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Stochastic Optimization of Data Access and Hybrid Transmission in Wireless Sensor Network

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ABSTRACT In recent years, the rapid advancements in Internet of Things boost the utilization of Wireless Sensor Network (WSN). Through WSN, a huge amount of various kinds of data can be acquired from different environments, which further facilitate us to harness the world we live. However, the error-prone and unpredictable natures of wireless links significantly impair the quality of data transmission and the utility of acquired data in WSN. Therefore, to solve this crucial problem, this paper focuses on data access control and hybrid transmission control of WSN. Based on the mathematical models of the two control operations, an intractable optimization problem is first formulated with numerous considerations, including data utility, energy consumption, network stability and data loss rate. Because of the complexity and intractability of the originally formulated problem, a Lyapunov function-based network optimization theory is utilized to transform and decompose it into three relatively simple subproblems. Stochastic Data Scheduling Mechanism (SDSM) is designed based on the solutions to the three subproblmes. The optimality and implementation of SDSM are also analyzed. Finally, the performance of SDSM is demonstrated through extensive evaluations.

INDEX TERMS Wireless sensor network, data access, hybrid transmission, stochastic scheduling.

I. INTRODUCTION

Nowadays, Wireless Sensor Networks (WSN) are widely utilized in the Internet of Things (IoT) [1]. They are able to collect and provide a large amount of data from various critical environments, including human bodies, cities, forests and underwater. Benefiting from the collected and provided data, real-time monitoring and intelligent controls can be achieved to further provide great convenience for all aspects of our lives. However, the error-prone and fragile wireless link is the bottleneck of WSN which greatly influences its performance of data transmission. Moreover, the unpredictable nature of wireless link also exerts significant pressure on making real-time and optimal decisions for the control operations of WSN. The utility of collected data is therefore greatly degraded. Consequently, transmitting data with high quality and achieving high data utility are still challenging in WSN.

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To address the above challenges, this paper focuses on two essential control operations of WSN including data access control and hybrid transmission control. Data access control is mainly responsible to determine the amount of data entered into WSN based on current network status and the utility of collected data. It also prevents the accessed data from overwhelming network transmission capability. Hybrid transmission control decides the amount of data transmitted through various and heterogeneous transmission links in real time, with the considerations of energy consumption, network stability and data loss rate. Even though WSN have attracted a lot of attentions of academia in recent years, there are still two major aspects which are not fully researched.

- The data access and hybrid transmission are seldom jointly researched and optimized. It results in a serious imbalance between data utility and network stability. Moreover, because of the error-prone and unpredictable natures of wireless links in WSN, it is difficult to perform optimal data access control to admit the appropriate amount of data into WSN. These natures also make great challenge for hybrid transmission control to establish an efficient and effective data scheduling algorithm over numerous kinds of wireless links.

- Because of the limitation of implemented optimization method and theory, current researches of data access and transmission in WSN mainly focus on a few considerations. Moreover, the derived mechanisms are not scalable and extensible. If more considerations and constraints are incorporated, the performance of the mechanisms will be greatly degraded. Therefore, jointly optimizing data access and transmission with numerous considerations and providing an optimization method which can be easily extended are still problematic in WSN.

Motivated by the above two aspects, careful investigation of WSN is conducted in this paper and Stochastic Data Scheduling Mechanism (SDSM) is proposed. The main contributions of this paper are presented in brief as follows:

- A general network model of WSN is researched and mathematical models of data access and hybrid transmission are established. Based on the established models, an intractable optimization problem is formulated with multiple considerations, including data utility, energy consumption, network stability and data loss rate.
- The Lyapunov function-based network optimization theory is introduced to transform and decompose the originally formulated problem into three simple subproblems, i.e. data access control problem, hybrid transmission control problem and intermediate computation problem. Such transformation and decomposition make the original problem tractable and scalable. By solving the three problems, SDSM is designed which is composed of four components. The optimality and implementation analyses of SDSM are also presented.
- The performance of SDSM is evaluated through extensive simulations. The evaluation results demonstrate that SDSM is able to improve the utility of collected data, reduce energy consumption and maintain the network stability of WSN.

The rest of this paper is organized as follows. Section II briefly reviews related work. Section III establishes the mathematical models of WSN. Section IV formulates the optimization problem based on the established WSN models. Section V performs the transformation and decomposition for the formulated optimization problem and three subproblems are derived. Section VI designs SDSM to solve the three subproblems. Optimality and implementation analyses of SDSM are also provided. Section VII evaluates the performance of SDSM. Section VIII concludes this paper.

II. RELATED WORK

Recently, data transmission in WSN has received increasing attentions. Considering sensors are always energy-limited, numerous valuable researches [2]–[5] perform the joint optimization of data transmission and energy consumption with different concerns. Zhang *et al.* [2] focus on the situation where charging vehicle is used to provide power for sensors. A three-stage method is proposed to optimize the uplink route of data and the travel path of charging vehicle. Fitzgerald *et al.* [3] concentrate on multiple-sink aggregation problem with the assistance of fog computing. Several algorithms are proposed to optimize total energy usage, per-node energy usage and transmission throughput. Farhan *et al.* [4] propose a long hop algorithm for WSN. This algorithm makes optimization on energy consumption by preferentially transmitting the data packets with with long distance. Shukla *et al.* [5] analyze the data transmission of WSN. An algorithm called Smart Pinging Without Groups is proposed to detect traffic hotspot and reduce energy consumption.

Routing mechanism also makes great influence on data transmission efficiency. Therefore, a lot of researches [1], [6]–[9] concentrate on optimizing routing algorithms and protocols in WSN. Kumar and Vidyarthi [1] propose an energy efficient routing mechanism for WSN in software defined networking architecture. Particle swarm optimization method is utilized to reduce energy consumption and elongate the lifetime of sensors. Benaddy *et al.* [6] propose a multipath routing algorithm to increase the reliability of data transmission. The transmission distance and energy consumption are also considered. Jiang [7] optimize a WSN routing protocol, i.e. LEACH protocol, using ant colony algorithm and particle swarm algorithm. The optimized LEACH protocol is able to balance the tradeoff between data transmission and energy consumption. Lai and Wang [8] research the broadcast data dissemination problem of WSN in IoT systems. Opportunistic routing is employed and Receiver Negotiation Opportunity Broadcast protocol is proposed which improves the trustworthiness and efficiency of data transmission. Qiu *et al.* [9] propose a multi-gradient routing protocol for WSN to support different traffic patterns, which is evaluated on real-world testbeds and achieves lower transmission delay.

Besides the above achievements about data transmission in WSN, Li *et al.* [10], Yue *et al.* [11] and Le and Vo [12] respectively propose data reconstruction algorithm, data fusion algorithm and data compression algorithm to improve the transmission efficiency. Shukla *et al.* [13] and Majumdar *et al.* [14] pay their attention to data packets in WSN. The problems of packet allocation and packet size are researched. Baharudin *et al.* [15] propose a frequency control mechanism for cognitive radio-based WSN. Xu *et al.* [16] study the transmission of multimedia data in WSN. A highly distributed algorithm is proposed to support smooth data collection and coordinated data dissemination. Rezaei *et al.* [17] exploit the wireless powered communication in IoT which is composed of base stations and sensor nodes. The secrecy throughput of sensors is optimized by the proposed max-min fair and proportional fair algorithms.

One of the networking method of WSN is to organize numerous sensor nodes into a cluster and select a cluster head to manage the cluster and forward collected data. Similar with data transmission, energy consumption is also an important consideration in sensor cluster. Therefore, energy-saving cluster head selection mechanisms are proposed in [18] and [19]. Meanwhile, how to organize sensor nodes into a cluster has a great impact on the performance of WSN. Numerous researches have been conducted based on traffic load analysis [20], network stability [21] and compressed data gathering [22], etc.

Because of the popularity of WSN, it is also researched in terms of networking method [23], network coverage [24], information security [25], [26], privacy protection [27], source localization [28] and fog computing [29].

Based on the above review of related work, we find out many achievements have been realized for WSN with different concentrations. However, few of them attempts to jointly optimize data access and hybrid transmission in real time. Moreover, a scalable optimization theory tailored toward WSN is also seldom researched.

III. WIRELESS SENSOR NETWORK MODEL

This section first presents an overview of WSN. Then the mathematical models of WSN are established, including data access model and hybrid transmission model.

A. OVERVIEW OF WIRELESS SENSOR NETWORK

The WSN considered in this paper is shown as in Figure 1. All the sensors include two platforms, i.e. data collection platform and data transmission platform. Data collection platform is responsible to collect data from surroundings. The data transmission platform is used to transmit the collected data to data processing center. The intermediate network connects data processing center and sensors through numerous routers and gateways. In WSN, the connections between sensors and gateways are established by wireless links and the ones between routers and gateways by wired links. It is obvious that the bottleneck of WSN is the wireless links of sensors because of their error-prone and fragile natures compared with wired links. Therefore, in this paper, we focus on the sensors and their wireless links to improve the performance of WSN. The mathematical models of data access in sensors and hybrid transmission of sensors' wireless links will be established in following sections.

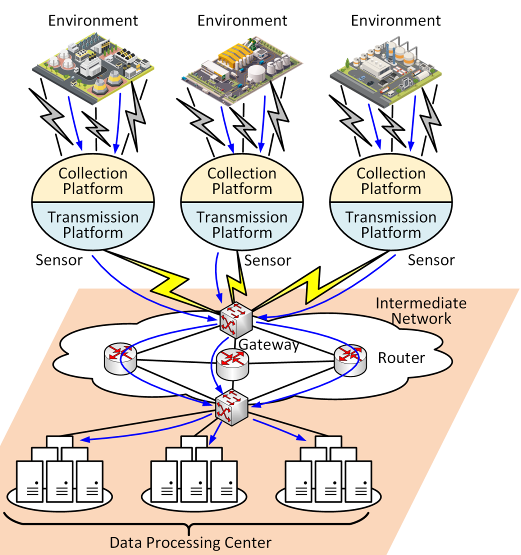

FIGURE 1. Overview of wireless sensor network.

B. DATA ACCESS MODEL

The data access model is shown as in Figure 2. In this paper, we assume the WSN operates in slotted time. The sensors in WSN is denoted as a set $\mathcal{N} = \{1, 2, \cdots n\}$. At time slot t, the amount of data collected by sensor $i\,(i \in \mathcal{N})$ is denoted as $C_i\,(t)$ which is counted in bit. It is worth noting that since the data collection process performed by different sensors in various environments are different, we do not assume $C_i\,(t)$ to have any statistical features or obey any stochastic process. Meanwhile, because of the limitation of data collection capability of sensor, we set the maximum value of $C_i\,(t)$ as C^i_{max}. It is immediate that $0 \leq C_i(t) \leq C^i_{max}, i \in \mathcal{N}$.

In WSN, data processing center always expects the sensors to access and transmit as more data as possible. However, because data transmission capability of wireless links in WSN is limited, accessing too much data into WSN will definitely result in serious data congestion problem. Therefore, it is necessary to perform the data access control to adjust the amount of data entered into WSN. Based on the above considerations, we denote the amount of accessed data as $A_i\,(t)$. Then we also have $0 \leq A_i\,(t) \leq C_i\,(t), i\,(i \in \mathcal{N})$.

C. HYBRID TRANSMISSION MODEL

The hybrid transmission model is shown as in Figure 3. The amount of data transmitted to data processing center by sensor $i\,(i \in \mathcal{N})$ is denoted as $D_i\,(t)$. To facilitate data transmission in WSN, sensors are able to utilize numerous different wireless transmission approaches to perform data transmission, such as WiFi, microwave technology and millimeter-wave technology. Because different transmission approaches have different transmission characteristic, such as transmission bandwidth and rate, hybrid transmission control is therefore necessary to schedule the data backlogged in sensors over these transmission approaches.

The utilized transmission approaches are denoted as set $\mathcal{M} = \{1, 2, \cdots m\}$. The amount of data transmitted through approach $j\,(j \in \mathcal{M})$ in sensor $i\,(i \in \mathcal{N})$ is denoted as $D_{ij}\,(t)$. It is obvious that $D_i\,(t) = \sum_{j \in \mathcal{M}} D_{ij}\,(t)$. Meanwhile, the transmission capacity of transmission approach $j\,(j \in \mathcal{M})$ in sensor $i\,(i \in \mathcal{N})$ at time slot t is denoted as $R_{ij}\,(t)$. The maximum value of $R_{ij}\,(t)$ is R^{ij}_{max}. Considering the error-prone and fragile nature of wireless links, we further denotes the data loss rate of transmission approach $j\,(j \in \mathcal{M})$ in sensor $i\,(i \in \mathcal{N})$ at time slot t as $L_{ij}\,(t)$. Therefore, we have $D_{ij}\,(t) \leq R_{ij}\,(t)\,L_{ij}\,(t)$.

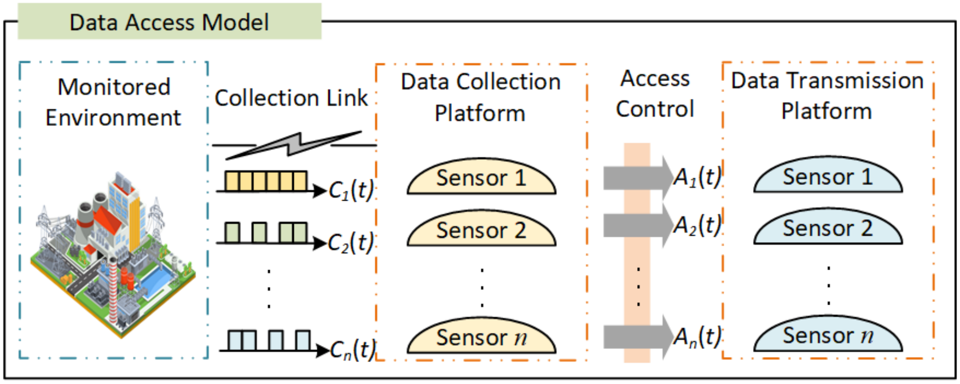

FIGURE 2. Data access model.

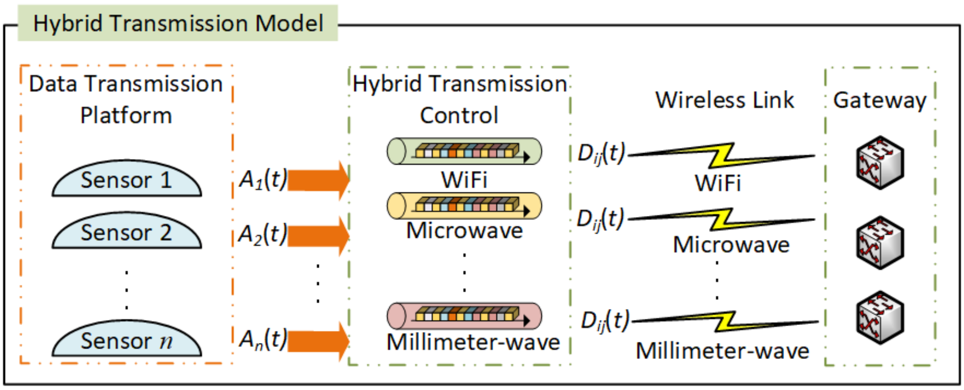

FIGURE 3. Hybrid transmission model.

IV. OPTIMIZATION PROBLEM FORMULATION

This section formulates the optimization problem based on the above established models. The considerations of energy consumption, data utility and network stability are also incorporated.

A. OPTIMIZATION OBJECTIVE

In WSN, accessing and transmitting large amount of information will be beneficial for fine-grained environment monitoring and controlling. However, it is also worth noting that too much data is also redundant. Therefore, the utility of the amount of data normally has diminishing returns property. Based on this consideration, we employ logarithmic function to depict the utility of accessed data, which is shown as follows:

$$U\left(\overline{A_i}\right) = \delta \ln\left(\overline{A_i} + \gamma\right)$$

where δ and γ are positive constants; $\overline{z}$denotes time-averaged value which is calculated as $\overline{z} = \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} z(t)$.

B. CONSTRAINTS FOR OPTIMIZATION PROBLEM

As for the data transmission in WSN, the first important constraint is to maintain the network stability of WSN and prevent the amount of backlogged data from unlimited growth. That is, we need to maintain the stability of sensors' transmission queues as follows:

$$Q_i(t+1) = \max\left[Q_i(t) - D_i(t), 0\right] + A_i(t+1) \tag{1}$$

where $\max[x, y] = x$ if $x > y$ and y otherwise. In this paper, we define the stability of transmission queue as follows:

$$\lim_{T\to\infty} \sup \frac{1}{T}\sum_{t=0}^{T-1} Q_i(t) < \infty \tag{2}$$

Meanwhile, since the sensors are always placed at hard-to-reach environments. It is difficult to provide the sensors with permanent power sources. Therefore, sensors are always energy-limited. In this context, it is also necessary to establish a constraint about energy consumption. In general, the energy consumption of sensors' network interface includes two parts. The one is consumed by the establishment and maintenance of data transmission links. This energy consumption is always a constant and it relates to the hardware and communication protocols, which is beyond the research scope of this paper. The other one is consumed by data transmission. We assume that transmitting one bit of data through transmission approach j $(j \in \mathcal{M})$ in sensor i $(i \in \mathcal{N})$ will consume a unit energy P_{ij}. Then at time slot t, the total energy consumed by data transmission in sensor $i\,(i \in \mathcal{N})$ through transmission approach $j\,(j \in \mathcal{M})$ is $W_{ij}(t) = P_{ij} \cdot D_{ij}(t)$. Based on the above analysis, the energy consumption constraint can be formulated as follows:

$$\overline{W_{ij}} \leq W_{max}^{ij}, \quad j \in \mathcal{M}$$

This constraint indicates that the time-averaged value of energy consumption of transmission approach $j\,(j \in \mathcal{M})$ in sensor $i\,(i \in \mathcal{N})$ should not be larger than the maximum value W_{max}^{ij}.

C. PROBLEM FORMULATION

Based on the above analysis, now we formulate the initial optimization problem for WSN as follows:

$$\begin{aligned}
&\max_{A_i(t),D_i(t),D_{ij}(t)} \sum_{i\in N} U\left(\overline{A_i}\right)\\
&\text{s.t.} \lim_{T\to\infty} \sup \frac{1}{T}\sum_{t=0}^{T-1} Q_i(t) < \infty, \quad i \in \mathcal{N}\\
&\overline{W_{ij}} \leq W_{max}^{ij}, \quad i \in \mathcal{N},\ j \in \mathcal{M}\\
&0 \leq C_i(t) \leq C_{max}^{i}, \quad i \in \mathcal{N}\\
&0 \leq A_i(t) \leq C_i(t), \quad i \in \mathcal{N}\\
&D_{ij}(t) \leq R_{ij}(t)\,L_{ij}(t), \quad i \in \mathcal{N},\ j \in \mathcal{M} \qquad (3)
\end{aligned}$$

In problem (3), the optimization objective means to maximize the utility of accessed data. The first constraint is to prevent the amount of accessed data from overwhelming transmission capacity so as to ensure the network stability of WSN. The second constraint is to maintain the data transmission consumption less than the pre-set maximum value.

However, the problem (3) is difficult to solve because it contains numerous factors, such as energy consumption, queue stability, data access and hybrid transmission. These factors tightly correlate with each other. The intricate relationships between these correlated factors essentially make great trouble to derive optimal solutions for problem (3). Therefore, it is necessary to perform problem transformation and decomposition so as to derive optimal solutions.

V. PROBLEM TRANSFORMATION & DECOMPOSITION

This section performs transformation and decomposition for the initially formulated optimization problem. Three subproblems are derived which can be solved easily.

A. PROBLEM TRANSFORMATION

According to the Lyapunov function-based network optimization theory [30], the optimization objective of problem (3) is a nonlinear function of time-averaged value $A_i(t)\,(i \in \mathcal{N})$. Therefore, we first need to establish an intermediate variable $a_i(t)\,(i \in \mathcal{N})$ which satisfies $\overline{a_i} \leq \overline{A_i}$. With the help of $a_i(t)$, the optimization objective of problem (3) can be transformed as $\sum_{i\in M} U[a_i(t)]$.

Then we need to establish two virtual queues to perform transformation for the two constraints, i.e. $\overline{W_{ij}} \leq W_{max}^{ij}$ and $\overline{a_i} \leq \overline{A_i}$, where $i \in \mathcal{N}$ and $j \in \mathcal{M}$. The built virtual queues are shown as follows:

$$\begin{aligned}
G_{ij}(t+1) &= \max\left[G_{ij}(t) - W_{max}^{ij}, 0\right] + W_{ij}(t)\\
H_i(t+1) &= \max\left[H_i(t) - A_i(t), 0\right] + a_i(t)
\end{aligned}$$

The virtual queues transform the original constraints into queue stability constraints. Specifically, the constraints $\overline{W_{ij}} \leq W_{max}^{ij}$ and $\overline{a_i} \leq \overline{A_i}$ can be held through maintaining the stability of $G_{ij}(t)$ and $H_i(t)$, respectively. The proof is given as follows using the example of $H_i(t)$.

Proof: We can derive the following inequality from virtual queue $H_i(t)$:

$$H_i(t+1) - H_i(t) \geq a_i(t) - A_i(t)$$

Then we substitute positive integer values into variable t as follows:

$$\begin{aligned}
H_i(1) - H_i(0) &\geq a_i(0) - A_i(0)\\
H_i(2) - H_i(1) &\geq a_i(1) - A_i(1)\\
&\vdots\\
H_i(T) - H_i(T-1) &\geq a_i(T-1) - A_i(T-1)
\end{aligned}$$

By summing the above inequalities and dividing by variable T, we can derive the following inequality:

$$\frac{1}{T}\left[H_i(T) - H_i(0)\right] \geq \frac{1}{T}\left[\sum_{t=0}^{T-1} a_i(t) - \sum_{t=0}^{T-1} A_i(t)\right]$$

Let $T \to \infty$. Then we can further obtain the following inequality:

$$\lim_{T\to\infty} \frac{1}{T}\left[H_i(T) - H_i(0)\right] \geq \overline{a_i} - \overline{A_i}$$

Conventionally, the initial queue length $H_i(0)$ is 0 or a bounded constant. Therefore, from the above inequality, it can be derived that the constraint $\overline{a_i} \leq \overline{A_i}$ is held when $\lim_{T\to\infty} \frac{1}{T} H_i(T) = 0$.

From the definition of queue stability, it is obvious that $\lim_{T\to\infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} H_i(t) < \infty$ indicates $\lim_{T\to\infty} \frac{1}{T} H_i(T) = 0$. That is, if the queue $H_i(T)$ is stable, then the constraints $\overline{a_i} \leq \overline{A_i}$ can be held. □

Based on the problem (3) and the above transformations, now we obtain a new optimization problem which is shown as follows:

$$\begin{aligned}
&\max_{\substack{A_i(t),\,a_i(t)\\ D_i(t),\,D_{ij}(t)}} \sum_{i\in\mathcal{N}} U(a_i(t))\\
&\text{s.t.} \lim_{T\to\infty} \sup \frac{1}{T}\sum_{t=0}^{T-1} Q_i(t) < \infty, \quad i \in \mathcal{N}\\
&\lim_{T\to\infty} \sup \frac{1}{T}\sum_{t=0}^{T-1} H_i(t) < \infty, \quad i \in \mathcal{N}
\end{aligned}$$

$$\lim_{T\to\infty} \sup \frac{1}{T}\sum_{t=0}^{T-1} G_{ij}(t) < \infty, \quad i \in \mathcal{N},\ j \in \mathcal{M}$$
$$0 \le C_i(t) \le C^i_{max}, \quad i \in \mathcal{N}$$
$$0 \le a_i(t) \le A_i(t), \quad i \in \mathcal{N}$$
$$0 \le A_i(t) \le C_i(t), \quad i \in \mathcal{N}$$
$$D_{ij}(t) \le R_{ij}(t) L_{ij}(t), \quad i \in \mathcal{N},\ j \in \mathcal{M} \tag{4}$$

It is worth noting that the intricate relationships between the numerous factors considered in this paper are clarified in the form of queue lengths with the help of virtual queues $H_i(t)\,(i \in \mathcal{N})$ and $G_i(t)\,(i \in \mathcal{N}, j \in \mathcal{M})$ and the intermediate variable $a_i(t)\,(i \in \mathcal{N})$. The difficulty of designing problem solution is therefore reduced a lot. Such phenomenon also indicates that we are able to add more consideration factors and constraints into the original optimization problem (3) without the concern of mathematical intractability. Therefore, the analysis and optimization method implemented in this paper is of high scalability.

B. PROBLEM DECOMPOSITION

Now we further decompose the optimization problem (4). The Lyapunov function is established as follows:

$$L(t) = \frac{1}{2}\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}} \left\{[Q_i(t)]^2 + [H_i(t)]^2 + \left[G_{ij}(t)\right]^2\right\} \tag{5}$$

$L(t)$ provides a holistic view of the queue stability. If one of the queues is unstable and becomes long, $L(t)$ will increase accordingly. Only when all the queues become short, $L(t)$ will decrease. Therefore, to solve the transformed problem (4), it is important to control $L(t)$ at a small value. Meanwhile, decreasing $L(t)$ is equivalent to minimize the increase of $L(t)$ at each time slot. Based on such consideration, we further establish the Lyapunov drift function as follows:

$$\Delta L(t) = L(t+1) - L(t) \tag{6}$$

Considering the optimization objective of transformed problem (4), we further formulate the drift-minus-objective function to simultaneously maximize the utility of accessed data and maintaining the stability of all queues. The drift-minus-objective function is shown as follows:

$$\Delta L(t) - V\sum_{i\in N} U(a_i(t)) \tag{7}$$

where V is a positive variable. It is used to balance the tradeoff between data utility and queue stability. Intuitively, when the value of V becomes large, the utility of data is attached more importance and queue lengths will become longer correspondingly. On the contrary, when the value of V becomes small, queue stability is more important compared with the utility of data.

To minimize the value of drift-minus-objective, its upper bound is first calculated as follows:

$$\Delta L(t) - V\sum_{i\in\mathcal{N}} U(a_i(t)) \le \frac{1}{2}B$$
$$-\sum_{i\in\mathcal{N}} [H_i(t)A_i(t) - Q_i(t)A_i(t)] \tag{8a}$$
$$-\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}} \left[Q_i(t)D_i(t) - G_{ij}(t)W_{ij}(t) + G_{ij}(t)W^{ij}_{max}\right] \tag{8b}$$
$$-\sum_{i\in\mathcal{N}} \{VU[a_i(t)] - H_i(t)a_i(t)\} \tag{8c}$$

where

$$B = \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}} \left[\left(1+P^2_{ij}\right)\left(R^{ij}_{max}\right)^2 + 3\left(C^i_{max}\right)^2 + \left(W^{ij}_{max}\right)^2\right].$$

Then the following three subproblems can be derived from (8a), (8b) and (8c), respectively.

1) Data access control problem

$$\max_{A_i(t)} \sum_{i\in\mathcal{N}} [H_i(t)A_i(t) - Q_i(t)A_i(t)]$$
$$\text{s.t. } 0 \le A_i(t) \le C_i(t),\ i \in \mathcal{N} \tag{9}$$

2) Hybrid transmission control problem

$$\max_{A_i(t),D_{ij}(t)} \sum_{i\in\mathcal{N}} \left[Q_i(t)D_i(t) - G_{ij}(t)W_{ij}(t) + G_{ij}(t)W^{ij}_{\max}\right]$$
$$\text{s.t. } 0 \le D_{ij}(t) \le R_{ij}(t)L_{ij}(t), \quad i \in \mathcal{N},\ j \in \mathcal{M}$$
$$D_i(t) = \sum_{j\in\mathcal{M}} D_{ij}(t), \quad i \in \mathcal{N},\ j \in \mathcal{M} \tag{10}$$

3) Intermediate calculation problem

$$\max_{a_i(t)} \sum_{i\in\mathcal{N}} \{VU[a_i(t)] - H_i(t)a_i(t)\}$$
$$\text{s.t. } 0 \le a_i(t) \le A_i(t), \quad i \in \mathcal{N} \tag{11}$$

It is obvious that the above three subproblems are relatively simple and can be solved independently. Utilizing the solutions to these subproblems, the original problem (3) can be solved.

VI. STOCHASTIC DATA SCHEDULING MECHANISM

In this section, SDSM is designed to solve the decomposed three subproblems. The optimality and implementation analyses of SDSM are also presented.

A. SDSM DESIGN

The overview of SDSM is shown as in Figure 4. SDSM is composed of four components, including data access component, hybrid transmission component, intermediate calculation component and iteration component. Data access component is responsible for determining the amount of data to be accessed by sensors. Mathematically, it solves the subproblem (9) and obtain the optimal value of $A_i(t)$.

Hybrid transmission component solves subproblem (10) and derives the optimal value of $D_i(t)$ and $D_{ij}(t)$. In physical sense, this component determines the amount of data to be transmitted through transmission approach $j\,(j \in \mathcal{M})$ in sensor $i\,(i \in \mathcal{N})$ at each time slot. Intermediate calculation component is used to solve the subproblem (11) and calculate the intermediate variable $a_i(t)$ so as to assist other components in making decisions. Iteration component updates the queue lengths of $Q_i(t)\,(i \in \mathcal{N})$, $H_i(t)\,(i \in \mathcal{N})$ and $G_{ij}(t)\,(i \in \mathcal{N}, j \in \mathcal{M})$.

During the operation of SDSM, the data access component, hybrid transmission component and intermediate calculation component first take queue lengths of present time slot as input and conduct their algorithms to obtain outputs. Then these outputs will further change queue lengths through iteration component. The changed queue lengths will then be used by the other three components to repeat their algorithms at next time slot. The detailed algorithms employed by data access component, hybrid transmission component and intermediate calculation component will be presented in following sections.

B. DATA ACCESS ALGORITHM

The subproblem (9) is used to determine the amount of accessed data at time slot t. This problem can be easily solved as follows:

$$A_i(t) = \begin{cases} C_i(t), & \text{if } H_i(t) > Q_i(t) \\ 0, & \text{otherwise,} \end{cases} \quad i \in \mathcal{N} \tag{12}$$

Equation (12) indicates that when $H_i(t) > Q_i(t)$, the amount of data backlogged at sensor $i\,(i \in \mathcal{N})$ is small. Therefore, the sensor is able to access more data. The detailed data access algorithm is shown as in **Algorithm 1**. The complexity of **Algorithm 1** is $\mathcal{O}(\mathcal{N})$.

C. HYBRID TRANSMISSION ALGORITHM

Considering $W_{ij}(t) = P_{ij}D_{ij}(t)$ and W_{max}^{ij} is a constant, the optimization objective of subproblem (10) can be rewritten as follows:

$$\sum_{i \in N} \left[Q_i(t) D_i(t) - G_{ij}(t) P_{ij} D_{ij}(t)\right]$$

This problem is difficult and complex because of the coupled variables $D_i(t)$ and $D_{ij}(t)$. To solve this problem,

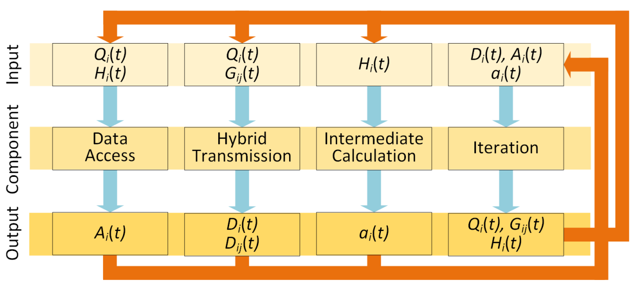

FIGURE 4. The overview of SDSM.

Algorithm 1 Data Access Algorithm

Input: queue lengths of $Q_i(t)$, $H_i(t)$ $(i \in \mathcal{N})$
Output: $A_i(t)$ $(i \in \mathcal{N})$
At each time slot;
for $i \in \mathcal{N}$ **do**
  if $H_i(t) > Q_i(t)$ **then**
    $A_i(t) = C_i(t)$;
  else
    $A_i(t) = 0$;
  end
  return $A_i(t)$;
end

we first assume that $D_i(t)$ is a determined variable and $D_{ij}(t)$ is unknown at time slot t. Then we have the following problem:

$$\begin{aligned} &\min_{D_{ij}(t)} \sum_{j \in \mathcal{M}} G_{ij}(t) P_{ij} D_{ij}(t) \\ &\text{s.t. } D_i(t) = \sum_{j \in \mathcal{M}} D_{ij}(t), \quad i \in \mathcal{N},\ j \in \mathcal{M} \end{aligned} \tag{13}$$

The problem (13) gives critical insight into allocating the data among transmission approaches $j \in \mathcal{M}$ in sensor $i \in \mathcal{N}$. The solution of problem (13) can be formulated as follows:

Allocate the data in sensor $i \in \mathcal{N}$ to the transmission approach $j \in \mathcal{M}$ with the shortest queue length $G_{ij}(t)$.

The above solution can also be presented mathematically as follows:

$$D_{ij}(t) = \begin{cases} D_i(t), & \text{if } j = \arg\min\limits_{j \in \mathcal{M}} \left[G_{ij}(t)\right] \\ 0, & \text{otherwise,} \end{cases} \quad i \in \mathcal{N} \tag{14}$$

Based on the above solution, the subproblem (10) can be rewritten as follows:

$$\begin{aligned} &\max_{D_i(t)} \sum_{i \in \mathcal{N}} Q_i(t) D_i(t) - G_{ij^*}(t) P_{ij^*} D_{ij^*}(t) \\ &\text{s.t. } 0 \le D_{ij}(t) \le R_{ij}(t) L_{ij}(t), \quad i \in \mathcal{N},\ j \in \mathcal{M} \end{aligned}$$

where $j^* = \arg\min\limits_{j \in M} \left[G_{ij}(t)\right]$. This problem can be solved as follows:

$$D_i(t) = \begin{cases} \min\left[R_{ij^*}(t) L_{ij^*}(t), Q_i(t)\right], & \text{if } Q_i(t) > G_{ij^*}(t) \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

The detailed hybrid transmission algorithm is shown as in **Algorithm 2**. The complexity of **Algorithm 2** is $\mathcal{O}(\mathcal{N})$.

D. INTERMEDIATE CALCULATION ALGORITHM

We first formulate an auxiliary function based on the optimization objective of subproblem (11) as follows:

$$f(x) = V\delta \ln(x + \gamma) - H_i x$$

Algorithm 2 Hybrid Transmission Algorithm

Input: queue lengths of $Q_i(t)$, $G_{ij}(t)$ $(i \in \mathcal{N}, j \in \mathcal{M})$
Output: $D_i(t)$ and $D_{ij}(t)$ $(i \in \mathcal{N}, j \in \mathcal{M})$
At each time slot;
for $i \in \mathcal{N}$ **do**
  Select the transmission approach using
  $j^* = \arg\min_{j \in M} \left[G_{ij}(t)\right]$;
  if $Q_i(t) > G_{ij^*}(t) P_{ij^*}$ **then**
    $D_i(t) = \min\left[R_{ij^*}(t) L_{ij^*}(t), Q_i(t)\right]$;
  else
    $D_i(t) = 0$;
  end
  $D_{ij^*}(t) = D_i(t)$;
  return $D_{ij^*}(t), D_i(t)$;
end

Algorithm 3 Intermediate Calculation Algorithm

Input: queue lengths of $H_i(t)$ $(i \in \mathcal{N})$
Output: $a_i(t)$ $(i \in \mathcal{N})$
At each time slot;
for $i \in \mathcal{N}$ **do**
  if $V\delta / H_i(t) - \gamma > 0$ **then**
    $a_i(t) = V\delta / H_i(t) - \gamma$;
  else
    $a_i(t) = 0$;
  end
  return $a_i(t)$;
end

The first and second order derivatives of $f(x)$ are calculated as follows:

$$f'(x) = \frac{V+\gamma}{x+\gamma} - H_i$$
$$f''(x) = -\frac{V\gamma}{(x+\gamma)^2}$$

At first, $f''(x) < 0$. It suggests that $f'(x)$ is a monotonic decreasing function. So there is only one root of the equation $f'(x) = 0$ in interval $x \in (-r, +\infty)$. The root is $x_r = V\delta / H_i - \gamma$. Then we can conclude that function $f(x)$ arrives at its maximum value when $x = x_r$.

Based on the above analysis, to solve the subproblem (11), we only need to let $a_i(t) = V\delta / H_i(t) - \gamma$. The detailed intermediate calculation algorithm is shown as in **Algorithm 3**. The complexity of **Algorithm 3** is $\mathcal{O}(\mathcal{N})$.

E. OPTIMALITY ANALYSIS

The optimality of SDSM is analyzed in terms of time-averaged utility of data and network stability. Three important conclusions are also obtained, including *utility conclusion*, *stability conclusion* and *tradeoff conclusion*.

1) OPTIMALITY OF UTILITY

We first assume there exists a feasible control mechanism Ω which performs control operations on $A_i(t)$, $D_i(t)$, $D_{ij}(t)$ and $a_i(t)$. Under these control operations, mechanism Ω has the following properties:

$$\begin{aligned}
A_i^{\Omega}(t) - D_i^{\Omega}(t) &\le \varepsilon, \quad i \in \mathcal{N} \\
a_i^{\Omega}(t) - A_i^{\Omega}(t) &\le \varepsilon, \quad i \in \mathcal{N} \\
W_{ij}^{\Omega}(t) - W_{max}^{ij,\Omega}(t) &\le \varepsilon, \quad i \in \mathcal{N},\ j \in \mathcal{M} \\
\sum_{i\in\mathcal{N}} U^{\Omega}(a_i(t)) &\ge \sum_{i\in\mathcal{N}} U_{max}^i - \varepsilon
\end{aligned}$$

where ε is a positive real number and $\sum_{i\in\mathcal{N}} U_{max}^i$ is the maximum utility of data.

Based on the above four properties of control mechanism Ω, the inequality (8) is reformulated as follows:

$$\Delta L(t) - V\sum_{i\in N} U(a_i(t)) \le \frac{B}{2} - V\sum_{i\in N}\left(U_{max}^i - \varepsilon\right)$$

Substitute $t = 0, 1, 2, \cdots, T$ into the above inequality and sum the derived inequalities. Then let $T \to \infty$, we have the following inequality.

$$\sum_{i\in\mathcal{N}} U_{max}^i - \sum_{i\in\mathcal{N}} \overline{U(a_i(t))} \le \frac{B+2\varepsilon}{2V} \tag{16}$$

From the inequality (16), we can draw the *utility conclusion* as follows:

The difference between the maximum utility and the achievable utility of data will be less than $\frac{B+2\varepsilon}{2V}$. Meanwhile, the difference between the maximum utility and achievable utility is inversely proportional to the parameter V. When V becomes large, the utility of data will become better.

2) OPTIMALITY OF NETWORK STABILITY

A similar assumption is made that a feasible control mechanism ω performs control operations on $A_i(t)$, $D_i(t)$, $D_{ij}(t)$ and $a_i(t)$. Under these control operations, mechanism ω has the following properties:

$$\begin{aligned}
A_i^{\omega}(t) &\le D_i^{\omega}(t) - \varepsilon, \quad i \in \mathcal{N} \\
a_i^{\omega}(t) &\le A_i^{\omega}(t) - \varepsilon, \quad i \in \mathcal{N} \\
W_{ij}^{\omega}(t) &\le W_{max}^{ij,\omega}(t) - \varepsilon, \quad i \in \mathcal{N},\ j \in \mathcal{M} \\
\sum_{i\in\mathcal{N}} U^{\omega}(a_i(t)) &= \sum_{i\in\mathcal{N}} U_i^*
\end{aligned}$$

where $\sum_{i\in\mathcal{N}} U_i^*$ is the achieved utility of data under control mechanism ω.

Based on the above four properties of control mechanism ω, the inequality (8) is reformulated as follows:

$$\begin{aligned}
\Delta L(t) - V\sum_{i\in\mathcal{N}} U(a_i(t)) &\le \frac{1}{2}B \\
&- V\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}}\left[Q_i(t) + G_{ij}(t) + H_i(t)\right] - V\sum_{i\in\mathcal{N}} U_i^*
\end{aligned} \tag{17}$$

Substitute $t = 0, 1, 2, \cdots, T$ into the above inequality and sum the derived inequalities. Then let $T \to \infty$, we can derive

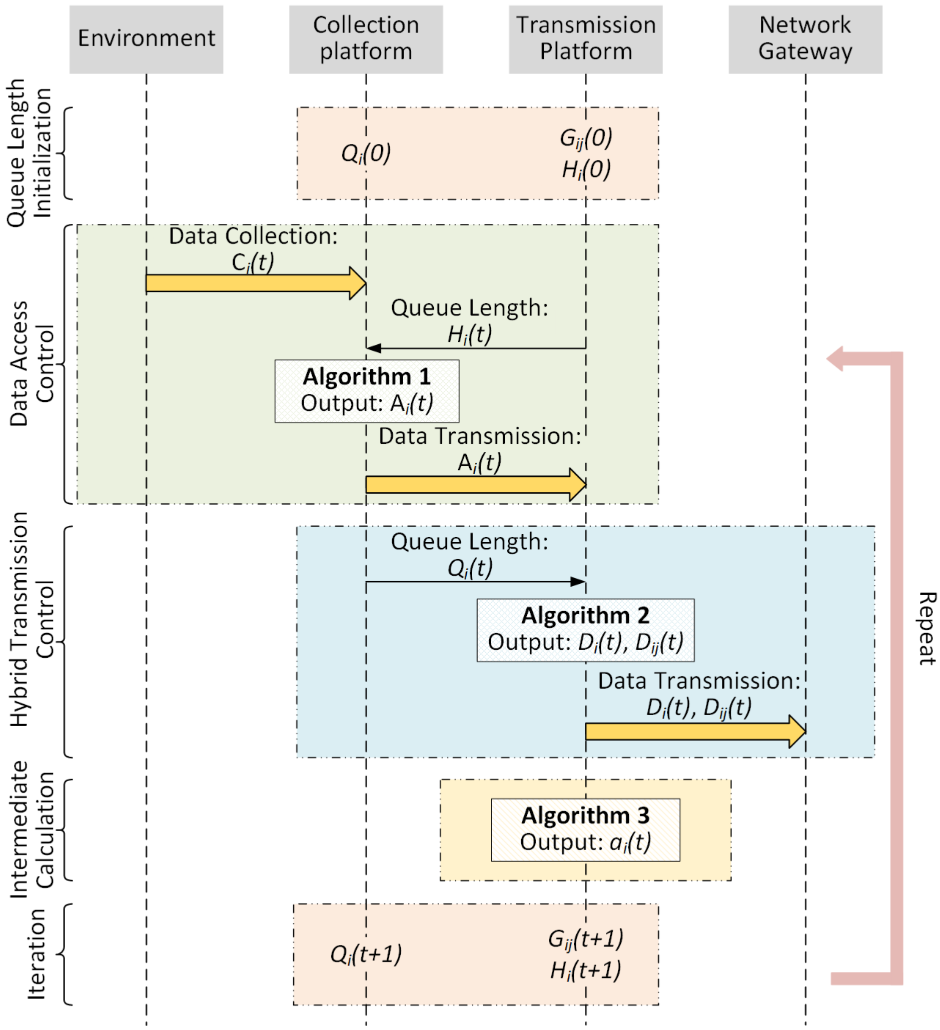

FIGURE 5. Working procedure of SDSM.

the inequality as follows:

$$\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}}\left[\overline{Q_i(t)}+\overline{G_{ij}(t)}+\overline{H_i(t)}\right] \leq \frac{B}{2\varepsilon}+\frac{V}{\varepsilon}\sum_{i\in\mathcal{N}}\left[U^i_{\max}-U^*_i\right] \quad (18)$$

From the inequality (18), we can draw the *stability conclusion* as follows:

The time-averaged queue lengths of $Q_i(t)$, $G_{ij}(t)$ and $H_i(t)$ $(i \in \mathcal{N}, j \in \mathcal{M})$ are proportional to the parameter V. That is when V becomes large, the network stability will be decreased.

Moreover, combining the *utility conclusion* with *stability conclusion*, we can obtain the *tradeoff conclusion* as follows:

The parameter V is able to balance the tradeoff between the utility of data and network stability. Specifically, a large V will improve the utility of data and impair the network stability. On the contrary, a small V will be positive for network stability but negative for the utility of data. Meanwhile, the *utility conclusion* and *stability conclusion* also suggest that performing control operations to minimize the inequality (8) is able to maintain the network stability and maximize the utility of data.

F. IMPLEMENTATION ANALYSIS

The implementation method and working procedure of SDSM is shown in Figure 5. Considering the two platforms of sensors, i.e. collection platform and transmission platform, the three algorithms of SDSM should be divided into two parts to be efficiently conducted by sensors. The first part is conducted by collection platform which includes data access algorithm. The second part is conducted by transmission platform which includes hybrid transmission algorithm and intermediate calculation algorithm. Meanwhile, the queue lengths of $Q_i(t)$, $G_{ij}(t)$ and $H_i(t)$ $(i \in \mathcal{N}, j \in \mathcal{M})$ should also be maintained by the two platforms. Combining with the algorithm partition, the $Q_i(t)$ $(i \in \mathcal{N})$ is recommended to be maintained by collection platform and $G_{ij}(t)$ and $H_i(t)$ $(i \in \mathcal{N}, j \in \mathcal{M})$ by transmission platform.

Based on the above implementation method, the working procedure of SDSM at each time slot is illustrated as follows:

1) Queue Length Initialization: Sensors initialize their queue lengths including $Q_i(t)$, $G_{ij}(t)$ and $H_i(t)$, where $i \in \mathcal{N}, j \in \mathcal{M}$.
2) Data Access Control: The data collection platform of sensor ($i \in \mathcal{N}$) first collects data from monitored environment. Then data access component takes $Q_i(t)$ and $H_i(t)$ as inputs to perform the **Algorithm 1**, i.e. data access algorithm. Finally, the collected data is transmitted to transmission platform. The amount of the transmitted data is $A_i(t)$. In this step, a signaling overhead is consumed by acquiring the value of $H_i(t)$ from transmission platform.
3) Hybrid Transmission Control: After receiving the data from collection platform, the hybrid transmission component in transmission platform takes $Q_i(t)$, $H_i(t)$ and $G_{ij}(t)$ as inputs to perform the **Algorithm 2**, i.e. hybrid transmission algorithm. Then the received data is allocated over various transmission approaches and transmitted to data processing center according to $D_i(t)$ and $D_{ij}(t)$. In this step, a signaling overhead is consumed by acquiring the value of $Q_i(t)$.
4) Intermediate Calculation: Intermediate calculation component in transmission platform conducts **Algorithm 3**, i.e. intermediate calculate algorithm, to calculate the intermediate variable $a_i(t)$.
5) Iteration: Based on the outputs of the three algorithms, the two platforms update the queue lengths they maintained and repeat the above procedure again at next time slot.

From the above working procedure, it can be concluded that two signaling overheads are consumed during the working procedure of SDSM at each time slot.

VII. PERFORMANCE EVALUATION

The performance of SDSM is evaluated in this section through extensive simulations. During the simulations, the simulated WSN is composed of 400 sensors. We assume the process of data collection obeys to Poisson process and the average data collection rate of sensor is set as $900kb/s$. Each of the sensor employs three kinds of transmission approach, including WiFi, microwave technology and millimeter wave technology. In this paper, the transmission rates of the three transmission approach are set as $600kb/s$, $1.2Mb/s$ and $100Mb/s$, respectively. The average data loss rates are correspondingly set as 5%, 10% and 80%. It is worth noting that the transmission rates and data loss rates are actually different in various communication environment. However, researching on the exact expression of transmission rates and data loss rates of different transmission approach is beyond the scope of this paper. Meanwhile, setting these parameters as constants is enough to evaluate the performance of SDSM. Therefore, we mainly perform the simulations using the relatively simple parameter settings to presents the performances of SDSM. It is also worth noting that the accurate and complex expressions of these parameters are also compatible with SDSM. Based on the similar consideration, δ and γ are set as 1.

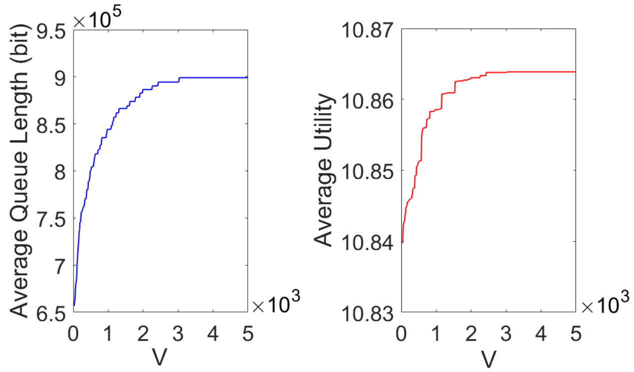

FIGURE 6. The effects of parameter V.

We first examine the effects of parameter V on the performance of SDSM, in terms of average queue length and average utility of data. During the simulations, the energy constraints of the employed transmission approaches are set as 5×10^5. The simulation results are shown as in Figure 6. Figure 6 first presents that the average queue length increases as V increases. Specifically, when V is less than 2500, the average queue length is growing rapidly. Then when V becomes larger than 2500, the average queue length almost remains stable and only increases with a small degree. In Figure 6, the average utility presents similar increase pattern with average queue length. With the increase of parameter V, average utility also increases. It increases fast when V is less than 2500 and almost remains stable when V is larger than 2500. From Figure 6, we can also observe that the increased V is positive for average utility but is negative for the network stability. Such phenomenon is coincident with the optimality analysis in Section VI-E. Therefore, the parameter V provides an efficient method to balance the tradeoff between network stability and average utility. Based on the above simulation results, we set $V = 1000$ in the following simulations. This is because when $V = 1000$, the average utility can be improved a lot without great increment of average queue length.

Figure 7 shows the effect of energy constraint on data transmission, queue length and average utility. As for the data transmission, it can be observed that the amount of total transmitted data increases with the increment of energy constraint. Meanwhile, the amount of transmitted data through microwave technology and WiFi first achieve monotonically increment with the increase of energy constraint and finally remains stable. The amount of transmitted data through millimeter wave technology arrives at its maximum value when energy constraint is about 1.1×10^6. Then it decreases a lot when energy constraint is in the interval $[1.1 \times 10^6, 3.6 \times 10^6]$. Finally, it remains stable, too. Among the three transmission approaches, microwave

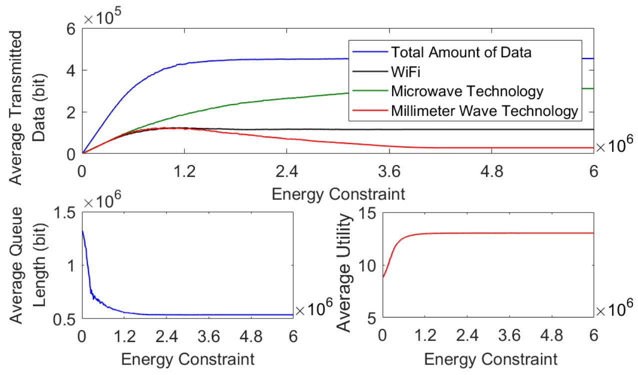

FIGURE 7. The effects of energy constraint.

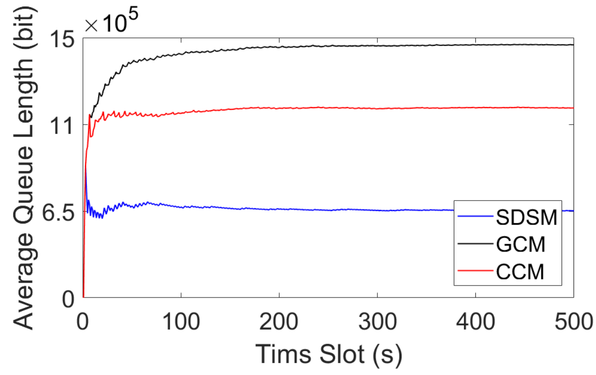

FIGURE 8. The comparison of average queue lengths.

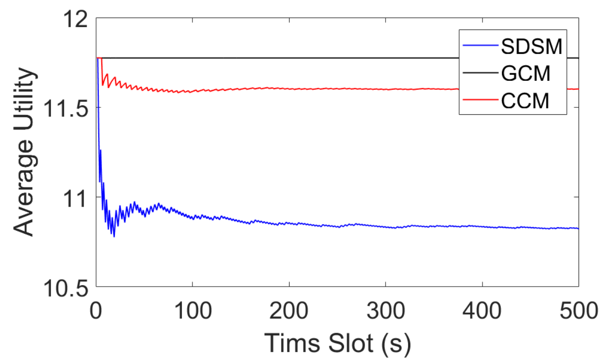

FIGURE 9. The comparison of average utilities.

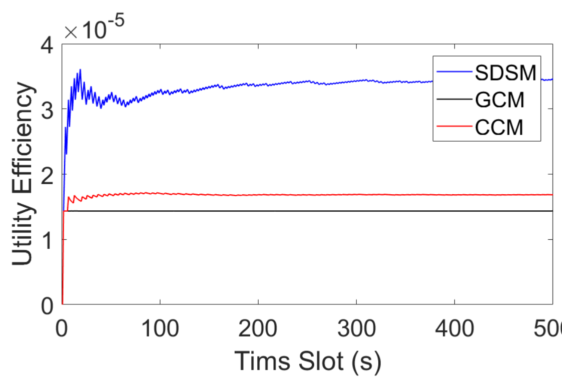

FIGURE 10. The comparison of utility efficiencies.

technology has the largest amount of transmitted data and millimeter wave technology has the least. This is because millimeter wave technology has the highest transmission rate and highest data loss rate. The two features will greatly impair the network stability. Therefore, to maintain network stability, SDSM is prefer to utilize microwave technology which has higher reliability than millimeter wave technology and higher transmission rate than WiFi. As for the average queue length, it can be observed from Figure 7 that it decreases with the increase of energy constraint. This is because with the increase of energy constraint, SDSM acquire higher transmission capability. The amount of backlogged data at each sensor is reduced. The average queue length consequently decreases. Figure 7 also shows that the average utility of data increases with the growth of energy constraint. This is because the increased energy constraint result in the increment of data transmission rate. It further leads to the increased amount of accessed data. Therefore, the average utility increases.

To further evaluate the performance of SDSM, we compare SDSM with Greedy Control Mechanism (GSM) and Congestion Control Mechanism (CCM). GCM accepts all of the collected data and transmits the data using the transmission approach with the shortest queue. CCM continuously detects network congestion [31]. When congestion is detected, the sensor will not access any data until the congestion is alleviated.

The average queue lengths of the three mechanisms are compared in Figure 8. It can be observed that SDSM has the shortest average queue length and GCM has the longest. This is because SDSM performs the controls on both data access and data transmission. Therefore, it is able to maintain the queue length at a low level. As for GCM, it accesses all of the data without the consideration of the queue length and data transmission rate. Therefore, GCM's average queue length is the longest. Meanwhile, CCM only reduces the amount of accessed data when congestion is detected. It cannot efficiently schedule the data over the transmission approaches.

The average utilities of the SDSM, GCM and CCM are compared in Figure 9. It can be observed GCM achieves the best average utility because it accesses all of the data. SDSM has the lowest average utility. This is because SDSM accepts the least amount of data. However, combined with Figure 8, we can find out that GCM and CCM improve their average utilities with a serious impairment of queue stability. Specifically, GCM and CCM only improve their average utilities about 8.3% and 6.9% compared with SDSM. But their average queue lengths are increased about 127.7% and 72.3%.

The comparison of utility efficiencies of the three mechanisms are presented in Figure 10. The utility efficiency is measured by the average utility divided by the average amount of accessed data. It can be observed that the utility efficiency of SDSM is the best. GCM and CCM achieve the similar utility efficiency. This is because SDSM incorporate the considerations of data utility and queue stability when it performs the control operations. Therefore, it is able to

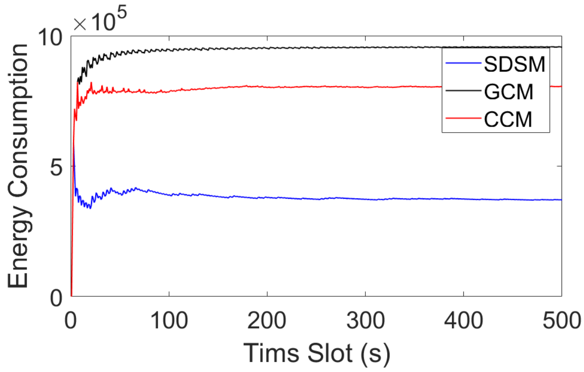

FIGURE 11. The comparison of energy consumptions.

access the appropriate and optimal amount of data so as to increase the achieved utility without the great increment of queue length. However, the other two mechanisms fail to incorporate such considerations. Even though they are able to access much more data, they cannot improve the data utility significantly and also lead to data congestions in sensors.

Figure 11 presents the comparison of energy consumptions between the three mechanisms. It can be observed that the SDSM consumes the least amount of energy and GCM consumes the most. This is because the SDSM performs the control operations with the constraint of energy consumption. It is able to transmit the data in a more efficient way. However, GCM and CCM make the data transmission decisions only based on the present queue lengths which is not sufficient to reduce their energy consumptions.

Based on the above performance evaluations, it can be concluded that SDSM is able to reduce the average queue lengths and energy consumption. In terms of average utility, though SDSM cannot achieve the same performance with GCM and CCM, the utility efficiency of SDSM is the best. Therefore, the overall performance of SDSM is better than the other two mechanisms. Meanwhile, SDSM is cost-efficient in terms of data utility and energy consumption.

VIII. CONCLUSION

This paper focuses on the wireless links of sensors to improve the performance of WSN. Based on data access control and hybrid transmission control, we first formulate a mathematically intractable optimization problem. The problem incorporates the considerations of data utility, network stability, energy consumption and data loss rate. Then it is further transformed and decomposed into three subproblems through a Lyapunov function-based network optimization theory. SDSM is designed to solve the three subproblems which is composed of four components. Finally, the performance of SDSM is evaluated and it is also compared with GCM and CCM to demonstrate its superiority.

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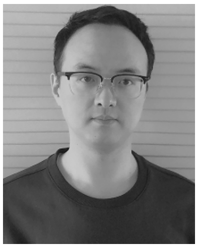

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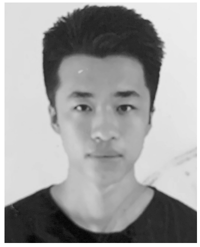

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