampling rate optimization problem is solved for IoT sensors which employ blockchain and tangle technologies for their transmission, with the aim of minimizing AoI experienced by end-users susceptible to processing and networking resources.

In [116], the authors investigate the optimal sampling policy which jointly optimizes wireless energy transfer and scheduling of status updates with the objective of minimizing the weighted sum-AoI in an environment in which IoT sensors sense potentially different physical processes and update a destination node via status updates.

In [117], randomly generated status updates are transmitted to a destination node over an unreliable link with the goal of minimizing the average AoI subject to limited average transmission power at the source. In [118], the primary objective is to obtain a scheduling policy with minimal AoI and minimal signaling exchange overhead and the optimal policy is shown to be a round-robin policy with the most recent packet, while the others are dropped; the optimality of this policy is proven using a generalized Poisson-arrival-see-time-average theorem.

3.7. Experimental and Application based Works

Finding a parking spot during rush hour in a congested city is challenging. The problem is that information regarding available parking places is not always readily accessible. IoT and advanced data analytics have paved the way for smart parking solutions to handle the problem of detecting available parking spaces in cities and garages. A smart parking IoT application utilizes data from IoT devices to recommend an available parking space in the vicinity of the target location. According to [119], 21.4% of parking sensors generate data that is several hours old in real-world conditions. In a case study of a smart parking IoT application, it is demonstrated that an age of data (AoD) model may be used by the application to generate AoD-aware recommendations. A parking data set analysis from the real life is also presented to demonstrate the applicability of the proposed method.

In [120], the AoI behavior on experimental implementations of packet flows between IoT nodes and via the Internet, including the IoT access link, and end-to-end UDP and TCP flows is explored from the standpoint of computer applications. Practical considerations are examined such as synchronization and hardware selection, as well as the transport protocol and its effect on AoI. The findings shed light on application and transport layer techniques that can be used to optimize AoI in actual networks.

As a result of recent improvements in blockchain technology, there has been a rise in interest in blockchain-based application development. The values stored in a blockchain can be withdrawn or altered while the data remains intact. It is not always clear whether the discovered data from the blockchain storage is relevant for blockchain-based applications' real-time decision-making processes. Consequently, the issue of data freshness is crucial, particularly in dynamic networks that process data in real time. According to [121], transactions to refresh data require additional processing time within the blockchain network, which is known as ledger-commitment delay. Therefore, some users may receive obsolete information. Since it is critical to determine if blockchain technology is suitable for supplying real-time data services, the authors of [121] define the AoI of blockchain-enabled networks and explore the factors that affect the AoI.

In [122], a system in which external requests for status updates of a remote source are received and monitored by an EH sensor is considered. Based on a probabilistic approach, an external request for a status update may be satisfied by retrieving either a freshly generated update from an EH sensor or a previously cached update from an aggregator. The average AoI is calculated as a function of several system characteristics, and the findings reveal how the energy delivery procedure and the status updating rule affect the system's information freshness.

In [123], a novel strategy for reducing storage costs known as generalized deduplication (GD) was proposed. Recently, this method has been extended to provide distributed, multisource lossless compression in sensor networks, hence lowering the total number of bits transferred. Considering the scenario in which one source node receives one symbol/sample per unit time and transmits bits to the sink node, the authors demonstrate how GD can provide instant decoding of data, thereby reducing the average age, and demonstrate that the proposed solution reduces the AoI by 25% for the standard version and 36% for the instantly decodable version when using real-world data sets.

3.8. AoX in IoT

Researchers have introduced novel metrics in the exploration of AoI in IoT, such as age upon decisions (AuD), age of changed Information (AoCI), age of processing (AoP), and spatially temporally correlated mutual Information (STI). These metrics address different aspects of data freshness and processing in IoT systems. Additionally, CVaR is proposed for risk-aware AoI minimization in real-time IoT applications. Coage of Information (CoI) considers the maximum AoI of constituent IoT devices, leading to CoI-aware policies for data transmissions. These advancements offer valuable tools for optimizing IoT systems and decision making processes. AuD is proposed which represents the time difference between the timestamp of the usage of last received information to make a decision (e.g., estimations, inferences, and controls) and the timestamp of its generation in [124] and [125], respectively. In these works, an IoT network based on the premise is considered, in which sensor updates have exponential service times and FCFS discipline. Scheduling schemes that adjusts the status update and decision-making process are proposed in order to improve the timeliness of updates at decision epochs. Three key theoretical results are demonstrated. The first is that the average AuD is minimized when the arrival process is periodic and the decision process is Poisson. The second result is that the average AuD is greater when both the choice process and the arrival procedure are periodic. Finally, by adjusting the offset between the two periodic processes, the average AuD can be minimized when both processes are periodic. Periodic arrival and random decision are suggested for the use in actual IoT systems.

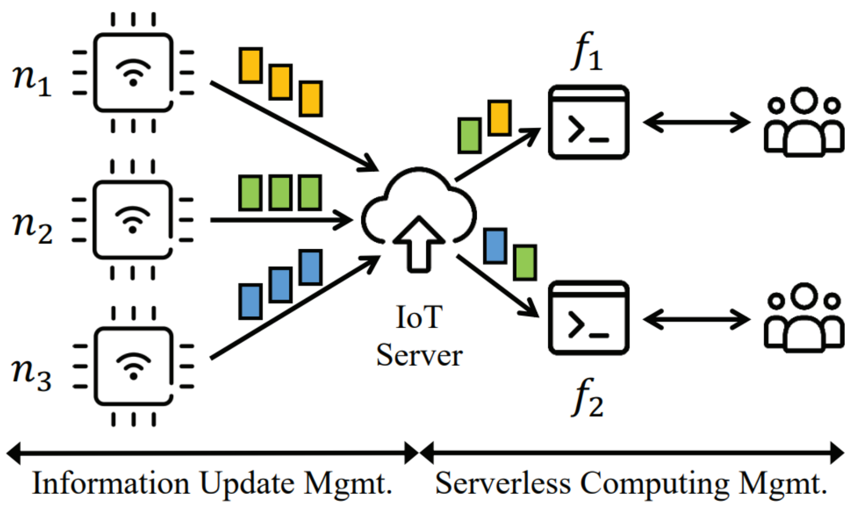

Figure 3.9. An IoT system with three IoT devices and two serverless functions [126], © 2021 IEEE.

In [126], minimization of the weighted sum of AoS of serverless services is considered for the problem of information update delivery and acquisition (IUDA) in IoT networks. The model consists of a set N of IoT devices and the execution of a set F of serverless functions is illustrated in Figure 3.9. An offline scheduling approach is proposed after the occurrences of serverless function arrivals are known. In addition, the authors analyze the scenario in which there is no knowledge regarding the arrival of serverless functions and propose an online algorithm. Simulations reveal that the proposed algorithms outperform baseline solutions regarding the AoS performance. In [127], the authors criticize the minimization of AoI's expected value due to its risk-neutral behavior. CVaR is proposed for the minimization of AoI in real-time IoT and an optimal status update mechanism is designed by jointly considering the AoI, the

CVaR of the AoI, and the energy cost. Using dynamic programming, the optimal stationary policy is proposed after reducing the risk-aware MDP to a standard MDP.

AoCI is a novel metric defined in [128] that takes into account both the freshness over time and freshness over changed content. The authors model the process as a discrete time Markov chain and formulate an infinite horizon average cost MDP in order to minimize the weighted sum of the AoCI and update cost. The optimal policy under a variety of circumstances are investigated and closed-form expressions are derived for the optimal solution.

In intelligent IoT applications such as video surveillance, the status update is generated after computation-intensive data processing. The authors in [129] define a novel metric, AoP, to account for these time-consuming processing activities, which influence the freshness of the status. The procedure is illustrated in Figure 3.10.

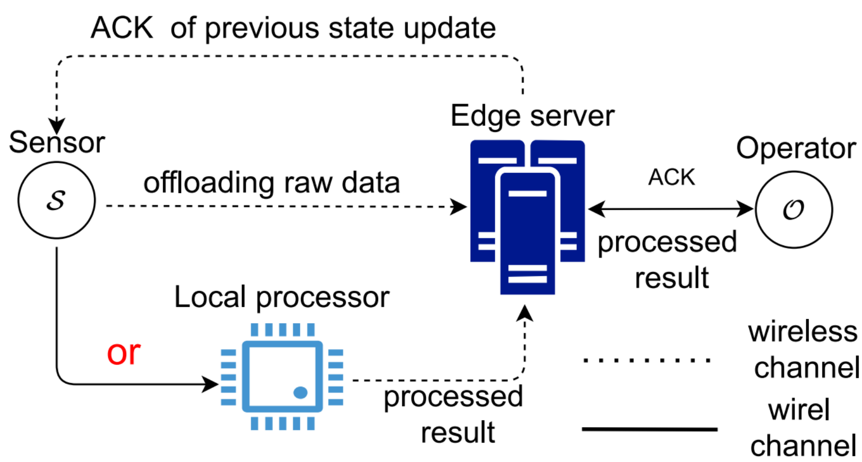

Figure 3.10. An example of status sampling and processing procedure [129], © 2021 IEEE.

The authors of [130] propose a novel metric, STI, by considering the correlation between the current status and the most recent update message. After formulating the problem as an MDP with potentially infinite state space, a policy is proposed to periodically update in order to maximize the average STI in satellite-integrated

IoT networks. In conclusion, it is shown by simulations that the proposed policy outperforms both slotted ALOHA and threshold-ALOHA.

According to [131], CoI (or information cofreshness) is determined by the maximum AoI of the constituent IoT device. The authors address the problem of grant assignment and transmission scheduling (GATS) and propose the CoI-aware age block elimination (CABEL) policy to minimize a weighted sum of CoI.

3.9. Discussion

In this chapter, we first present the basics of AoI and IoT, then we present the studies in which AoI is used as a timeliness metric in various types of IoT networks. Furthermore, we investigate optimization problems, learning-based algorithms, and scheduling policies. Then, we state the application-based AoI studies. Finally, we define the term AoX which stands for some additional constraints on the freshness of timeliness.

There are interesting topics to be explored for open challenges. Firstly, several works which focus on the case in which multi-source information is needed to generate a single status update. On the other hand, multi-hop networks are considered in many works with graph-based approaches. However, multi-hop networks is generally considered that a single piece of information is used at the destination. In other words, all studies consider a one-to-one relationship between source and destination. Therefore, the case that both considers multi-source information and multi-hop IoT networks is not studied yet.

While UAV-assisted data collection problems are usually considered for a single UAV, multi-UAV usage might be a promising solution for a large geographical area. Therefore, trajectory optimization or optimal scheduling policy for AoI and UAV's energy consumption in a multi-UAV assisted IoT network may serve as a good research direction.

In satellite-based IoT networks, there is significant propagation delay due to the long communication distances. Many transmission protocols such as non-ARQ, ARQ, and HARQ have been investigated under AoI performance. Moreover, NC-HARQ scheme has also been proposed. However, channel coding and scheduling policies for AoI optimization have not been studied yet. On the other hand, the majority of the studies consider a small set of IoT end devices which makes problems simple. Extending these studies to large-scale wireless networks, which is the more realistic scenario, might affect the optimality of the proposed schemes. On the other hand, impact of network coding and channel coding especially in multi-source and multi-hop IoT networks will also be a good research directions.

4. Impact of Network Coding on Age of Information

4.1. Introduction

The growth of digitalization and the IoT demands faster, reliable wireless communication. Time-sensitive IoT applications, like real-time surveillance and autonomous driving, require sustainable, fast and accurate data delivery, which may be expressed in short as data freshness. Ensuring the data freshness is a vital challenge due to the massive amounts of the IoT data and the time-sensitive nature of some applications. In this regard, the concept of AoI, introduced in [3], has become a crucial metric in IoT, quantifying the data timeliness from source to destination.

A comprehensive overview of contemporary research in the growing field of AoI in IoT networks, covering factors influencing network performance, diverse IoT applications, and optimization methods, including traditional and machine learning-based approaches is provided in [132]. The survey in [15] presents AoI within cellular IoT, examining the hurdles associated with achieving real-time updates over fading wireless channels. In [19], AoI works are discussed especially in the context of large-scale IoT networks. Trajectory optimization for UAV assisted IoT networks in order to minimize AoI is considered in several works such as [37, 91, 94, 133, 134]. Minimizing the AoI in NOMA-based IoT systems is investigated in [42, 64, 108]. In dense IoT networks, deep reinforcement learning is commonly used optimization methods to find globally optimal solutions because the problems involving scheduling and path optimization are NP-hard and non-convex [81–85, 87]. In [105–107], minimum AoI is analyzed for non-periodic scheduling and varying packet sizes.

In various IoT models such as cellular IoT, UAV-assisted IoT, and dense IoT, intermediate nodes are required for information to reach from the source to the destination. In these so-called multi-hop IoT networks, data does not travel directly between the source and destination, which, in turn, makes it necessary to optimize the

AoI within a multi-hop deployment scenario. For this reason, this problem, namely AoI optimization for multi-hop IoT systems, has been considered in a number of previous works such as [29,35,36,73,74]. In [36], AoI minimization in multi-hop IoT networks is considered with interference constraints for multiple source-destination pairs and stationary policies based on link activation probabilities are proposed. Interference-free multi-hop networks are explored in [35], analyzing the impact of preemptive LGFS policy on the AoI and its optimality. In the context of satellite-based networks, the age-optimal redundancy allocation problem is considered in [73] using HARQ and IR-HARQ transmission schemes. For single-hop IoT networks, [29] presents a network code HARQ (NC-HARQ) protocol that outperforms the existing HARQ schemes in terms of average AoI. Additionally, different ARQ schemes are investigated in [74], including truncated hybrid ARQ with chase combining (HARQ-CC), revealing insights into their average AoI and energy efficiency performance under varying network conditions.

Contemporary IoT systems commonly generate singular status updates based on the data from a solitary sensor. However, practical IoT networks frequently necessitate multiple data inputs from various sensors, leading to the existence of correlated devices or diverse information sources within the system. In scenarios where a status update is contingent upon the successful reception of data from all sources, it becomes imperative to assess the AoI independently for each individual physical observation. In [135], a discrete-time queueing model is considered in multisource IoT systems. In [136], both AoI-aware and AoI-reduction-aware multi-source information update problems are investigated.

In multi-hop and multi-source network model, data packets are delivered to the destination by being carried over multiple intermediate nodes or routers. In [66], the authors explore a discrete-time queueing model for multisource IoT systems, investigating AoI and peak AoI distributions for various queueing disciplines. In [67], the focus shifts to multi-packet reception scenarios, presenting a Whittle index-based scheduling policy that outperforms existing strategies. A similar network architecture is examined in [68], addressing AoI-aware multi-source information updates through efficient optimization algorithms. Additionally, joint AoI and energy consumption reduction for IoT device scheduling is considered in [69] by identifying optimal threshold-based policies where multiple information packets are necessary for a single status update.

Network coding has been introduced as one of the potential solutions to address the growing demands of networks [137]. The essence of network coding lies in aggregating incoming message packets at intermediate nodes to generate outputs for transmission. This approach offers increased efficiency and network resilience, as demonstrated in works such as [138–141]. In conventional uncoded networks, resources like intermediate nodes and routers process and transmit data packets independently. With the emergence of network coding, intermediate nodes in the network can combine multiple packets to create and transmit new ones. Utilizing the transmission of aggregated packets enhances data rates in networks by leveraging the network coding capabilities. It can also enhance network redundancy for more reliable data transmission. These advantages, however, result in an increase in computational complexity for network nodes.

In [142], the impact of network coding on AoI is investigated for a single source where the source is assumed to have a status update, which is divided into a number of packets, in order to forward to a set of monitors. Notice that the analysis is presented over direct links between the source and the monitors and multiple sources or transmission over multiple hops are not taken into account. However, in majority of the dense IoT deployments as given in [48], there are also multiple sources and multiple hops. Therefore the primary contribution of this paper is to extend the analysis methodology of [142] to a generalized IoT multicast scenario with multiple sources, multiple hops and multiple receivers and to present analytical derivations for the AoI performance with and without network coding. The specific contributions can be summarized as follows:

- The derivations of average AoIs are provided for multi-source and multi-server first stage of transmissions where the transmissions are not coded.

- The derivations of average AoIs are provided for multi-server and multi-monitor second stage of transmissions. The comparison of AoIs with and without network coding is given. For both of the transmission stages, probabilistic open expressions are given instead of closed AoI expressions due to the complexity of the network model.
- Extensive numerical experiments are conducted and are shown to corroborate the theoretical findings which demonstrate significant AoI gains offered by network coding.

The rest of this paper is organized as follows: In Section 4.2, system model and problem formulation are provided. In Section 4.3, AoI calculations are considered from simple network to general network. Moreover, theoretical results and simulation results are presented for each hop. Simulation results and commentary discussions are provided in Section 4.4. Final remarks and open problems are given in Section 4.5.

4.2. System Model

Figure 4.1 demonstrates a general multi-source and multi-hop network model consisting of sources (transmitters), servers, and monitors (receivers). Information sources I_i $(i = 1, 2, \ldots, N_t)$ make real-time observations from the environment. These independent observations are transmitted to the monitors M_k $(k = 1, 2, \ldots, N_r)$ through intermediate servers S_j $(j = 1, 2, \ldots, N_s)$ which are assumed to cooperate with each other in order to eliminate redundancy. Moreover, it is assumed that a status update is generated when all monitors receive all the packets from all information sources.

If an observation has been successfully sent to a server, only this server transfer this observation to the monitors. Thus, the power consumption due to the successful transmission of the information from a source to all servers will be prevented.

There is a transmission success probability from the i-th source to the j-th server which is denoted by p_{ij}. Moreover, waiting time for a packet transmission from the

i-th source to the j-th server follows exponential distribution with mean λ which is

$$f(t_{wait};\lambda) = \begin{cases} \lambda e^{-\lambda t_{wait}} & t_{wait} \geq 0, \\ 0 & t_{wait} < 0. \end{cases} \tag{4.1}$$

Similarly, transmission success probability from the j-th server to the k-th monitor is denoted by q_{jk} and arrival time for a successfully transmitted packet from the j-th source to monitor follows exponential distribution. In this work, success probabilities for all pairs are assumed to be identical, *i.e.*, $p_{ij} = q_{jk} = p$ for $1 \leq i \leq N_t$, $1 \leq j \leq N_s$ and $1 \leq k \leq N_r$. The transmission process from sources to monitors is assumed to occur in two stages. In the first stage, sources send their observations to the servers. In order to complete the first stage, all information must be sent successfully to one of servers. In the second stage, the servers start sending their packets to the monitors. After all the packets are transmitted successfully to the monitors, a status is updated. Then, the sources make observations and the first stage is started immediately.

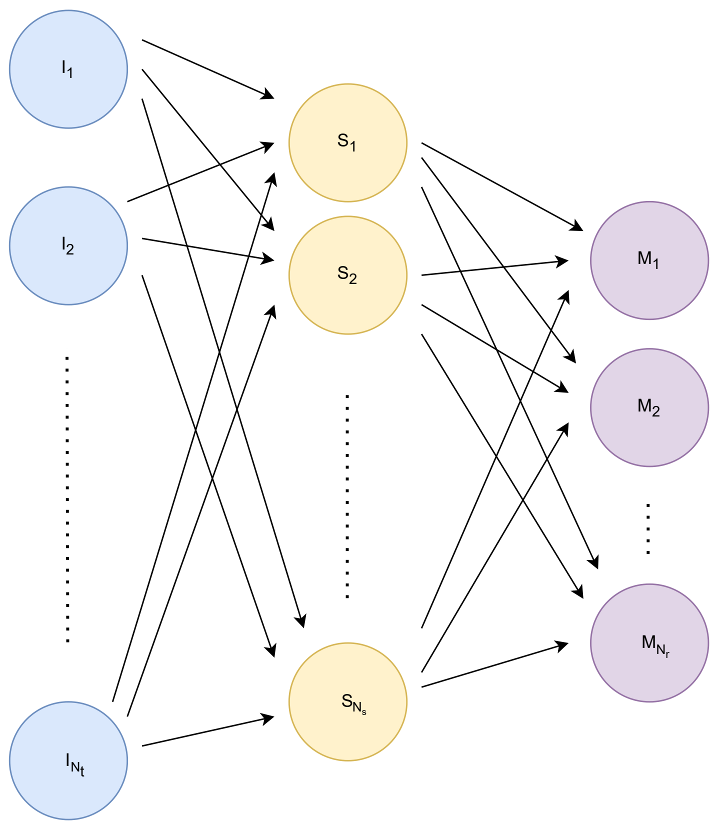

Figure 4.1. Multi-hop, multi-source network model.

A set, denoted as $P = \{p_1, p_2, \ldots, p_{N_t}\}$, is defined as the collection of all source packets. Also, the sets $P_1, P_2, \ldots, P_{N_s}$ are defined such that P_j contains the source packets that the j-th server will send to the monitor. Note that these subsets are disjoint, some of them might be empty sets and $\cup P_j = P$

For j-th server, the packets can be sent sequentially or network coded message can be sent. In this paper, we will compare linear network coded transmission to uncoded transmission in terms of AoI performance at the monitor. For the j-th server, the encoded message can be expressed as

$$E_j = \sum_{i=1}^{s_j} f_i M_i \mod q \tag{4.2}$$

where s_j is the number of packets at the j-th server, f_i is encoding coefficient for packet p_i, $M_1, M_2, \cdots, M_{s_j}$ are information packets that will be sent from the j-th server. Encoding coefficients are randomly generated as stated in [143]. To decode encoded packets, the encoding coefficient should be known at the receiver side. Therefore, the encoding coefficients are embedded at the end of the message can be expressed as

$$E = [E_j, f_1, f_2, \cdots, f_{s_j}]. \tag{4.3}$$

In order to decode message with matrix operations, at least s_j number of encoded messages should be received successfully.

For non-negative integer m where $2^m < q \leq 2^{m+1}$, elements of $\mathcal{Z}_q$ field can be represented by $m + 1$ bits. In this work, we assume that the number of bits for the packets at each information source is identical and represented by l. Moreover, the transmission rate between any node is also identical and represented by R.

When the transmission of a packet is considered to be dependent on the packet's length and transmission rate, the time it takes for packet transmission is expressed as

$$\begin{aligned} t_\tau &= \frac{l(m+1)}{R}, \\ t_\tau^{NC} &= \frac{(l+n)(m+1)}{R}, \end{aligned} \tag{4.4}$$

where n is number of packets to be encoded, t_τ and t_τ^{NC} are transmission times for the strategies uncoded and network coded, respectively. Note that the final message is longer than the original packets. However, transmission rate is assumed to be sufficiently high, therefore, the transmission time increment due to the packet combination coefficients is negligible. Moreover, computational capacities of the servers and monitors are assumed to be sufficiently high. Therefore, the computation time for encoding and decoding is also negligible. Thus, the main issue in this system model is decreasing the total number of transmission.

To compare the network coded and uncoded strategies, the average AoI is used as a performance metric and expressed as

$$\Delta = \frac{1}{T} \lim_{T \to \infty} \int_0^T \Delta(t) dt. \tag{4.5}$$

Note that the $\Delta(t)$ graph behavior appears as a sawtooth, therefore the average AoI is the middle point of the low-end and the high-end. Therefore,

$$\Delta = 3\frac{E[T_{stage_1}] + E[T_{stage_2}]}{2}. \tag{4.6}$$

4.3. AoI Analyses

It is already stated that the average AoI can be calculated by the passing time on the first and the second stages. In this section, the expected passing time for the first and second stages with and without network coding are calculated separately.

4.3.1. Transmission From Sources to Servers

To find the expected passing time for the first stage, three cases are investigated step-by-step as follows: 1) $N_t = N_s = 1$. 2) $N_t = 1$, $N_s > 1$. 3) $N_t, N_s > 1$.

4.3.1.1. $N_t = N_s = 1$. The probability of successful transmission at step k is

$$p(k) = (1 - p)^{k-1} p. \tag{4.7}$$

At step k, the total waiting time is a random variable $T = \sum_{i=1}^{k} T_i$ where $T_i \sim \text{Exp}(\lambda)$ is the waiting time at step i. Sum of k independent exponential distribution with the same parameters is known as Erlang distribution and expressed as

$$f(t; k, \lambda) = \lambda^k \frac{t^{k-1}}{(k-1)!} e^{-\lambda t} \quad t, \lambda \geq 0. \tag{4.8}$$

As a result, the probability density function (PDF) of the total waiting time follows exponential distribution which is expressed as

$$\begin{aligned} f_T(t) &= \sum_{k=1}^{\infty} p(k) f(t; k, \lambda) \\ &= \sum_{k=1}^{\infty} (1-p)^{k-1} p \lambda^k \frac{t^{k-1}}{(k-1)!} e^{-\lambda t} \\ &= p\lambda e^{-\lambda t} \sum_{k=1}^{\infty} \frac{[(1-p)\lambda t]^{k-1}}{(k-1)!}. \end{aligned} \tag{4.9}$$

The summation is the Taylor series expansion of $e^{(1-p)\lambda t}$. Then the PDF of the total waiting time is expressed as

$$f_T(t) = p\lambda e^{-\lambda t} e^{(1-p)\lambda t} = p\lambda e^{-p\lambda t}. \tag{4.10}$$

As a result, the total waiting time also follows an exponential distribution, *i.e.*, $T \sim \text{Exp}(p\lambda)$. Then, the expected waiting time is

$$E[T] = \frac{1}{p\lambda} \tag{4.11}$$

and when transmission time is included, the expected total passing time is given by

$$E[T] = \frac{1}{p}\left[\frac{1}{\lambda} + t_\tau\right]. \tag{4.12}$$

<u>4.3.1.2. $N_t = 1$, $N_s > 1$.</u> In this network model the source initiates multicast transmission of the message to all servers. The source then waits to receive an acknowledgement (ACK) or a negative acknowledgement (NACK) message from each server. If the source receives the NACK message from all servers, it restarts the multicast transmission. However, once the source receives an ACK message from any server indicating successful receipt of the packet, the source stops the multicast transmission. In this context, a random variable, denoted by T_i, is defined as the the total waiting time for the transmission from a source to all servers at the i-th try. Then, $T_i = \max(t_1, \cdots, t_j, \cdots, t_{N_s})$ where $t_j \sim \text{Exp}(\lambda)$. Then, the cumulative distribution

function (CDF) of the random variable T_i can be expressed as

$$F_{T_i}(t, N_s) = P(t \geq t_1, t \geq t_2, \cdots, t \geq t_{N_s}). \tag{4.13}$$

Moreover, the expression can be formulated as

$$F_{T_i}(t, N_s) = [F_T(t)]^{N_s}, \tag{4.14}$$

where $F_T(t) = 1 - e^{-\lambda t}$ is the CDF of the waiting time between each source and server pair. Because T_i is a non-negative random variable, the expected value of T_i can be calculated from its CDF as

$$E[T_i] = \int_0^\infty (1 - F_{T_i}(t, N_s))\, dt \; = \frac{H_{N_s}}{\lambda} \tag{4.15}$$

where $H_{N_s} = \sum_{k=1}^{N_s} \frac{1}{k}$ is the N_s-th harmonic number. Then, the expected passing time for this stage is given by

$$\begin{aligned} E[T] &= \sum_{k=1}^{\infty} p(k)k\Big[E[T_i] + t_\tau\Big] \\ &= \sum_{k=1}^{\infty} [(1-p)^{N_s}]^{k-1} k[1-(1-p)^{N_s}]\left[\frac{H_{N_s}}{\lambda} + t_\tau\right]. \end{aligned} \tag{4.16}$$

On the other hand, for $0 < x < 1$

$$\sum_{k=1}^{\infty} x^{k-1}k = \frac{d}{dx}(\sum_{k=0}^{\infty} x^k) = \frac{d}{dx}(\frac{1}{1-x}) = \frac{1}{(1-x)^2}. \tag{4.17}$$

By substituting $x = (1-p)^{N_s}$, equation (4.17) can be written as

$$\sum_{k=1}^{\infty} [(1-p)^{N_s}]^{k-1} k = \frac{1}{[1-(1-p)^{N_s}]^2}. \tag{4.18}$$

Finally, by using equation (4.18), the total expected passing time for this stage on equation (4.16) is expressed as

$$E[T] = \frac{1}{1-(1-p)^{N_s}}\left[\frac{H_{N_s}}{\lambda} + t_\tau\right]. \tag{4.19}$$

<u>4.3.1.3. $N_t, N_s > 1$.</u> For a single source and multiple server case, the CDFs of the waiting time and passing time at step i are

$$\begin{aligned} F_{T_i}(t) &= (1 - e^{-\lambda t})^{N_s} \quad t \geq 0, \\ F_{T_i}(t) &= (1 - e^{-\lambda (t - t_\tau)})^{N_s} \quad t \geq t_\tau, \end{aligned} \tag{4.20}$$

respectively. Then, the PDF of the passing time for step i is expressed as

$$f_{T_i}(t) = N_s(1 - e^{-\lambda(t-t_\tau)})^{N_s - 1} \lambda e^{-\lambda(t-t_\tau)} \quad t \geq t_\tau. \tag{4.21}$$

Considering that the process ends at step k, the total passing time for the first source can be mathematically expressed as

$$T_{I_1,k}(t,k) = T_1 + T_2 + \cdots + T_k. \tag{4.22}$$

If the process is finished at step k, the PDF of the total passing time for the first source is convolution of k independent and identically distributed (i.i.d.) random variables which can be represented as

$$f_{T_{I_1},k} = f_{T_i}(t) * f_{T_i}(t) * \cdots * f_{T_i}(t) \tag{4.23}$$

where $*$ denotes the convolution operation. The PDF of the total passing time for the first source is mathematically expressed as

$$f_{T_{I_1}}(t) = \sum_{k=1}^{\infty} p(k) f_{T_{I_1},k}(t,k) \tag{4.24}$$

where $p(k) = (1-p)^{N_s(k-1)}(1-(1-p)^{N_s})$. Equation (4.24) is valid for all sources because they are all identical with the same parameters. A new random variable for the total passing time in the first stage is defined as the maximum transmission duration among all sources, i.e., $T_{stage_1} = \max(T_{I_1}, T_{I_2}, \cdots, T_{I_{N_t}})$. The PDF of the total passing time for the first source is given as

$$f_{T_{I_1}}(t) = \sum_{k=1}^{\infty} p(k) f_{T_{I_1},k}(t,k), \tag{4.25}$$

the CDF of T_{stage_1} is expressed as

$$F_{T_{stage_1}}(t) = [F_{T_{I_1}}(t)]^{N_t}. \tag{4.26}$$

Because T_{stage_1} is a nonnegative random variable, the expected value of the total passing time for the first stage can be found as

$$E[T_{stage_1}] = \int_0^{\infty} (1 - F_{T_{stage_1}}(t))\, dt. \tag{4.27}$$

4.3.2. Uncoded Transmission From Servers to Monitors

To find the expected passing time for the second stage, two cases are investigated step-by-step as follows: 1) $N_s = 1, N_r > 1$. 2) $N_s, N_r > 1$.

4.3.2.1. $N_s = 1, N_r > 1.$ Similar to first stage, when there is a single server and the number of monitor is N_r, the CDF and PDF of the passing time at step i are given as

$$\begin{aligned} F_{T_i}(t) &= (1 - e^{-\lambda(t-t_\tau)})^{N_r} \quad t \geq t_\tau, \\ f_{T_i}(t) &= N_r(1 - e^{-\lambda(t-t_\tau)})^{N_r-1} \lambda e^{-\lambda(t-t_\tau)} \quad t \geq t_\tau, \end{aligned} \tag{4.28}$$

respectively. If the process is finished at step k, the total passing time for the first server can be expressed as

$$T_{S_1,k}(t,k) = T_1 + T_2 + \cdots + T_k. \tag{4.29}$$

The PDF of the total passing time for the first server is the convolution of k i.i.d. random variables which is expressed as

$$f_{T_{S_1},k} = f_{T_1}(t) * f_{T_1}(t) * \cdots * f_{T_1}(t). \tag{4.30}$$

If a monitor has a correct packet, then the server is in a "success state". Conversely, if a monitor has no correct packet, then the server is said to be in a "failure state". In order for all servers to be in a success state at the k-th step, there should be some monitors which are in a failure state at the $(k-1)$-th step. To finish the multicasting at the k-th step, the probability should be such that

$$\begin{aligned} p(k) &= \sum_{\alpha=1}^{N_r} \binom{N_r}{\alpha} \left[(1-p)^{k-1}\right]^{\alpha} \left[1-(1-p)^{k-1}\right]^{N_r-\alpha} p^{\alpha} \\ &= \sum_{\alpha=1}^{N_r} \binom{N_r}{\alpha} \left[(1-p)^{k-1}p\right]^{\alpha} \left[1-(1-p)^{k-1}\right]^{N_r-\alpha}. \end{aligned} \tag{4.31}$$

The PDF of the total passing time for the first server is calculated as

$$f_{T_{S_1;1}}(t) = \sum_{k=1}^{\infty} p(k) f_{T_{S_1},k}(t,k) \tag{4.32}$$

where $p(k)$ is expressed in equation (4.31).

4.3.2.2. $N_s, N_r > 1.$ The PDF of the total passing time for a single packet under a single server and multiple monitor scenario has been calculated in the subsection 4.3.2.1. Considering that the number of packets to be transmitted is s_1 for the server

S_1, the random variable for total passing time for the first server is expressed as

$$T_{S_1;1:s_1} = T_{S_1;1} + T_{S_1;2} + \cdots + T_{S_1;s_1}. \tag{4.33}$$

Because the process is independent and identical for all packet transmission, the PDF of the total waiting time for the first server and s_1 packet can be calculated by the convolution of the s_1 i.i.d. random variables, which can be expressed as

$$f_{T_{S_1;1:s_1}}(t) = f_{T_{S_1;1}}(t) * f_{T_{S_1;1}}(t) * \cdots * f_{T_{S_1;1}}(t). \tag{4.34}$$

Similar calculations can be generated for the PDF of the total passing time at server S_i, *i.e.*, $f_{T_{S_i;1:s_i}}(t)$. Then the random variable for the total passing time for a given number of packets is expressed as

$$T_{stage_2,\mathrm{UC}} = \max(T_{S_1;1:s_1}(t), \cdots, T_{S_{N_s};1:s_{N_s}}(t)). \tag{4.35}$$

Then, the CDF of the total passing time for a given number of packets is found as

$$F_{T_{\mathrm{stage}_2},\mathrm{UC};s_1,\cdots,s_{N_s}}(t) = \prod_{i=1}^{N_s} F_{T_{S_i;1:s_i}}(t). \tag{4.36}$$

The expected total passing time for a given number of packets for uncoded transmission is calculated as

$$E[T_{\mathrm{stage}_2,\mathrm{UC};s_1,\cdots,s_{N_s}}] = \int_0^\infty (1 - F_{T_{\mathrm{stage}_2},\mathrm{UC};s_1,\cdots,s_{N_s}}(t))\, dt \tag{4.37}$$

due to the fact that the random variable is non-negative. Then, the expected total passing time for the second stage can be calculated as

$$E[T_{\mathrm{stage}_2,\mathrm{UC}}] = \sum_{\sum s_i = N_t} \frac{N_t!}{\prod s_i!} \frac{1}{{N_s}^{N_s}} E[T_{\mathrm{stage}_2,\mathrm{UC};s_1,\cdots,s_{N_s}}] \tag{4.38}$$

where $i = 1, 2, \cdots, N_s$.

4.3.3. Network Coded Transmission From Servers to Monitors

Network coding changes the transmission time for a single packet due. Therefore, when there is a single server and the number of monitor is N_r, the CDF and PDF of the passing time at step i are given as

$$
\begin{aligned}
F_{T_i}(t) &= (1-e^{-\lambda(t-t_\tau^{NC})})^{N_r} \quad t \geq t_\tau^{NC}, \\
f_{T_i}(t) &= N_r(1-e^{-\lambda(t-t_\tau^{NC})})^{N_r-1}\lambda e^{-\lambda(t-t_\tau^{NC})} \quad t \geq t_\tau^{NC},
\end{aligned}
\tag{4.39}
$$

respectively.

To decode information packets successfully, at least s_1 correct packets should be received from all monitors. If a monitor receives s_1 correct packets, it is in the success state. After k steps, the probability of all monitors to be in the success state should be determined. The probability of all the monitors being in the success state in step k can be calculated as

$$
\begin{aligned}
p'(s_1,k,N_r) &= \left[\sum_{t=s_1}^{k}\binom{k}{t}p^t(1-p)^{k-t}\right]^{N_r} \\
p'(s_1,k,N_r) &= [1-F(s_1-1,k,p)]^{N_r}
\end{aligned}
\tag{4.40}
$$

where $F(\cdot)$ represents the CDF of the binomial distribution. Then, the probability of finishing the second stage at the k-th transmission can be expressed as

$$
p(s_1,k) = p'(s_1,k,N_r) - p'(s_1,k-1,N_r). \tag{4.41}
$$

The random variable for the total passing time after k steps and its PDF can be expressed mathematically as

$$
\begin{aligned}
T_{S_1,k}(t) &= T_1 + T_2 + \cdots + T_k, \\
f_{T_{S_1},k}(t) &= f_{T_1}(t) * f_{T_1}(t) * \cdots * f_{T_1}(t),
\end{aligned}
\tag{4.42}
$$

respectively. The PDF of the total passing time for the first server is given as

$$
f_{T_{S_1;1:s_1}}(t) = \sum_{k=1}^{\infty} p(s_1,k) f_{T_{S_1},k}(t). \tag{4.43}
$$

Similarly, the PDF of the total passing time for the server S_i is denoted by $f_{T_{S_i;1:s_i}}(t)$. Then the random variable for the total passing time for the second stage is given as

$$
T_{stage_2,\mathrm{NC}} = \max(T_{S_1;1:s_1}(t), \cdots, T_{S_{N_s};1:s_{N_s}}(t)), \tag{4.44}
$$

and consequently the CDF of the total passing time for second stage is expressed as

$$
F_{T_{\mathrm{stage}_2},\mathrm{NC},s_1,\cdots,s_{N_s}}(t) = \prod_{i=1}^{N_s} F_{T_{S_i;1:s_i}}(t). \tag{4.45}
$$

Due to the non-negativeness of the random variable, the expected passing time for the second stage with network coded transmission can be calculated as

$$E[T_{\text{stage}_2,\text{NC};s_1,\cdots,s_{N_s}}] = \int_0^{\infty} (1 - F_{T_{\text{stage}_2},\text{NC},s_1,\cdots,s_{N_s}}(t))\, dt. \tag{4.46}$$

As a result, the expected total passing time for the second stage is

$$E[T_{\text{stage}_2,\text{NC}}] = \sum_{\sum s_i = N_t} \frac{N_t!}{\prod s_i!} \frac{1}{{N_s}^{N_s}} E[T_{\text{stage}_2,\text{NC};s_1,\cdots,s_{N_s}}] \tag{4.47}$$

where $i = 1, 2, \cdots, N_s$.

4.4. Numerical Results

Monte Carlo simulations have been conducted to observe the average AoI performance. The expected waiting time for each packet is chosen as $\frac{1}{\lambda} = 1$ s. The success probability for each packet is chosen as $p = \frac{1}{3}$, the length of each packet is defined as $l = 50$, the number of bits for each message is chosen as $m + 1 = 8$ bits, the transmission rate is established as $R = 10^6$ bps, and the number of monitors is configured as $N_r = 3$.

4.4.1. Transmission From Sources to Servers

Figs. 4.2 and 4.3 illustrate that the simulation results and theoretical calculations for the transmission from sources to servers match perfectly. The increment in the number of sources or servers leads to an extended elapsed time due to the greater number of transmission pairs.

4.4.2. Uncoded Transmission From Servers to Monitors

Figs. 4.4 and 4.5 illustrate that the simulation results and theoretical calculations for uncoded transmission from servers to monitors match perfectly. The increase in the number of sources, as expected, increases the elapsed time, while the increase in the number of servers reduces the elapsed time.

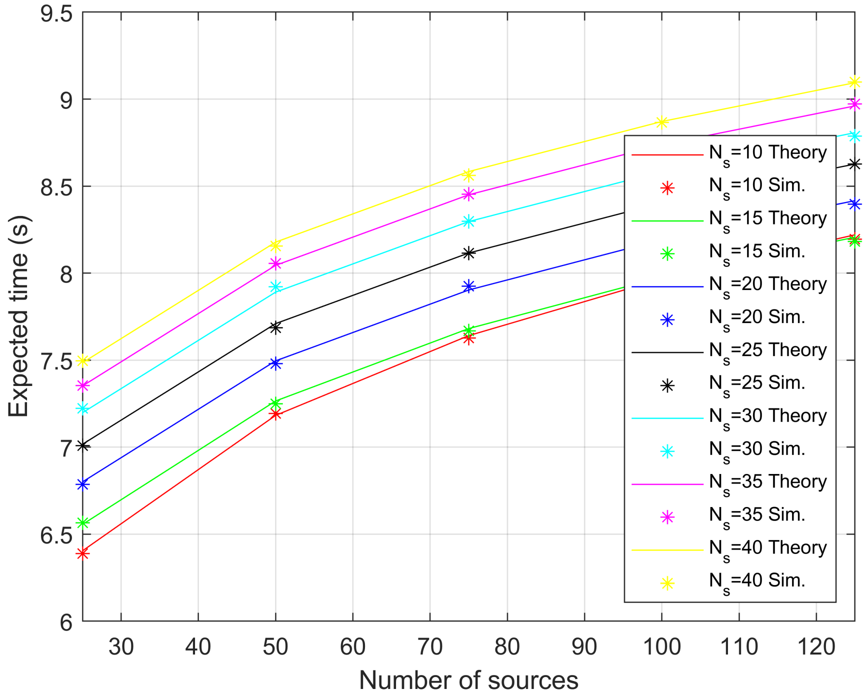

Figure 4.2. Number of sources vs. expected passing time for the first stage.

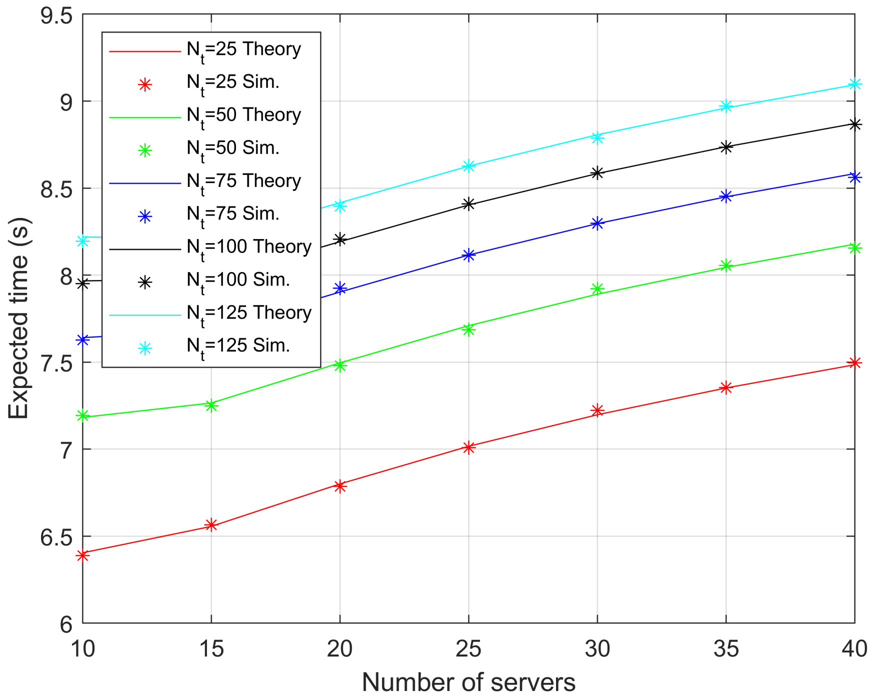

Figure 4.3. Number of servers vs. expected passing time for the first stage.

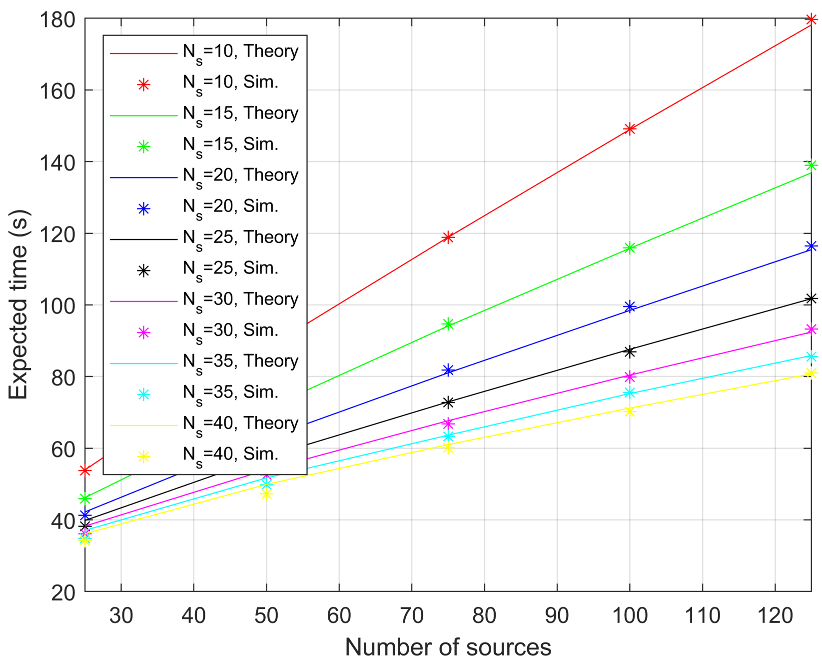

Figure 4.4. Number of sources vs. expected passing time with uncoded transmission for the second stage.

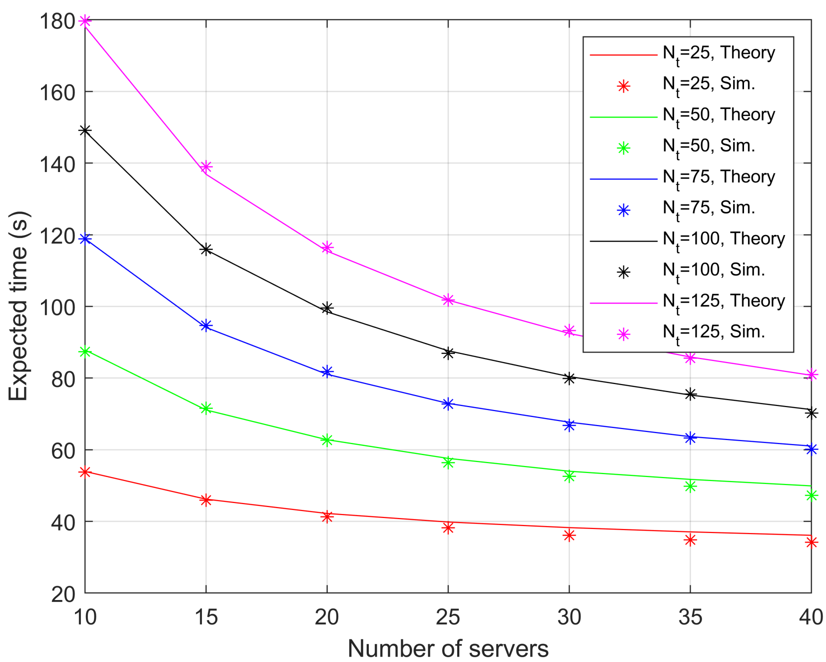

Figure 4.5. Number of servers vs. expected passing time with uncoded transmission for the second stage.

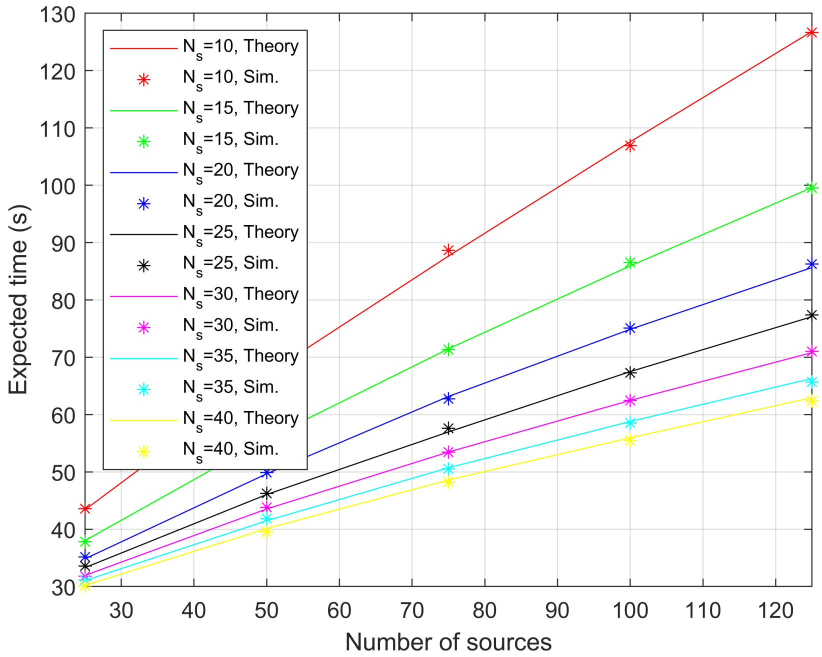

Figure 4.6. Number of sources vs. expected passing time with network coded transmission for the second stage.

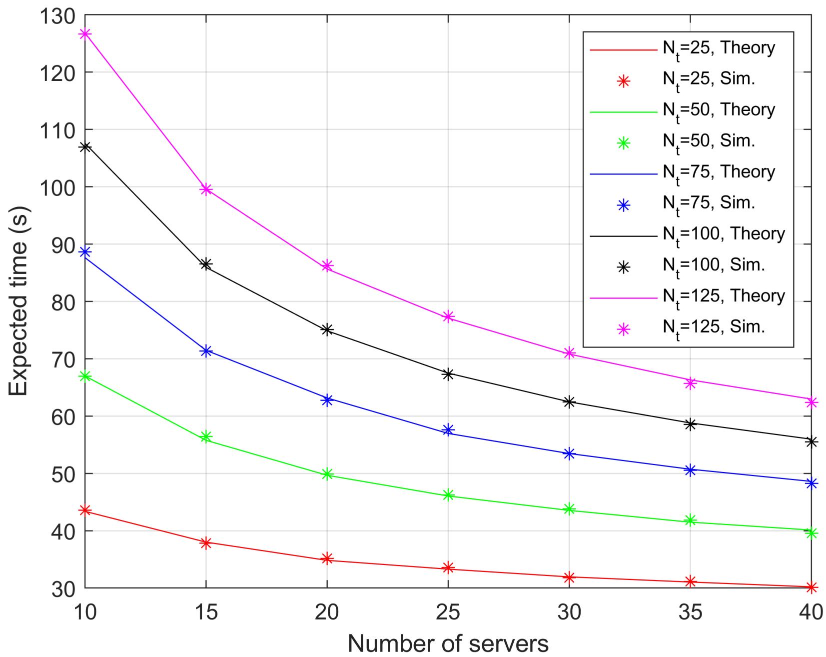

Figure 4.7. Number of servers vs. expected passing time with network coded transmission for the second stage.

4.4.3. Network Coded Transmission From Servers to Monitors

Figs. 4.6 and 4.7 illustrate that the simulation results and theoretical calculations for network coded transmission from servers to monitors match perfectly. Similar to uncoded transmission, an increase in the number of sources increases elapsed time, whereas an increase in the number of servers reduces elapsed time.

4.4.4. Numerical Results for Overall Network

In Figure 4.8, the average AoI measurement is provided for uncoded and network coded cases with respect to number of sources (N_t) for $N_s = 10, 15, \ldots, 40$. First, there is an approximately linear relationship between N_t and average AoI. For small values of N_t , the effect of network coding is limitted. For instance, when $N_s = 10$ and $N_t = 25$, network coding reduces the AoI measurement from 90.52 seconds to 74.69 seconds which is approximately 18%. When $N_s = 10$ and $N_t = 125$, network coding reduces the AoI measurement from 279.59 seconds to 202.61 seconds which is approximately 28%.

In Figure 4.9, the average AoI measurement is provided for uncoded and network coded cases with respect to number of servers (N_s) for $N_t = 25, 50, \ldots 125$. When the number of servers increases, the average number of packets per server decreases, leading to a reduction in the average AoI. For small values of N_s, the impact of network coding is more noticeable. For instance, when $N_s = 10$ and $N_t = 100$, network coding reduces the AoI measurement from 235.40 seconds to 173.34 seconds which is approximately 26%. When $N_s = 40$ and $N_t = 100$, network coding reduces the AoI measurement from 120.11 to 97.26 which is approximately 19%. Moreover, while increasing the number of servers had a serious impact at first, its effect on AoI performance decreased in the later stages. To provide a more insightful interpretation of the results, it is crucial to examine the ratio between the average AoI in network coded transmission and uncoded transmission which is denoted as Δ_{NC}/Δ_{UC}. Figure 4.10 illustrates how network coded transmission improves AoI performance compared to the uncoded transmission for varying values of the number of sources. Network coded transmission significantly improves performance when there are a larger number of sources. Conversely, when the number of sources is low, the improvement in AoI performance is smaller. The primary reason for this lies in the fact that when there are fewer sources, the number of packets delivered to the servers is less. Then, the probability of being able to encode and transmit packets becomes smaller. Conversely, when there is an abundance of sources, a higher number of packets are delivered to each servers. Therefore, the impact of network coding becomes more pronounced. Figure 4.11 shows how the ratio Δ_{NC}/Δ_{UC} varies with changes in the number of servers. As expected, with an increase in the number of servers, the number of packets per server decreases, resulting in a limited impact of network coding. For example, when there are 100 sources and 10 servers in use, network coding has improved the AoI performance by approximately 26%. However, when 40 servers are used, network coding has improved the AoI performance by approximately 19%. As a result, if there is a significantly large number of information sources in the environment but a relatively small number of servers transmitting data to monitors, using network coding becomes more appealing.

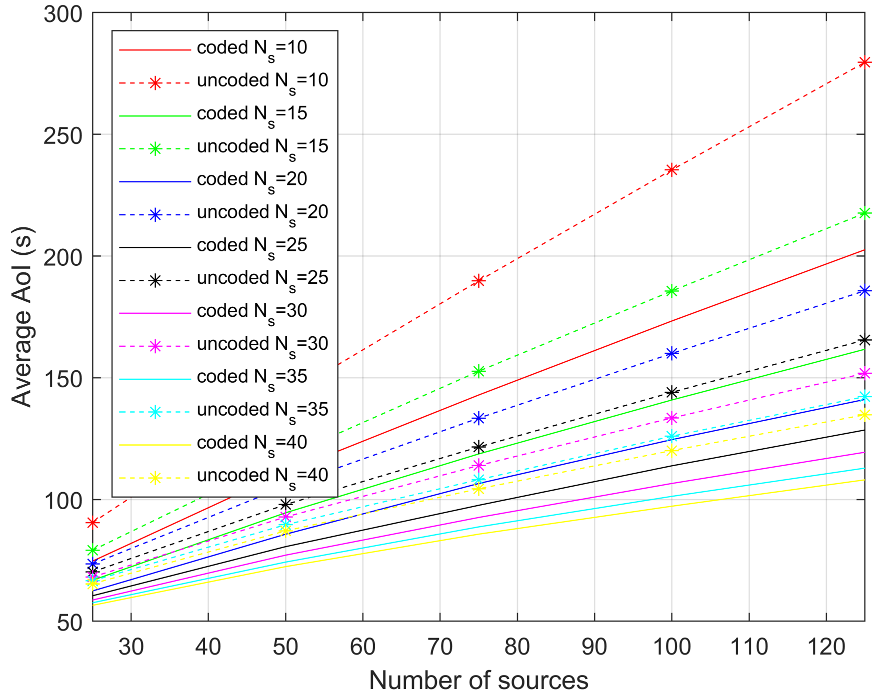

Figure 4.8. Number of sources vs. average AoI.

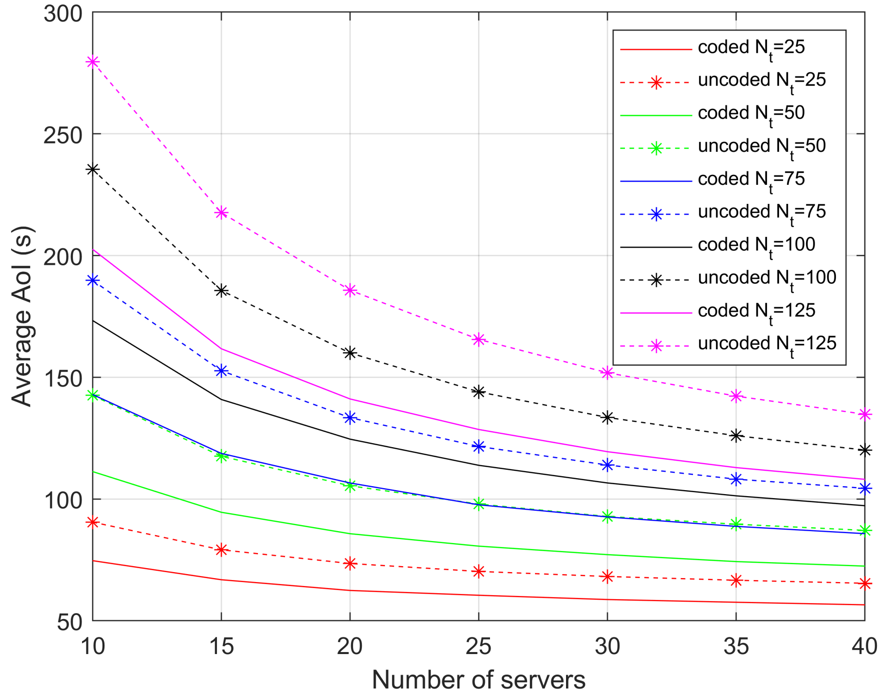

Figure 4.9. Number of servers vs. average AoI.

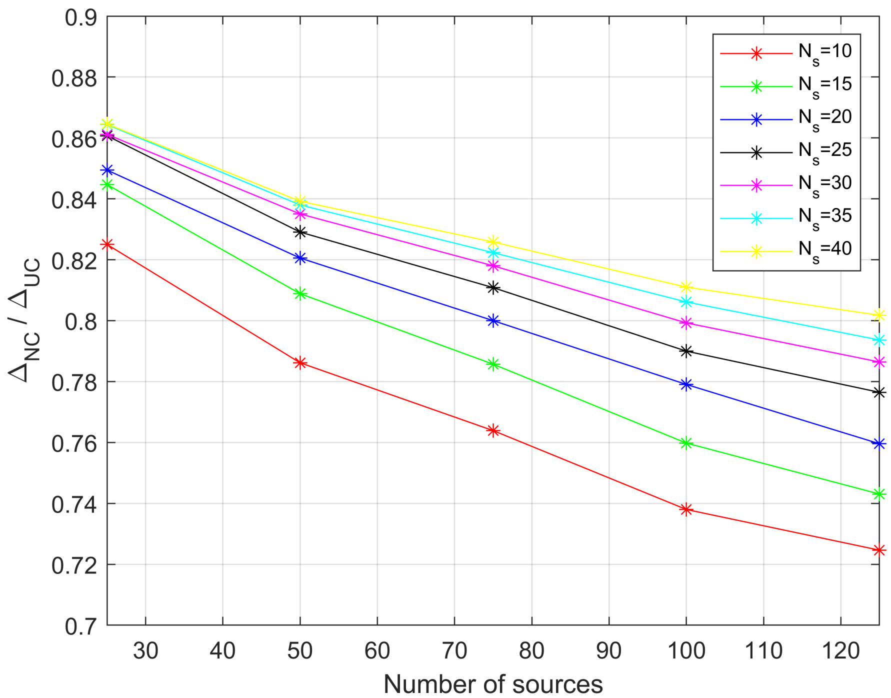

Figure 4.10. Number of sources vs. Δ_{NC}/Δ_{UC}

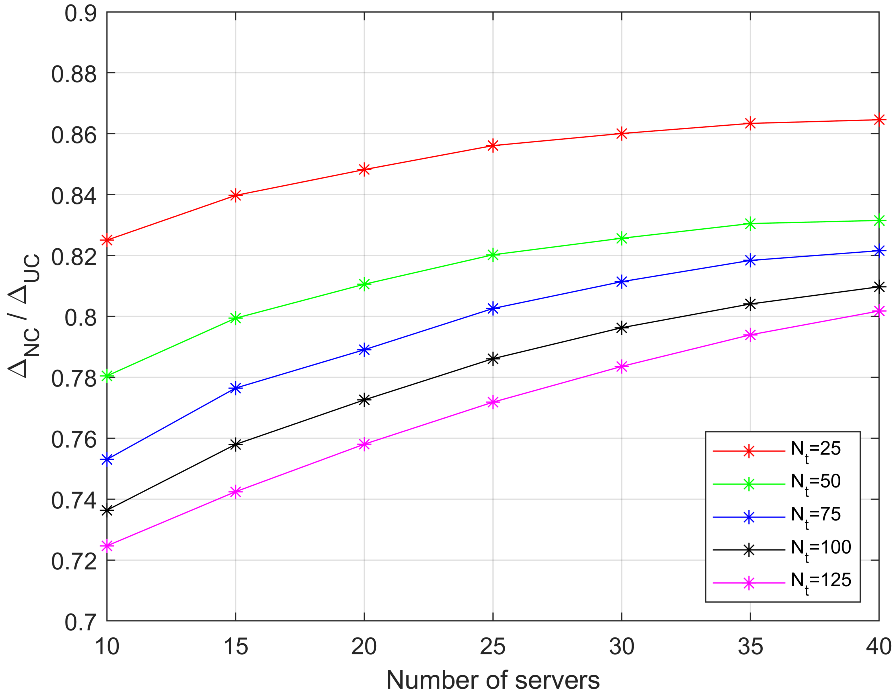

Figure 4.11. Number of servers vs. $\mathit{\Delta}_{NC}/\mathit{\Delta}_{UC}$

4.5. Discussion

In the literature, a substantial body of research has concentrated on scenarios where multiple sources are required to generate a single status update. Similarly, a significant body of literature has delved into the analysis of multi-hop networks through the utilization of graph-based techniques. On the other hand, prior works have examined the influence of network coding on AoI performance for simple IoT networks.

In this chapter, we investigated the impact of network coding on AoI performance in multi-source and multi-hop IoT networks. We derived average AoIs as probabilistic open expressions due to the complexity of the network model for the stages from sources to servers and servers to monitors. Moreover we provide a comparison of AoIs with and without network coding for the stage from servers to monitors. Finally, we demonstrate the improvement of AoI performance for various number of sources, servers and monitors when network coding is employed. We have assumed that the internal nodes are half-duplex. In scenarios where they are full-duplex, meaning that the transmission does not wait for any stage to finish, determining the optimal number of packets to wait before initiating transmission becomes a significant problem in terms of AoI performance. Furthermore, the incorporation of the energy harvesting aspect into such scenarios represents a promising avenue for future research.

5. CONCLUSION

In this thesis, we have explored the realm of AoI within the context of IoT networks. The first chapter laid the foundation by introducing the fundamental concepts of AoI and IoT, underscoring their vital roles in contemporary networked systems. Following this, we delved into a comprehensive examination of works that have harnessed AoI as a pivotal timeliness metric across diverse IoT network scenarios.

Furthermore, the impact of network coding on AoI performance in multi-source and multi-hop IoT networks has been explored. Average AoIs have been derived as probabilistic open expressions due to the complexity of the network model for the stages from sources to servers and servers to monitors. Additionally, a comparison of AoIs with and without network coding for the stage from servers to monitors has been provided. Finally, the improvement of AoI performance for various numbers of sources, servers, and monitors when network coding is employed has been demonstrated.

There are interesting topics to be explored for open challenges. These include the need for studies that consider both multi-source information and multi-hop IoT networks, which has not been explored extensively. Another promising area of research involves optimizing the trajectories and scheduling policies of multiple UAVs for data collection in large geographical areas. Additionally, in satellite-based IoT networks, there's a lack of research on channel coding and scheduling policies for AoI optimization, especially in the context of large-scale wireless networks. The impact of network coding and channel coding in multi-source and multi-hop IoT networks also presents an interesting avenue for further investigation.

Finally, we assumed that the internal nodes operate in a half-duplex mode. However, in situations where these nodes function in a full-duplex manner, allowing for simultaneous transmission and reception without waiting for any stage to complete, the task of determining the optimal number of packets to delay before initiating transmission becomes a considerably challenging problem when considering AoI performance. Additionally, the integration of energy harvesting capabilities into these scenarios presents a promising and unexplored avenue for future research.

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