Age of Information in the Internet of Things: Concepts, Metrics, and Applications

***Abstract*—Age of Information (AoI) is an emerging metric used to evaluate the timeliness of data updates in the Internet of Things (IoT). It has gained significant attention in recent years in the fields of network optimization, communication scheduling, and resource allocation. This paper systematically summarizes the fundamental concepts, key metrics, and optimization strategies of AoI, while exploring its applications in typical IoT scenarios. Special emphasis is placed on challenges and practices in energy-constrained devices and multi-hop networks. Finally, the paper discusses the future research directions of AoI in intelligent systems and the potential technical bottlenecks that may arise.**

Keywords*—*Age of Information, Internet of Things, Data Freshness, Real-time Communication, Queue Optimization, Wireless Sensor Networks

I. Introduction

The rapid development of the Internet of Things (IoT) has significantly increased the scale and complexity of data exchange between devices. Real-time transmission and processing of environmental data are critical to ensuring the safety and reliability of IoT systems. For example, in intelligent transportation systems, the timeliness of vehicle position, speed, and environmental data directly impacts driving decisions. Similarly, in industrial automation, outdated data can lead to abnormal equipment operations.

In these scenarios, updates generated by data sources, often timestamped, are transmitted through networks to the receiving end, which must access this information as promptly as possible. Despite advancements in low-latency networks such as 5G and edge computing, the challenge of maintaining data freshness during status updates persists. Factors such as network congestion, queuing delays, and suboptimal update frequencies can lead to delays or even failures in status updates.

To address this, researchers introduced the concept of Age of Information (AoI), a metric that quantifies the freshness of information at the receiver. Unlike traditional metrics such as delay or throughput, AoI measures the timeliness of updates considering both transmission delays and the freshness of the received data. This makes it particularly suitable for real-time updates in IoT and modern cyber-physical systems.

This paper provides a comprehensive review of AoI, focusing on its key challenges, current research status, and future directions. The structure of the paper is as follows: Section 2 introduces the definition, primary metrics, and analytical tools of AoI; Section 3 summarizes the performance and optimization methods of AoI in single-server queue systems; Section 4 explores scheduling strategies in multi-source networks; Section 5 addresses the optimization of AoI in energy-constrained scenarios; Section 6 extends the discussion to wireless networks; and Section 7 presents future research directions and conclusions.

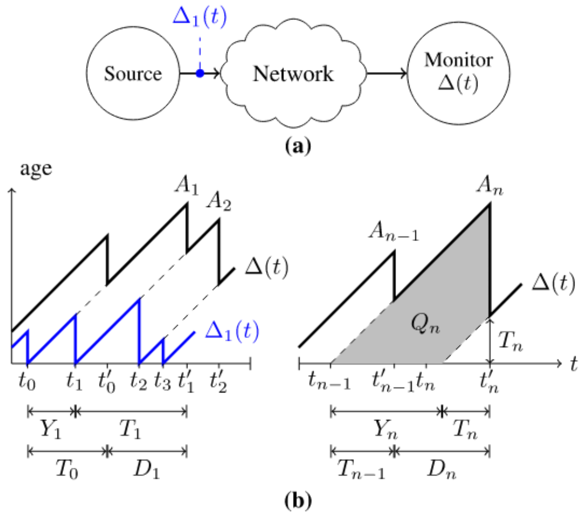

Fig. 1. (a) Fresh updates from the source node are transmitted through the network to the destination monitor. Monitor 1 (marked as •) receives the fresh update packet at the network access link. (b) Since the fresh updates seen by Monitor 1 at time t_i are treated as a point process, its information age process $\Delta_1(t)$ is reset to 0 at time t_j. The destination monitor receives the update packet, which arrives through the network at time t'_j. Its information age process $\Delta(t)$ is reset at time t'_j to $\Delta(t'_i) = t'_j - t_j$, which represents the age of update j at the time of transmission. For the n-th transmitted update in the information age process, Y_n, T_n, and D_n represent the arrival time interval, system time, and departure time interval, respectively, while A_n denotes the corresponding age peak. The shaded area Q_n is used to calculate the average information age.

II. Fundamental Analysis of AoI

A. Basic Definition

The Age of Information (AoI) is defined as the time elapsed since the latest received update was generated. Its core formula is as follows:

$$\Delta(t) = t - u(t) \tag{1}$$

where t is the current time, and $u(t)$ is the timestamp of the most recently received update at the receiver. AoI reflects the "freshness" of information at the receiver; a smaller AoI indicates more timely updates.

In practical systems, the AoI typically exhibits a "sawtooth" pattern: when a new update arrives, the AoI resets to 0; otherwise, it increases linearly over time (see **Figure 1**). Updates transmitted through the network to the destination monitor experience changes in AoI with each new update.

B. Key Metrics

- **Time-Average AoI**: The time-average AoI evaluates the system's long-term performance and is calculated as:

$$\Delta_{avg} = \left(\frac{1}{T}\right)\int_0^T \Delta(t)dt \tag{2}$$

It is particularly suitable for periodic tasks and long-term operations [1].

- **Peak AoI**: The Peak AoI represents the maximum AoI observed before an update arrives, which evaluates the worst-case timeliness of updates [2]. It is defined as:

$$\Delta_{peak} = \max(\Delta(t)), t \in [t_{i-1}, t_i] \quad (3)$$

  Where t_{i-1} and t_i are the time points of two consecutive updates. Referring to **Fig. 1**, the AoI reaches its peak value at- t'_n before the arrival of update j:

$$A_n = T_{n-1} + D_n \quad (4)$$

- **AoI Distribution**: For systems with random arrivals and services, the AoI can be analyzed using its probability distribution, typically represented by the probability density function $f_{\Delta(x)}$ or the cumulative distribution function $F_{\Delta(x)}$.

C. Analytical Tools

- **Geometric Decomposition**: By decomposing the sawtooth-shaped AoI curve into multiple geometric shapes (e.g., triangles or trapezoids), the time-average AoI or peak AoI can be calculated directly. For example, in periodic update systems, the time-average AoI can be quickly derived using geometric area formulas.

- **Stochastic Hybrid Systems (SHS)**: Stochastic Hybrid Systems combine Markov chains with continuous-time dynamic processes to analyze AoI in complex networks. For example, SHS can be used to evaluate the impact of update frequency and transmission delay of multiple source systems on overall AoI.

- **Nonlinear Analysis Methods**: In some application scenarios, the impact of AoI may be nonlinear. For example, in state estimation tasks, system errors may increase exponentially or saturate with AoI. To quantify such nonlinear losses, researchers often introduce penalty functions $p(\Delta(t))$ to indirectly optimize AoI by minimizing nonlinear losses.

D. Optimization Trade-offs of Information Age

When designing update mechanisms, optimizing information age typically requires balancing update frequency, network resource utilization, and latency: excessively high update frequencies may lead to network congestion or task backlog, increasing the transmission delay of updates; conversely, too low a frequency might cause the receiving end to remain in an outdated information state for extended periods, negatively affecting system performance. This optimization trade-off is reflected in the design of queue management and transmission scheduling strategies. For example, in multi-source systems, prioritizing the processing of source data with higher information age can reduce overall information age; in energy-constrained networks, dynamically adjusting update intervals can maintain timely information updates while prolonging device lifespan.

E. Relationship Between Information Age and Other Performance Metrics

As an emerging performance metric, information age significantly differs from traditional network performance metrics (such as latency and throughput):

- **Difference from Latency:** Latency measures the transmission time of a single data packet, while information age focuses on both the generation time of the packet and its transmission timeliness. For example, a packet with very low transmission delay may still have a high information age if it contains outdated information.

- **Relationship with Throughput:** High throughput does not necessarily imply low information age. Excessively high throughput may lead to packet backlog, thereby increasing update delays and causing the receiving end to receive outdated information.

- **Relationship with Utilization:** Strategies that maximize system utilization may conflict with the goal of minimizing information age. For instance, excessively high utilization can lead to task queuing and service delays, which in turn increase information age.

III. AoI in Single-Server Queue Systems

A. Fundamental Queue Models

In single-server queue systems, the arrival and service processes of information updates are typically random. Common models include M/M/1 queues, M/D/1 queues, and D/M/1 queues. The analysis and optimization of AoI in these models have well-established theoretical results, providing a foundation for studying AoI optimization in more complex networks.

For consistency in the following analysis, we define:

$\lambda = 1/E[Y]$: the arrival rate of updates;

$\mu = 1/E[S]$: the service rate;

$\rho = \lambda/\mu$: the system load factor.

- **M/M/1 Queue**: For an M/M/1 queue, assuming the service time and inter-arrival times follow exponential distributions, and the service follows the First-Come-First-Served (FCFS) rule, the average AoI is given by [1]:

$$\Delta_{M/M/1} = \frac{1}{\mu}\left(1 + \frac{1}{\rho} + \frac{\rho^2}{1-\rho}\right) \quad (5)$$

  The average AoI comprises three components: the update arrival rate, queuing delay, and service time. When the system load ρ approaches 1 (i.e., the queue becomes saturated), the average AoI increases rapidly, indicating the significant impact of service delays on update timeliness. This formula shows that optimizing AoI does not simply equate to maximizing the update sending rate but requires finding a balance between the update arrival rate and system load.

- **M/D/1 Queue**: In an M/D/1 queue, the arrival times of updates follow a Poisson distribution, but the service time is deterministic. The average AoI for this model is given by [3]:

$$\Delta_{M/D/1} = \frac{1}{\mu}\left(\frac{1}{2(1-\rho)} + \frac{1}{2} + \frac{(1-\rho)\exp(\rho)}{\rho}\right) \quad (6)$$

  Compared to the M/M/1 queue, the fixed service time in the M/D/1 model reduces the uncertainty in service time, thereby improving AoI. The three terms in the formula represent different influencing factors: fixed service time, the inverse effect of the load factor, and the exponential growth term under high load. When ρ→1\rho \to 1ρ→1, the queue becomes saturated, and the average AoI increases rapidly.

- **D/M/1 Queue**: In a D/M/1 queue, the arrival times of updates are deterministic, while the service time follows an exponential distribution. The average AoI for this model is [4]:

$$\Delta_{D/M/1} = \frac{1}{\mu}\left(\frac{1}{2\rho} + \frac{1}{1+\rho\mathcal{W}(-\exp[-1/\rho]/\rho)}\right) \quad (7)$$

Here, $\mathcal{W}(\cdot)$ is the Lambert-W function, which solves equations of the form $x \cdot e^x = c$.

The fixed arrival intervals in this model make updates more uniform, but the randomness of service time still significantly affects AoI. The presence of the Lambert-W function indicates that the analysis of average AoI in the D/M/1 queue is more complex, but its core characteristics still depend on the update load ρ. By adjusting the arrival intervals and service rates, AoI can be effectively optimized.

B. Comparison of Models

The characteristics of the M/M/1, M/D/1, and D/M/1 queue models and their respective average AoI formulas are summarized in **Table 1**:

TABLE I. COMPARISON OF AVERAGE AOI FORMULAS FOR DIFFERENT QUEUE MODELS

Queue Model	***Average AoI Formula***	***Characteristics***
M/M/1	$\frac{1}{\mu}\left(1+\frac{1}{\rho}+\frac{\rho^2}{1-\rho}\right)$	Suitable for random arrivals and services, AoI is significantly affected by load and service rate.
M/D/1	$\frac{1}{\mu}\left(\frac{1}{2(1-\rho)}+\frac{1}{2}+\frac{(1-\rho)\exp(\rho)}{\rho}\right)$	Fixed service time reduces AoI fluctuations, suitable for stability under high load.
D/M/1	$\frac{1}{\mu}\left(\frac{1}{2\rho}+\frac{1}{1+\rho\mathcal{W}(-\exp[-1/\rho]/\rho)}\right)$	Fixed arrival times offer better predictability; service randomness still impacts AoI.

From **Table 1**, the time-average AoI is influenced by the following factors:

- **Update Arrival Rate (λ)**: As the update arrival rate increases, queuing delays also increase, leading to higher AoI.
- **Service Rate (μ)**: As the service rate increases, the system's processing capacity improves, significantly reducing AoI.
- **Service Time Distribution**: Deterministic service times (e.g., in M/D/1 and D/M/1) generally result in lower average AoI than exponential distributions (e.g., in M/M/1), as randomness in service time is reduced.

Figure 2 illustrates the comparison of average AoI as a function of the load factor $\rho = \lambda/\mu$ for the M/M/1, M/D/1, and D/M/1 queue systems [1].

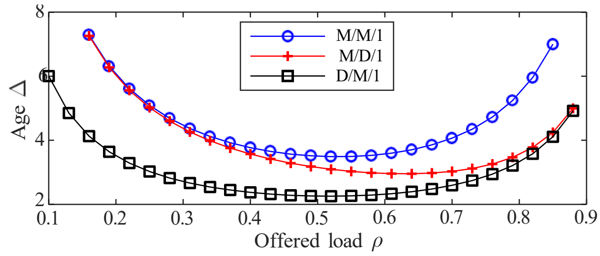

Fig. 2. Average Age as a Function of Offered Load ρ for M/M/1, M/D/1, and D/M/1 Queue Models

C. Preemption and Discarding Strategies

When the queue system is under high load, simply increasing service capacity may not significantly reduce AoI. Therefore, researchers have proposed various preemption and discarding strategies to optimize the update mechanism within the queue and minimize overall AoI.

- **Preemptive Servicing**: Preemptive servicing allows newly arrived updates to interrupt the service of outdated updates, significantly reducing AoI under high-load conditions. Under the Last Generated First Served (LGFS) strategy, the most recently generated update is prioritized for service. The reduction in AoI arises from avoiding delays caused by servicing outdated updates. For example, in an M/M/1 queue, adopting the LGFS strategy yields a lower time-average AoI compared to the traditional First Come First Served (FCFS) strategy.
- **Intelligent Discarding Policies**: In systems with limited service capacity, intelligent discarding of low-priority or outdated updates can prevent queue backlogs and reduce AoI. Examples include:

  Drop the Oldest (DTO): This strategy eliminates the oldest update in the queue, reducing delay caused by outdated data.

  Drop Based on Priority (DBP): Updates are discarded based on their importance, prioritizing high-value updates to minimize AoI.

IV. AOI IN MULTI-SOURCE AND MULTI-SERVER SYSTEMS

Multi-source and multi-server scenarios are common in network communications. Compared to single-server systems, these scenarios introduce greater complexity, requiring dynamic resource allocation and prioritization to minimize AoI.

A. Multi-Server Systems

In multi-server queue systems, multiple service nodes process data streams in parallel, significantly reducing queuing delays and optimizing AoI. For example, in the M/M/2 model, increasing the number of service nodes reduces update waiting times, thereby lowering the average AoI.

Key optimization strategies include:

- **Task Allocation**: Intelligent scheduling algorithms dynamically allocate tasks based on the urgency of updates and the current load of servers. Under low task loads, balancing server workloads improves resource utilization and reduces AoI. Under high loads, prioritizing updates with high AoI ensures system timeliness.

- **Preemptive Service Adjustment**: High-priority updates can interrupt low-priority tasks, ensuring critical updates maintain low AoI.

In smart manufacturing scenarios, updates generated by different sensors may have varying priorities. Through dynamic task allocation and priority adjustment, it is possible to ensure that the status updates of critical equipment (such as industrial robotic arms) maintain low information age while ensuring that updates from non-critical devices do not lag significantly.

B. Information Age Scheduling in Multi-Source Systems

Multi-source update scheduling represents another major challenge in optimizing information age. In multi-source systems, data streams from different devices need to share the same network resources, making dynamic bandwidth allocation and update task scheduling crucial.

The main issues in multi-source systems are:

- **Competing Resource Conflicts**: Multiple data streams share network bandwidth or server resources. Improper scheduling may lead to excessively high information age for some data sources, negatively impacting overall system performance.
- **Differences in Data Priority**: Different data sources may have varying importance and real-time requirements. For example, vehicle location data updates are more critical than entertainment data updates.

The corresponding optimization strategies are as follows:

- **Priority Scheduling**: By assigning different update priorities, prioritize data streams with high information age or critical tasks. For instance, in intelligent transportation systems, prioritize updates on real-time vehicle location and speed information.
- **Bandwidth Allocation**: Dynamically adjust the bandwidth allocation ratio for each data source, triggering updates based on information age thresholds.
- **Polling Scheduling**: Implement a polling mechanism that ensures each source has a fair opportunity while dynamically adjusting the scheduling frequency to prioritize sources with higher information age.

For example, in smart cities, streetlights, traffic lights, and vehicle sensors may simultaneously send data to a central server. For regular streetlight updates, a lower priority can be assigned since their update frequency has less impact on the system; however, traffic light status updates need to be prioritized, as high information age could lead to traffic accidents or congestion. Vehicle sensor data requires the highest real-time responsiveness, necessitating dynamic bandwidth adjustments to ensure timely data updates.

C. Joint Optimization of Multi-Servers and Multi-Sources

In complex networks, multi-server and multi-source updates often coexist. Research indicates that combining multi-server task allocation with multi-source scheduling strategies can further reduce overall system information age.

The joint optimization framework is as follows:

- **Multi-Level Scheduling**: At the server level, use dynamic task allocation to optimize the load on individual servers; at the multi-source level, enhance the update performance of critical tasks through priority scheduling.
- **Cross-Layer Resource Allocation**: Coordinate bandwidth allocation and server scheduling to minimize overall information age. For example, reserve a portion of bandwidth or service capacity for high-priority update tasks.

In industrial IoT, multiple sensors and actuators on the production line connect to multiple servers: temperature and humidity sensors generate high data traffic but have lower real-time requirements; fault detection sensors generate lower data traffic but have higher requirements for information age; updates for industrial robotic arms should combine priority scheduling and dynamic task allocation to ensure that their information age remains at a minimum level.

V. Information Age in Energy-Constrained Scenarios

In IoT scenarios, many sensor nodes face resource constraints, particularly those relying on energy harvesting. Energy-constrained sensor nodes need to perform state updates under energy budget constraints, with the key challenge being how to optimize information age within a limited energy budget, ensuring that the receiving end obtains sufficiently fresh status update information.

A. Basic Research Background

Energy-constrained sensors typically have the following characteristics:

Key optimization strategies include:

- **Intermittent Operating Capability**: Relying on external sources such as solar energy, vibrational energy, or radio frequency energy, sensors can only update their status when energy is sufficient.
- **Limited Energy Storage**: The battery capacity of sensors is finite, and limitations on energy harvesting rates and storage capacity affect their update frequency.

These characteristics necessitate that design strategies for optimizing information age consider both the timing and frequency of updates, achieving a balance between energy and update efficiency.

B. Dynamic Threshold Strategy

A common optimization strategy is the dynamic threshold update strategy, where updates are triggered when the information age reaches a certain threshold value. This approach is suitable for periodic energy harvesting scenarios, such as solar-powered sensor networks, where sensors can dynamically adjust their update frequency based on changes in sunlight. Research indicates that threshold strategies can effectively reduce average information age under limited energy conditions [8][9].

C. Combining Energy Harvesting with Scheduling Optimization

In complex networks, sensors must not only optimize their own update frequencies but also coordinate with other nodes to avoid conflicts. For example, in multi-hop wireless sensor networks, a node's update strategy must consider the energy consumption and congestion of the transmission path. Introducing intelligent scheduling algorithms (such as adaptive scheduling based on reinforcement learning) can dynamically allocate update tasks based on network conditions to minimize overall network information age.

Research has also found that for sensors with low energy harvesting rates, delayed updates and batch transmission strategies can significantly enhance energy utilization efficiency while maintaining low information age in certain scenarios.

D. Theoretical Limits of Information Age

In energy-constrained systems, the optimal theoretical limit of information age depends on the energy harvesting model and transmission conditions. For sensors with fixed interval harvesting, mathematical modeling can be used to calculate the time average of information age, thereby optimizing the update interval. In scenarios with uncertainty in energy harvesting (such as random vibrational energy sources), stochastic dynamic programming methods can be employed to derive the expected value of information age and its upper and lower bounds.

VI. Information Age in Wireless Networks

In wireless networks, information age is influenced by various factors such as network topology, transmission protocols, and channel interference. Compared to wired networks, wireless networks have greater uncertainty, including signal interference, data loss, and transmission failures, all of which can significantly increase information age. In response, researchers have proposed a range of optimization strategies and techniques aimed at reducing information age in wireless networks and enhancing the system's responsiveness to real-time data.

A. Channel Models and Information Age

In wireless networks, the quality of the channel determines the success rate of data packet transmission. Common channel models used for studying information age include:

- **Ideal Channel**: Assumes data transmission occurs without interference, primarily used for theoretical analysis to assess the potential performance of scheduling strategies.
- **Random Channel**: Considers the randomness of channel states and is suitable for scenarios with significant interference. Studies show that appropriately increasing redundant transmissions can reduce information age under unstable channel conditions.
- **Limited Bandwidth Channel**: In bandwidth-constrained networks, competition among different data sources increases update delays, making optimized scheduling strategies crucial.

B. Automatic Repeat and Hybrid Automatic Repeat

In wireless networks, Automatic Repeat reQuest (ARQ) and Hybrid Automatic Repeat reQuest (HARQ) are common transmission mechanisms used to enhance data transmission reliability:

- **ARQ**: When the receiver detects an error in a data packet, it requests the sender to retransmit until the packet is successfully received. Although ARQ improves data accuracy, frequent retransmissions can lead to cumulative update delays, increasing information age.
- **HARQ**: Combines forward error correction and retransmission mechanisms, only retransmitting the differing portions of data after the first transmission fails, thereby reducing the number of retransmissions and lowering information age.

C. Scheduling and Priority Mechanisms

In multi-source, multi-receiver wireless networks, effective scheduling strategies are central to reducing information age. The following typical strategies have been proposed:

- **High Information Age Priority Strategy**: Prioritizes the transmission of data packets with the highest current information age to reduce the maximum information age in the system. This strategy is suitable for scenarios with high real-time requirements, such as vehicle status updates in vehicular networks.
- **Channel State-Based Scheduling**: Dynamically adjusts the transmission order of packets based on channel quality, prioritizing data from nodes with good channel conditions to improve overall transmission efficiency.
- **Polling Scheduling Strategy**: Allocates fixed transmission time slots to each node, effectively avoiding competition among data sources, but may perform poorly under high load.

D. Cross-Layer Optimization of Information Age

Optimizing information age in wireless networks relies not only on physical layer channel modeling but also on multi-level collaborative design:

- **Physical Layer**: Reduces channel interference through dynamic power control and beamforming, thereby improving the success rate of data transmission.
- **Link Layer**: Designs efficient retransmission mechanisms (such as HARQ) to minimize information delay caused by transmission failures.
- **Network Layer**: Optimizes routing protocols to avoid increased transmission delays and information age due to poor path selection.
- **Application Layer**: Develops priority allocation strategies based on specific scenario requirements (e.g., autonomous driving or industrial monitoring) that are oriented toward information age.

VII. SUMMARY AND OUTLOOK

Despite significant progress in the research on information age, many challenges remain, and future research can further explore the following directions:

- **Intelligent Scheduling and Dynamic Optimization**: Current optimization of information age mainly focuses on update strategies and queue scheduling; however, as network scale increases and the number of devices grows, how to intelligently schedule information updates in dynamic environments remains an urgent issue. Incorporating artificial intelligence and machine learning scheduling methods, particularly reinforcement learning (RL) and deep learning (DL) algorithms, can help systems automatically adjust update strategies based on real-time network states and device needs, thereby optimizing information age. This data-driven dynamic optimization approach may become a key technology for addressing timeliness issues in large-scale IoT environments.

- **Cross-Layer Optimization and Collaborative Design**: Information age is not merely a performance issue at the communication layer; it is closely related to the design of the application layer, transport layer, and even the perception layer. Future research needs to explore cross-layer optimization methods, integrating the needs of the network layer, transport layer, and application layer to collaboratively design system architectures. By reasonably configuring network resources, adjusting transmission protocols, and optimizing data collection methods, information age can be significantly reduced, enhancing overall system performance. Cross-layer optimization strategies will also help achieve optimal balance of information age across different application scenarios.

- **Integration of Edge Computing and 5G/6G Networks**: With the rapid development of edge computing and future 5G/6G networks, the optimization of information age will no longer rely solely on traditional data center processing methods. Edge computing allows data to be processed closer to the devices, reducing data transmission delays and optimizing information age performance. Future research can focus on exploring solutions that combine edge computing with 5G/6G networks, examining how to increase the frequency of information updates and reduce information age accumulation, especially in applications with high mobility and dynamic environments.

- **Data Privacy and Security**: In IoT and cyber-physical systems, as data collection frequency increases and information updates accelerate, issues of data privacy and security become more prominent. Ensuring user data privacy and system security while maintaining timely information updates is an important direction for future research. Particularly in scenarios involving sensitive data (such as healthcare, finance, smart homes, etc.), exploring how to resolve conflicts between information age optimization and data security through encryption technologies, privacy protection protocols, and secure communication mechanisms will be a worthwhile topic for in-depth discussion.

- **Information Age Management in Large-Scale Networks**: The explosive growth of IoT devices presents new challenges for optimizing information age. How to manage information age in large-scale, heterogeneous network environments and ensure that different types of devices and application scenarios receive appropriate information update strategies will be an important direction for future research. Distributed and decentralized management methods, cross-network coordination mechanisms, and efficient resource scheduling algorithms may become key solutions to this problem.

- **Further Expansion of Application Areas**: Currently, research on information age primarily focuses on smart transportation, industrial automation, and telemedicine. As IoT technology continues to evolve, the application areas of information age will expand. For instance, in smart city development, optimizing the flow of data in urban management systems to enhance the responsiveness of urban infrastructure; in smart agriculture, leveraging real-time data updates to improve crop production efficiency; and in environmental monitoring, reducing information age to enhance the accuracy and timeliness of climate change warnings are all future research directions worth exploring.

- **Intelligent Scheduling and Dynamic Optimization**: Despite significant progress in the research on information age, many challenges remain, and future research can further explore the following directions:

As an emerging performance metric, information age shows great application potential in real-time communication systems. By optimizing information update frequency, queue scheduling, and resource allocation, information age can be effectively reduced, enhancing the real-time performance and responsiveness of systems. In the future, with the continuous development of IoT, 5G/6G, and edge computing technologies, research on information age will evolve toward more intelligent and dynamic approaches, providing better solutions for various low-latency, high-performance application scenarios.

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