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PAPER

A Novel Low-Complex Optimized Resource Allocation Algorithm Using GWO Optimization Technique in Energy Scavenging for WBAN

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ABSTRACT

In wireless body area networks (WBANs) powered by energy scavenging, effectively managing renewable energy is critical to ensuring delay-sensitive services. This paper proposes a novel low-complex optimized resource allocation algorithm using the Grey Wolf Optimization (GWO) technique to allocate resources, specifically energy and communication channels, and maximize user utility while guaranteeing the worst-case delay. To achieve this, firstly, a formulation of a user utility optimization problem that accounts for the stochastic nature of energy scavenging and consumption without requiring prior knowledge of these processes is performed. Utilizing GWO optimization techniques, optimization problems broke down into four sub-problems: battery management, collection rate control, transmission power allocation, and drop rate control. Additionally, the proposed algorithm's performance is analyzed by examining the upper bounds of queues and required battery capacity. Simulation results confirm our theoretical analysis and the effectiveness of the proposed algorithm.

KEYWORDS

wireless body area networks (WBAN), Grey Wolf Optimization (GWO)

1 INTRODUCTION

With the aging population growing in developing countries and the rising costs of healthcare, wireless body area networks (WBANs) have emerged as a key solution to enhance healthcare efficiency, garnering significant attention from both industry and academia [1]. A WBAN comprises a series of miniaturized, low-power, intelligent sensors equipped with wireless communication capabilities [2, 3]. These sensors are either implanted in or attached to the human body without restricting the user's movements [4, 5]. In this paper, the resource allocation is investigated with worst-case delay requirements in WBANs consisting of several medical sensors by jointly considering

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the data buffers and energy buffer management of sensors. The sensors transmit data to a personal device over the time-varying channel. Due to the motion and shadowing effect of the human body, the channel variation varies unpredictably over time. They aim to maximize the time-average user utility to ensure the worst-case delay.

These sensors monitor specific physical conditions and collect physical information from the body or around, such as electroencephalographs (EEG) and electrocardiographs (ECG) [6, 7], then transmit the information to the sink for further analysis. The publication of IEEE 802.15.6 standards specifically for wireless communication in or near the human body has also contributed to the development of BANs [8]. However, challenges remain for efficient healthcare data collection using banks. The first challenge lies in the limited longevity of sensors powered by batteries [9]. For example, a pacemaker or a glucose monitor would require a lifetime lasting more than 5 years [10]. Upon energy deficiency, the battery replacement may require surgical procedures. Although the battery capacity can be improved by increasing the size, the size of sensors in BANs has strict weight and size requirements, so only relying on battery power is not feasible [11, 12]. To address this issue, it is desirable to power sensors with renewable energy harvested from ambient energy sources related to the human body [13], such as kinetic and mechanic sources, to continuously monitor the specific physical condition [14, 15].

However, WBANs face significant challenges, with energy efficiency being one of the most critical. The ability to provide long-lasting service in WBANs is closely tied to how the sensors are powered. Currently, most WBAN sensors depend on batteries, which have a very limited capacity. Frequent battery replacements are impractical due to patient comfort, especially for sensors implanted in the human body, like blood pressure or pH sensors, where battery replacement is not feasible. To address this issue, energy-scavenging technology has been developed [16]. This technology is crucial for extending the lifespan of sensors in WBANs, which often require a service life of more than five years, such as in pacemakers or glucose monitors. By utilizing energy scavenging, sensors can harness energy from renewable and ambient sources in their environment. WBAN sensors are now equipped with energy-scavenging modules that provide a continuous energy supply independent of batteries. These sensors can collect and transmit data continuously by scavenging energy, ensuring their uninterrupted operation.

To overcome these limitations, this paper introduces a novel framework that effectively captures the stochastic nature of energy scavenging. The goal is to design a problem formulation that optimizes user utility by considering both energy scavenging and power consumption dynamics. By accounting for the stochastic processes involved in energy scavenging, besides developing a more comprehensive and realistic approach to addressing energy management challenges in networks. The proposed framework seeks to achieve an optimal balance between energy scavenging and consumption to maximize the system's overall utility [17]. Additionally, by applying the Grey Wolf Optimization (GWO) technique, the framework ensures the optimality of user utility.

The contributions of this paper are firstly proposing a stochastic problem of the user utility optimization problem for the BANs while guaranteeing worst-case delay and the stability of the BANs system by characterizing the stochastic nature of the energy scavenging process, the energy consumption of data collection and transmission, and channel fading, which does not need any prior knowledge of the stochastic process. Secondly, the GWO optimization approach is used to decompose the user utility optimization problem into four sub-problems, i.e., battery management, collecting rate control, transmission power allocation, and dropping rate control, which are solved by a low-complexity algorithm. The algorithm makes decisions at the beginning of each time slot and then updates the queue length. Finally, the performance of the proposed resource allocation algorithm is analyzed in terms of the required battery capacity, bounded queue length, and the optimality of the proposed algorithm. The required battery capacity is derived to support data collection and transmission. Also, showing the bound worst-case delay to ensure that the transmission time is bounded. The performance addresses the gap between the user utilities achieved by the proposed algorithm and the optimal utility.

The remainder of the paper is organized as follows: Section 2 utilizes the system model details. Section 3 illustrates problem formulations. Section 4 presents the proposed resource allocation algorithm. Section 5 shows the simulation results and their discussion. Finally, concluding remarks are illustrated in Section 6.

2 SYSTEM MODEL

The system model of WBANs is presented in this section. It is considered a single-hop BAN with delay-sensitive traffic, which consists of N biomedical sensors and a personal device. Each sensor is equipped with a limited-capacity battery and energy-scavenging module. The energy scavenging to prolong sensors' lifetime of sensor such as Personal Device Wireless Links, EGG for hearing aid positioning, ECG for measuring glucose lactic acid and Artificial Knee Pressure Sensor as shown Figure 1. Let $N = \{1, 2, 3, \ldots, \mathrm{N}\}$ be the set of all sensors operating over the time slots $t \in T = \{0, 1, 2, 3 \ldots\}$. The sensor collects data from the body or surrounding environment and then transmits it to the personal device in a limited time.

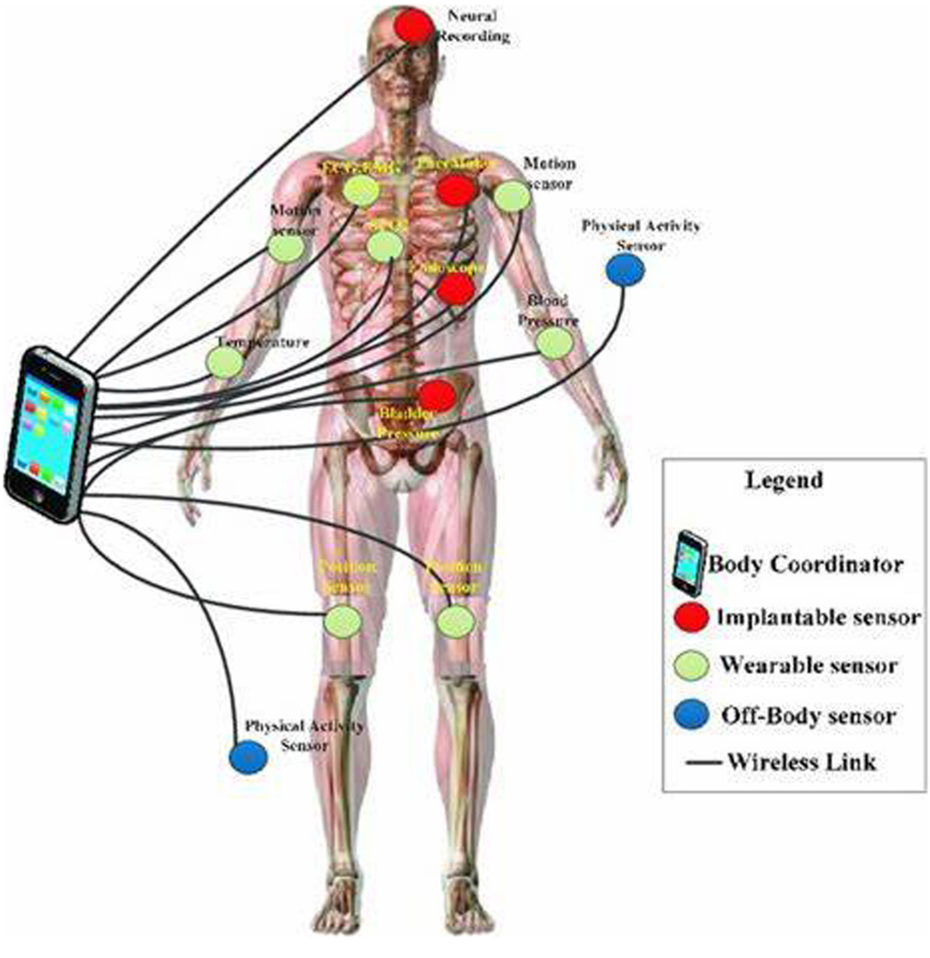

Fig. 1. An example of biomedical sensor utilization

2.1 Data transmission model

In WBANs, data transmission and transmission power are related. If it is defined as the transmission power for data transmission in time slot t, then the following inequality should be satisfied $p_n(t)$:

$$0 \le p_n(t) \le p^{max},\ n \in N \tag{1}$$

where p^{max}, is a finite constant that indicates the maximum transmission power restriction at sensor n, and $\alpha_n(t)$ is the signal-to-interference plus noise ratio of sensor n:

$$\alpha_n(t) = \frac{i_n(t)p_n(t)}{s + \sum_{i=1, i\ne n}^{N} f_i(t)a_i(t)} n \in N \tag{2}$$

where S is the noise, and $f_n(t)$ represent the fading coefficient from sensor n and to the personal device in time slot t. It is assumed that $f_n(t)$ is a time-varying independent and identically distributed (i.i.d.) in every time slot.

The transmit rate $\eta_n(t)$ is defined as

$$\eta_n(t) = \log(1 + G\alpha_n(t)),\ n \in N \tag{3}$$

where G represents the gain of processing. Since for the log(G $\alpha_n(t)$) is very close to log($1 + G\alpha_n(t)$), so later equation will be

$$\eta_n(t) = \log(G\ \alpha_n(t)),\ n \in N \tag{4}$$

2.2 Data transmission queue dynamic model

Let $W_n(t)$ denote the data queue occupancy of senson, n and $\boldsymbol{W}(\boldsymbol{t}) = \{W_1(t), W_2(t), W_3(t), \ldots, W_N(t)\}$ represents a vector with the length of data queues of all sensors in time slot t. Let $C_n(t)$ represent the collected data of sensor n to the data queue. It is assumed arrivals have a finite maximum C^{max}, so that

$$0 \le C_n(t) \le C^{max},\ n \in N \tag{5}$$

A networking scheduler determines how much of the collected data should be admitted, how much existing data in the queue should be transmitted, and how much existing data should be dropped. The data queue is given by:

$$W_n(t+1) = max[W_n(t) - \eta_n(t) - d_n(t), 0] + C_n,\ n \in N \tag{6}$$

where $max[W_n(t) - \eta_n(t) - d_n(t), 0]$ is the first term of the data queue. It represents the amount of data left in the data queue after the data is transmitted and dropped in time slot t. To emphasize that it is greater than or equal to zero, a max function is add to take a large value between $W_n(t) - \eta_n(t) - d_n(t)$ and zero. $d_n(t)$ is the amount of dropped data in time slot t, which falls in the range:

$$0 \le d_n(t) \le d^{max},\ n \in N \tag{7}$$

The d^{max} is the maximum drop rate in time slot t. The system is stable, which implies a finite average backlog, i.e., all the sensors have a bounded time-average length.

2.3 Energy supply model

Let in time slot t, the moving distance of sensor n carried by the patient is denoted by $m_n(t)$ with a maximum m^{max}. $m_n(t)$ is time-varying, independent and identically distributed (i.i.d) in every time slot.

The energy supply comes from two parts:

1. Movement
2. Other stable energy source such as body heat

The energy supply by moving is a linear function of $m_n(t)$ and is denoted by $\lambda m_n(t)$ the stable energy supply is constant in each time slot. The total energy supply rate in time slot t is:

$$uS_n(t) = \lambda m^{max} + e, n \in N \tag{8}$$

and is bounded by $uS_n(t) \leq \lambda m^{max} + e$ then $uS^{max} = \lambda m^{max} + e$ is used to denote the upper bound of energy supply.

$$uC_n(t) \leq cC_n(t) + P_n(t), n \in N \tag{9}$$

2.4 Energy consumption and energy queue dynamics model

In every time slot t, each sensor n collects data with collecting rate $C_n(t)$ and saves it in its data queue. The energy consumption of collecting data is a linear function of $C_n(t)$ and is denoted by $cC_n(t)$, the energy usage for data collection is a linear function of $C_n(t)$. So, the total energy consumption of sensor n in time slot t is:

$$uC_n(t) = cC + p \tag{10}$$

where, the total energy consumption is bounded by $uC_n(t) \leq cC^{max} + p^{max}$, $\forall\ n \in N$. So, $uC^{max} = cC^{max} + p^{max}$ denoted the upper bound of any sensor energy consumption. In time slot t, the harvested energy $S_n(t)$ of sensor n is bounded by

$$0 \leq S_n(t) \leq uS_n(t), n \in N \tag{11}$$

Thus, the energy queue of sensor n evolves according to:

$$K_n(t+1) = K_n(t) - C_n(t) + S_n(t), n \in N \tag{12}$$

For each time, slot t, sensor n carried by the patient is equipped with a battery of limited capacity Ω. The battery capacity is the same for all sensors. When $t = 0$, $K_n(t) = \Omega$, the total energy in the battery is limited by the capacity.

3 PROBLEM FORMULATION

3.1 Worst case delay queue model

For delay-sensitive traffic, the delay performance is significant. The data in the sensor carried by the patient is transmitted to the personal device, which should be in a bounded time. To ensure that worst-case delay is bounded, we define an ε – persistent service queue, being a virtual queue $M_n(t)$ for each $n \in \{1, 2, 3, ..., N\}$ with $M_n(0) = 0$ and with dynamics:

$$M_n(t+1) = max\left[M_n(t) + 1_{\{W_n(t)>0\}}(\in - \eta_n(t)) - d_n(t) - 1_{\{W_n(t)>0\}}\eta_n^{max}, 0\right] \tag{13}$$

where $\varepsilon > 0$ is constant, and $W_n(t) > 0$ is an indicator function that is 1 and 0 otherwise. When $W_n(t) > 0$, $M_n(t)$ has a departure process that is the same as $W_n(t)$, but it has an arrival of size ε every slot. This ensures that $M_n(t)$ grows if there are requests in the $W_n(t)$ queue that have not been transmitted for a long time. If there is a scheduling algorithm that is used to ensures $M_n(t) \leq M^{max}$ and $W_n(t) \leq W^{max}$, for all n, then we can ensure all requests are served within worst case delay.

Suppose $W_n(t)$ and $M_n(t)$ evolve according to the mentioned, and an algorithm is used to ensures $M_n(t) \leq M^{max}$ and $W_n(t) \leq W^{max}$ for all time slots $t \in \{0, 1, 2, ...\}$. Then the worst-case delay of all non-dropped data in queue n is I^{max}, defined as:

$$I^{max} = [W^{max} + M^{max}]/\varepsilon,\ n \in N \tag{14}$$

3.2 Optimization problem formulation

Based on the delay-sensitive traffic and energy scavenging models, formulate the stochastic optimization problem of maximizing the time-average aggregate user utility of BANs with energy scavenging. For each sensor $n \in \{1, 2, 3, ..., N\}$, it's defined as an $O_n(C_n(t))$, as a continuous, concave, and non-decreasing function over the interval $0 \leq C_n(t) \leq C^{max}$. It is assumed that the function $O_n(C_n(t))$, has a finite maximum slope of v. The utility function can be written as:

$$U_n(t) = O_n((C_n(t)) - \beta v C_n(t)) \tag{15}$$

$\beta \geq 1$, so βv is greater or equal to the v. βv is the slope of cost function for packet drops $d_n(t)$, $\beta v\ d_n(t)$, is the "penalty" for packet dropping. The objective is to maximize the time-average user utility of WBANs. The time-average user utility can be written as:

$$U_{ser} = \lim_{t\to\infty} \frac{1}{T} \sum_{t=0}^{T} \sum_{n\in\mathbf{N}} Ui_n(t). \tag{16}$$

where $Ui_n(t) = U_n((C_n(t))C(t), S(t), p(t)$, and $d(t))$ are used to denote the collecting data rate $C_n(t)$, energy scavenging rate $h_n(t)$, transmission power $p_n(t)$ and dropping data rate $d_n(t)$. Therefore, $Z(t) = (C(t), S(t), p(t), d(t))$ are defined to represent the set of variables in time slot t. The goal is to maximize the time average user utility. To attain this, formulate of user utility optimization problem as follows, subject to the constraints

$$(\text{UEDP})\max_{z(t)} \bar{\text{U}} \tag{17}$$

4 RESOURCE ALLOCATION ALGORITHM

Let $\Theta(t) = (W(t), K(t), M(t))$ denote the network state in time slot t. $\Theta(t)$ represents the occupancy of the data queue, energy queue, and virtual queue. To decompose the objective into optimization goals for each time slot, GWO theory is adopted, which introduces a method to control the delay of such a system and other utilities at the same time. The authors developed an aggregate network utility optimization framework for the design of an online energy management, spectrum management, and resource allocation algorithm based on GWO. The Grey Wolf function was defined as $G(t)$, the sum of squares of backlogs in the data queue, virtual data queue, and the spare capacity in sensor batteries.

4.1 Grey Wolf

Grey Wolf optimization theory introduces a method to control the utility problem. The GWO technique is implemented by decomposing it into four sub-problems for each time slot: power supply management, data collection rate, transmission power allocation, and dropping rate control, respectively. It is defined by the Grey Wolf function as the network state in the time slot t that represents the length of the data queue, energy queue, and virtual queue.

4.2 Sub-problem solution

$G(t)$ is an expansion of the set of variables $F(t) = S(t)$, $C(t)$, $p(t)$, $d(t)$. So, $G_n(\mathrm{t})$ is divided into four sub-problems. Each part is a subproblem that needs to be optimized. These sub-problems are power supply management $S(t)$, data collection rate $C(t)$, transmission power allocation $p(t)$, and dropping rate control $d(t)$.

The sub-problems power supply management optimizes the energy scavenging rate, which requires information on the energy queue occupancy and energy supply rate. The sub-problem of data collection rate optimizes the data collection rate, which requires information on the energy queue occupancy and data queue occupancy. The sub-problem of transmission power allocation optimizes the transmission power rate, which requires information on data queue occupancy and transmission rate. The sub-problem of dropping rate control optimizes the dropping rate, which requires information on energy queue occupancy and virtual queue.

5 PROPOSED ALGORITHM

The proposed resource allocation algorithm is to minimize $DV(t)$ in each time slot. it achieves the optimal harvested energy $S^*(t)$, collecting rate $C^*(t)$, dropping rate $d^*(t)$, and transmission power $p^*(t)$ by solving the four sub-problems: battery management (BM), collecting data rate control (CRC), transmission power allocation (TPA), and dropping data rate control (DRC), separately. Moreover, the occupancies of data queue $W(t)$, energy queue $K(t)$, and virtual queue $M(t)$ are updated according to their respective queue dynamics.

The proposed online resource allocation algorithm consists of four main parts are as follows:

1. Focuses on solving the sub-problem scavenging energy $S(t)$ to obtain the optimal scavenged energy $S^*(t)$ for the current time slot t.
2. The second part solves the sub-problem of the data collection rate $C(t)$, aiming to achieve the optimal collecting rate $C^*(t)$.
3. The third part addresses the sub-problem of transmission power rate $p(t)$, seeking the optimal transmission power $p^*(t)$.
4. The fourth part addresses the sub-problem of dropping rate control $d(t)$, seeking the optimal dropping rate $d^*(t)$.

Lastly, the updates the data queue occupancy $W_n(t + 1)$, energy queue occupancy $K_n(t + 1)$, and the virtual queue $M_n(t + 1)$ based on the results obtained from the previous three parts.

Algorithm (1): Online Resource Allocation Algorithm

```
INPUT: Data Queue X(t), Energy Queue E(t), Virtual Queue M(t), Supply Energy us(t) at time slot (t),
 Result: Optimal Collecting Rate Control, Optimal Transmission Power Allocation, Optimal Power
Supply Management,
  Update the Data Queue, Energy Queue, Virtual Queue, and lengths at the time slot (t + 1).
 /* Battery Management*/
For each n ∈ N do
if Data Queue < Battery capacity, ∀n ∈ N then
      Optimal Energy scavenge rate at time slot (t) = min (Battery capacity – Energy Queue (t),
at certain
     Energy supply rate)]; at time slot (t);
     end
     else
      Optimal Energy scavenge rate at time slot (t) = 0;
     end
  end
  /* Data Collecting Rate Control*/
  For each n ∈ N do
     Compute Collecting Rate Control at time slot (t);
  end
 /* Transmission Power Allocation*/
  For each n ∈ N do
     Compute Transmission Power Allocation at time slot (t);
  end
 /* Dropping rate control*/
  For each n ∈ N do
   if Virtual Queue +Data Queue <V* β*v, ∀n ∈ N then
   Optimal dropping rate = max dropping rate;
  else
  Optimal dropping rate = 0;
  end
  /* Update the queue lengths*/
  For each n ∈ N do
          Compute Data Queue, lengths X_n(t + 1) at time slot (t + 1) based on Eq. (6).
          Compute Energy Queue, lengths K_n(t + 1) at time slot (t + 1) based on Eq. (12).
          Compute Virtual Queue lengths M_n(t + 1) at time slot (t + 1) based on Eq. (13).
end
```

Analyzing the stability and performance of our proposed system framework and algorithm. A derivation for the required battery capacity, the bounded data queue, the bounded virtual queue, and the gap between the user utility achieved by the proposed algorithm and the optimal utility. An examination of the proposed algorithm, which guarantees a worst-case delay.

5.1 Measuring algorithm efficiency

In our proposed algorithm case, the measuring algorithm efficiency is finding the average case scenario time complexity of the linear search algorithm as it is defined in the conditional Grey Wolf drift by:

$\Delta(t)$=⇨$\left[G(t+1)G(t) \mid \Theta(t)\right]$, where this means that it is expected to find the averaged case scenario time complexity at the stated condition. By minimizing $\Delta(t)$ in each slot time, the data queue $W_n(t)$ is pushed to zero to stabilize the data queue. Furthermore, the energy queue $\boldsymbol{K}(t)$ pushed their batteries to guarantee having enough energy for data collection and data transmission.

5.2 Required battery capacity

To ensure that the system has enough energy to achieve stable operation, we determine the battery capacity of the sensor carried by the patient in BANs in such a way that if the available energy is greater than the maximum energy consumption, i.e., $K_n(t) > uc^{max}$, the sensor collect data or transmits data; other, else not.

Suppose that the required battery capacity Ω is given by:

$$\Omega = \frac{Vv}{c} + uc^{max}, n \in N \tag{18}$$

if and only if, $K_n(t) > uc^{max}$, i.e., length of energy queue is less than the maximum of energy consumption, sensor will not collect and transmit data, i.e., $c_n(t) = 0$ and $\eta_n(t) = 0$.

5.3 Bounded data queue

It is shown the upper bound of the data queue by constant W^{max}. The existence of the upper bound of the data queue shows that the data queue system is stable. It shows that the data queue has a finite time-average occupancy.

$$X^{max} = Vv + C^{max} \tag{19}$$

The length of data queue always does not exceed the upper bound:

$$0 \leq X_n(t) \leq X^{max}, n \in N \tag{20}$$

These inequalities are satisfied at time $t = 0$.

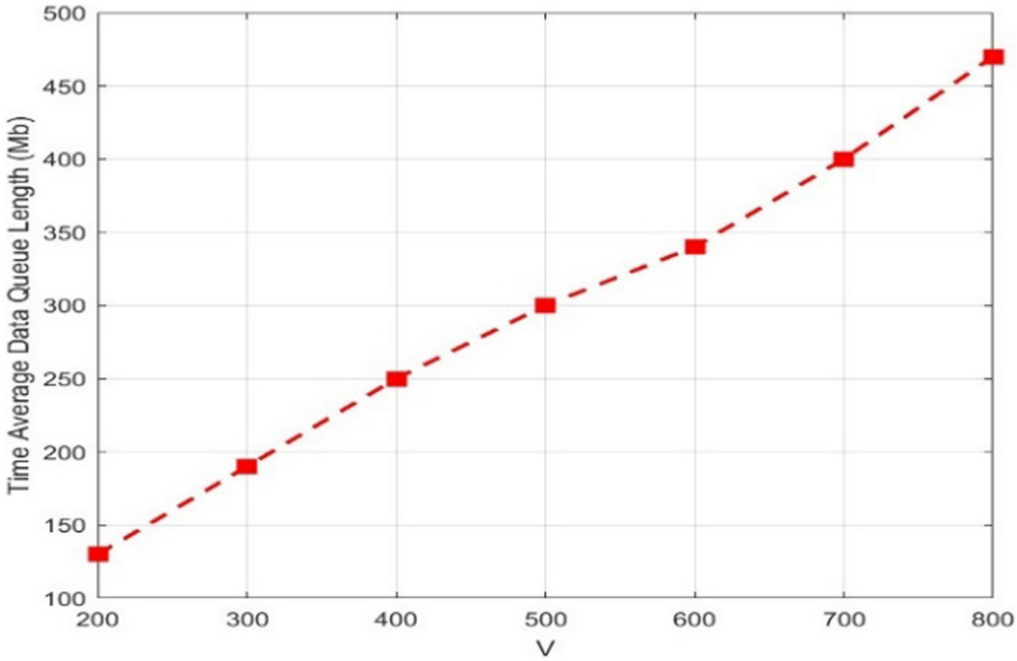

Fig. 2. Time-average data-queue length

The upper bound of the data queue increases linearly with the weight V. Since V means how much we emphasize user utility, i.e., the bigger V, the greater user utility. But a larger V also brings a longer data buffer.

5.4 Bounded virtual queue

Show the upper bound of the virtual queue by constant M^{max}. The existence of the upper bound of the virtual queue shows that the virtual queue system is stable. It also indicates that the virtual queue has a finite time-average occupancy.

6 SIMULATION RESULTS

6.1 Simulation parameters

Simulation results are presented to evaluate the performance of the proposed algorithm, considering the following parameters in Table 1:

Table 1. Simulation parameters

#	Parameter	Definition
1	N = 5	WBANs composed of sensor node
2	$\mathbf{v} = 1$	For the define a concave utility function
3	$\mathbf{e} = 8$	The scavenging energy from body heat is a constant *e*
4	$C^{max} = 40$	The maximum collecting data rata
5	$t^{max} = 13$dBm	The maximum transmission power

(Continued)

Table 1. Simulation parameters *(Continued)*

#	Parameter	Definition
6	$d^{max} = 3$	The maximum drop rate
7	$us^{max} = 15.5;$	The upper bound of energy supply
8	$uc^{max} = 4.$	Upper bound of energy consumption
9	$m_n(t)$, [0, 3000]	Set the movement of patient to distribution range.
10	$\lambda = 250 \times 10^{-4}$	Linear function conversion coefficient of the patient movement.
11	$S_n(t)$, [8W, 15.5W]	The energy scavenging rate of all sensors are distributed range.
12	$f_n(t)$, $[0.9, 1.1] \times \varphi^{-4}$	The channel state is uniformly distribution interval.
13	$\varphi = 30$ cm	The distance between sensor and personal device.
14	$s = 5 \times 10^{-13}$	The noise spectral density is.
15	$c = 5 \times 10^{-4}$	Linear function conversion coefficient

Set of several default constant values as follows:

$\varepsilon = 2$; $\beta = 1$.

Figure 3 shows the user utility. Under different weights V ranging from 100 to 4000, the user utility increased from 0 to 4.9. The figure shows that the user utility increases with the increase of V, which means how much we emphasized user utility. But when V becomes larger, the growth trend decreases. This shows that user utility is a concave function of V.

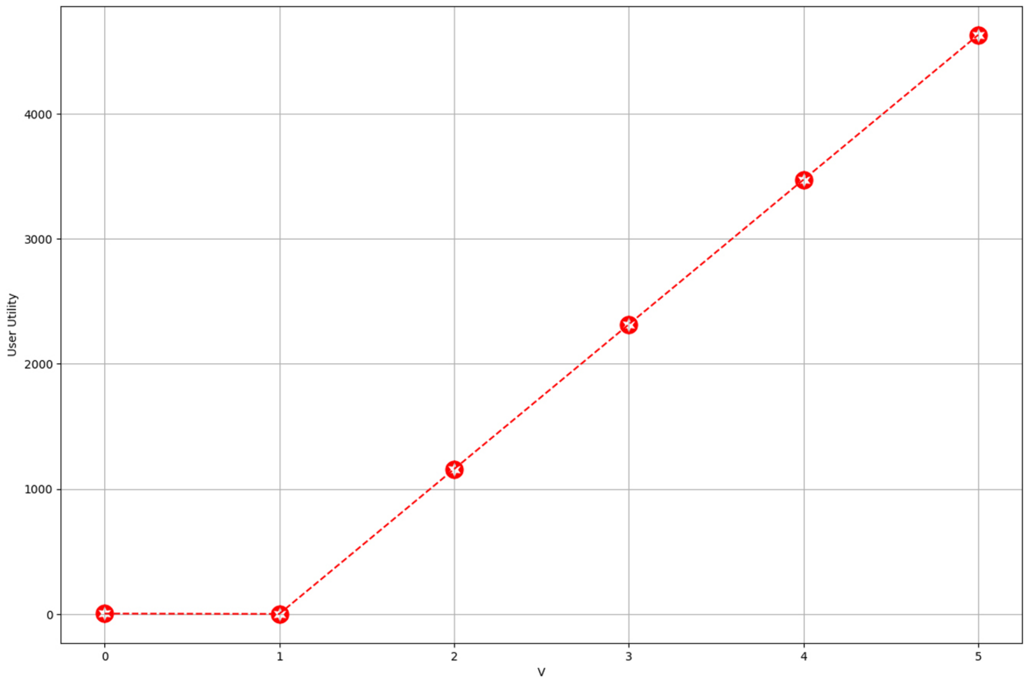

Fig. 3. User utility versus V

Figure 4 shows the energy queue dynamics with different values of V over 5000 time slots. In time slots $t = 0$, the value of the energy queue is equal to the battery capacity, that is, the battery is full of energy. From the figure, we can see the energy queue is almost stable around battery capacity. The energy queue has been fluctuating, while the fluctuation range is stable. This is because the sensor needs to consume energy when collecting and transmitting data. Also, we can see that the value of the energy queue does not exceed the capacity of the battery.

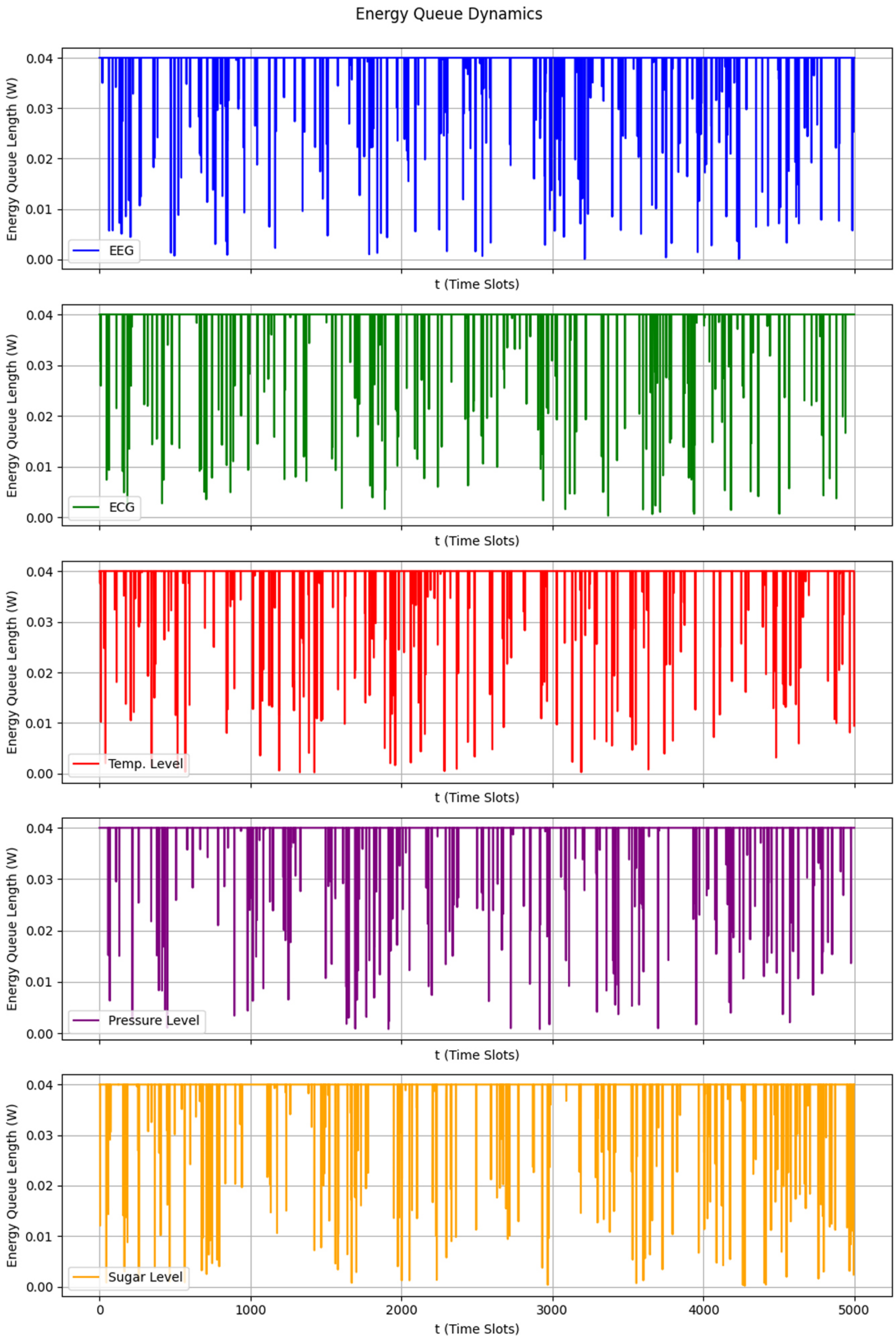

Fig. 4. Energy-queue dynamics

Figure 5 shows the time-average queue length. From this figure, we can see that the time-average queue length increases linearly with the increase of weight V. As stated previously, the upper bound of the energy queue increases linearly with the increase in weight V. From Figure 5, we can see that the energy queue quickly stabilized at a time-average length. From Figure 4, we can see that if we want to get more user utility, we need a longer data buffer, a virtual queue buffer, and a larger battery capacity.

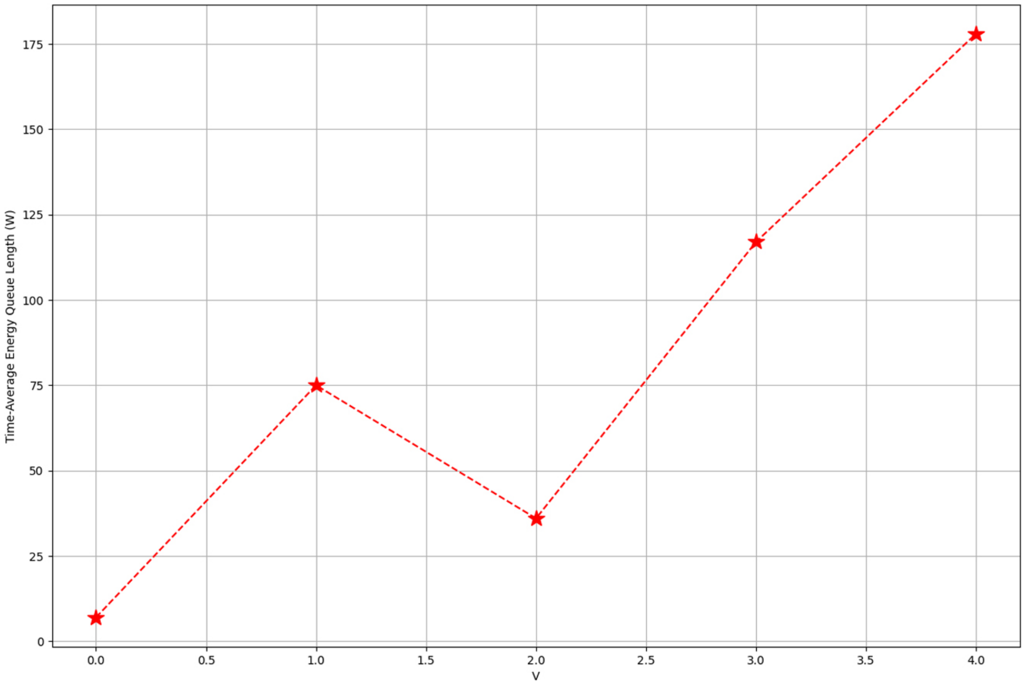

Fig. 5. Time-average energy-queue length

7 CONCLUSION

This paper has addressed the problem of energy management in WBANs with guarantees for worst-case delay. It explores energy scavenging techniques in WBANs, where energy is sourced from two main areas: movement and stable sources such as body heat. To tackle the worst-case delay issue, it employs a virtual queue mechanism to control its upper bound. Also, a formulation for the stochastic optimization problem aimed at maximizing the long-term average user utility in WBANs and proposed a low-complexity resource allocation algorithm. Given the stochastic nature of energy scavenging and consumption, the GWO method is applied to decompose the utility optimization problem into four sub-problems: battery management, collection rate control, transmission power allocation, and drop rate control. It also deduced the optimality gap and established the bounds for the energy queue, data queue, virtual queue, and worst-case delay. Simulation results validate the stability and optimality of the WBANs and demonstrate the effectiveness of the proposed algorithm. The findings of this paper offer valuable insights into the practical design of WBANs, ensuring their sustainability.

For future work, it is planned to further investigate energy management and channel allocation in WBANs, as well as consider the interference between sensors. Additionally, exploration of sleep scheduling strategies will be performed.

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