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Reinforcement learning based energy-neutral operation for hybrid EH powered TBAN[☆]

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ABSTRACT

The aging population, outbreak of new infectious diseases and shortage of medical resources promote rapid development of telemedicine. Wireless textile body area network (TBAN), which combines functional textile and wireless body area network (WBAN), is gaining great attention as an efficient medium of remote medical care. This is because of its unique materials and application scenario, as well as its convenience and friendliness to the elderly. Moreover, it is an effective application for integrating edge computing with next generation of wearable technology. Nonetheless, it is unavoidable that TBAN has to deal with reliability and energy issues. Given these deficiencies and challenges, this paper focuses on the feasibility of achieving wearable energy neutral operation (ENO) in TBAN while maintaining robustness. In addition to adding user posture factors regarding network specifics, we combine hybrid energy harvesting (EH) techniques and duty cycle schemes. A hybrid radio frequency (RF) energy and Triboelectric nanogenerator (TENG) EH-assisted TBAN system is built in this work. We analyze and discuss the delay, data rate and packet error rate (PER) under five typical daily activities (standing, sitting, lying, walking, and running). To optimize the ENO problem, two reinforcement learning (Q-learning and Deep Q-Network (DQN)) based algorithms are proposed. According to numerical results, both algorithms ultimately lead to stable power levels compared to the continuous decline of battery power without optimization. DQN-based optimization performs better than Q-Learning. For instance, 14% and 56% improvements in PER and battery power, respectively.

1. Introduction

In recent years, due to the pandemic and inappropriate lifestyle habits. Chronic and infectious disease prevalence has been steadily increased. In addition, the aging population has led to a revolutionary boom in telemedicine and home physical therapy. Textile is a necessary piece of our life and the tendency of electronics development is towards wearability. E-textile gives garments more functions than simply fashion and warmth. Wireless textile body area network (TBAN), as an extension of wireless body area network (WBAN), relies on sensor nodes integrated in smart textiles to detect data [1]. It can provide continuous detection of physiological information and facilitate the development of universal health care programs [2]. As shown in Fig. 1. In TBAN, the biosensors distributed on the human body all have the ability to compute and process. At the same time, It is also an application of edge computing in wearable systems [3]. Data is gathered by the dispersed sensors, which then send it to the HUB for processing. In order for doctors can conduct long-term health monitoring of the patient's natural physiological state without interfering with the patient's daily activities, the HUB then transfers information to a remote database server or medical cloud platform. The utilization of TBAN meets the urgent need for long-term, real-time, high-quality healthcare monitoring service.

There are some unavoidable challenges in the development of TBAN. In order to fit body seamlessly and comfortably, size and material issues are essential concerns for TBAN. Battery life and computational capability are constrained by a small form factor and production cost restrictions. Severe communication issues can arise during data transfer in TBANs due to the composition of materials as well as muscles. Moreover, constantly changing posture states cause variations in the ambient environment, which affects the quality of service (QoS) and network topology. Different signal attenuation results from the nodes on the limbs' relative orientation. In addition to the aforementioned energy constraints and postural impacts, TBAN has many other obstacles that must be addressed, including those related to security, privacy, weight, comfort, etc.

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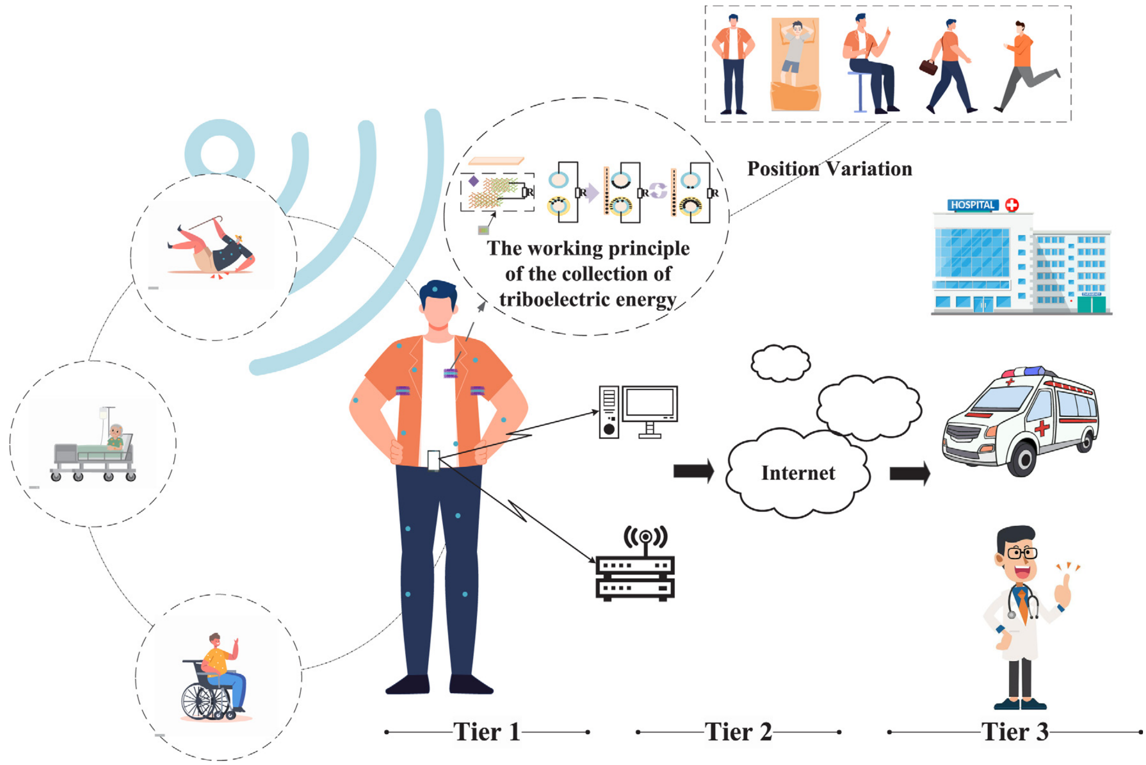

Fig. 1. System model of TBAN and application areas.

Exploiting energy from external or internal sources and implementing appropriate energy-saving measures can solve the problem of the limited battery capacity. On the one hand, Energy-harvesting (EH) technology can provide a long-term energy supply and ensure more sustainable information transmitting. A number of prior researches have conducted corresponding investigations on EH technologies [4–6]. On the other hand, The energy saving scheme can effectively reduce the energy consumption. Numerous studies from various aspects are also available. Such as clustering-based protocols, adaptive data collection protocols, advanced routing and MAC protocols, and duty-cycle techniques [7–9]. This paper adopts the duty cycle technology, which is defined as the percentage of time sensor nodes spend in active states as compared with the total time [10]. Appropriate use of duty cycle technology can secure the rational use of energy and guarantee the balance of expended and generated energy.

TBANs powered by EH technology have the potential to achieve infinite lifetime and permanent operation, which is called energy neutral operation (ENO) [11]. It is a mode of operation in which a sensor system can operate continuously and its energy consumption is always less than the energy it captures from environment. In the traditional case, because of the irrelevance of energy collected and used, ENO technology is typically accompanied by precise energy prediction techniques. And this not only increases the cost but also make it even harder to use the device extensively [12]. But in the TBAN scenario, movement has a significant impact on both the tribological energy that can be collected and the energy used by nodes, these two quantities are tightly related. To ensure a seamless service, a rechargeable flexible battery is used as a booster. Battery can balance the power supply and demand if harvested energy is not sufficient. Moreover, the harvested renewable energy can also be stored in batteries for subsequent use. It is essential to adjust duty cycle dynamically to make it possible to implement ENO in TBAN. If the node is full of energy, it performs more tasks, while in the case of insufficient energy, it performs fewer tasks.

The contributions can be concluded as follows:

- We build a TBAN model considering multi-posture with hybrid energy harvester. Devices are powered by a mixture of captured RF and tribological electrical energy along with rechargeable battery.
- Hybrid EH strategy and duty cycle technology are employed to overcome the energy efficiency and reliability challenges that exist in TBAN. Five common daily activities are discussed separately to analyze the energy consumption and acquisition as well as the network reliability of TBAN.
- Reinforcement learning based methods are applied to solve the proposed ENO problem in TBAN. We achieve a trade-off between energy consumption and collection to achieve long-term use of the equipment. Q-Learning and DQN based algorithms are proposed to verify its feasibility.

2. Related work

The development of wireless communication and the technological advancement is the reason why WBAN is widely used in medical system and many other fields. TBAN is a further development of WBAN, leads the next generation of care trend. It is much better to realize the personalized development of telemedicine and home healthcare. In [2], numerous existing challenges and open issues of WBAN have been raised. The paper details the effective applications of WBAN in various fields and the improvements in performance that can be achieved. There has been extensive discussion about the optimization and performance improvement of this network.

2.1. The state of the art of TBAN

For one thing, the consistency of power supply to maintain TBAN operation is critical. However, due to the size limitation of sensor nodes. It is difficult to maintain the battery power for long-term applications. For another, dynamic link feature cannot be ignored in TBAN. [9] has described the requirements of enhancing wearable technology's energy efficiency and have proposed energy-saving solutions for IoT application. This paper also discussed the difficulties and potential directions for future research in relation to energy efficiency in IoT. The author in [13] has pointed out the energy, delay, and channel interference challenges that exist in WBAN. For the energy efficiency problem of mobile ad hoc network. The authors in [7] have proposed a distributed and adaptive hybrid MAC scheme to fulfill the high throughput and QoS requirements of this network. For the problems of hardware design and charging efficiency in EH-WSN, a method has been proposed in [14] to maximize the energy efficiency of the PV supercapacitor energy system. In [15,16], the issue of WBAN systems being unable to operate for long time has been pointed out, along with the necessity to ensure QoS of the network. In [17], the application of MEC in intelligent healthcare systems can effectively ensure efficient real-time and classification accuracy have been presented. Likewise, the authors have noted out that MEC can effectively solve computationally intensive and latency-sensitive problems in [18]. And the problem of user mobility cannot be ignored. In experiments at [19], which shown the channel characteristics between sensor nodes in different positions on body during walking. The paper has presented how energy efficiency and reliability are affected by different positions. The author has considered dynamic characteristics between nodes resulting from limb changes in [20], and has proposed the importance to ensure the network throughput and QoS of WBAN. In [21], it is proposed that when human moves, sensor nodes distributed on the body is highly correlated with the shadowing of the body.

2.2. ENO strategies

The concept of ENO has been proposed in [22] in order to achieve a permanent use of IoT devices. To overcome deficiencies and implement ENO in TBAN, energy saving and energy harvesting solutions can be an effective remedy to effectively increase the lifetime of the equipment. A combination of solar energy and algorithms to manage power are taken in [23]. An effective scheduling scheme been used to improve the overall quality of service of the sensors and has achieved the goal of maintaining the system at ENO. In [24], author has used flexible solar panels as EH modules to supply power, while low-power circuits and radio frequency modules have been employed to reduce power consumption. One thing which makes TBAN different is the wide range of mechanical energy available for harvesting in human body. Once there is a small movement, a considerable amount of tribological electricity can be generated for utilization. [25] has proposed to sew EH belt on elastic textiles to form a highly stretchable triboelectric textile to harvest various human motion energy. Similarly, the paper has been proposed in [26] by sewing EH threads to an elastic textile. To form a TENG textile with high stretchability for capturing various human movement energies. As proposed in [27], the t-TENG could be used with other EH technologies to store irregular energy for long-term use, which provide more powerful textile energy for wearable technology. In [28], authors indicated that EH-powered WBANs have the potential to achieve ENO if the energy available for harvesting is sufficient and stable. Although EH measures are the solution for implementing ENO. But accurate prediction of information on the amount of collection is inevitable. In [10] the authors have introduced a framework for energy neutral power management without predicting future energy harvesting profiles to address this issue. The sensor performance level has been effectively improved and the battery cycle life has also been increased.

2.3. RL based optimization

A variety of optimization algorithms are applied to solve real-life problems.

Under the premise of satisfying end-to-end delay and reliability and QoS requirements. The authors in [29] presented a JPCTARS algorithm to improving the energy efficiency of WBAN. In [30], Samanta adopted Lagrangian Optimization method to solve the management cost optimization and opportunistic communication problem. RL has gained significant attention for fast processing capabilities with real-time prediction. Furthermore, it has been widely used to solve various problems and challenges. In [31], A combination of reinforcement learning and game theory is presented in this paper. A multi-intelligent RL model is built using Q-learning. Moreover, a PQL algorithm is proposed to implement the optimal decision strategy on this basis. Authors in [32] have proposed a multi-objective reinforcement learning algorithm to solve the multi-route bicycle dispatch problem of Dockless Public Bicycle-sharing System. The experimental results showed that this approach can find higher quality Pareto bounds with shorter execution time. In [33], Breakthroughs of RL in solving various complex problems especially in healthcare systems have been pointed out in the paper. It has also indicated the applicability of different RL models in diverse scenarios. To alleviate the dependence on batteries and resource allocation problem, [28] used RL method for making optimal decisions to maximize the energy efficiency. The author in [34,35] stated that RL can be used to address caching, offloading and energy problems in the network. A "hotbooting" Q-learning and a fast DQN based computation offloading schemes are proposed in [36] to achieve the optimal offloading performance.

To the best of our knowledge, although some of the above mentioned works have started to focus on energy deficiency and reliability of TBAN or WBAN, and proposed solutions that combined EH technology and energy saving schemes. But there are little research on the association between numerous positions and energy or equipment reliability in daily life. The close correlation between collected energy and consumed energy has not received much attention. Owing to the special application scenario and material of TBAN, this paper focuses on ENO by realizing energy consumption and energy trade-offs in different conditions.

3. System model

This section describes the network system model of hybrid EH powered TBAN, followed by in-depth discussions of the human motion model, the energy harvesting model, the energy consumption model, and the QoS model in detail, respectively. The main goal of implementing ENO in the TBAN is to increase node lifespan and thus achieve long-term device use. The main variables used in the text are given in Table 1.

3.1. Network model

Similar to WBAN, the communication level of TBAN can be divided into three layers: Tier1: intra-TBAN, tier2: inter-TBAN and tier3 is beyond-TBAN. The first layer refers to the communication between decentralized sensors and HUB. Between a HUB and access points (APs) or mobile devices is referred to as inter-TBAN. Tier3 points to the interaction with the cloud and medical center. We concentrate on the energy of TBANs involving different poses and human motions. Hence, Intra-TBAN communication, which primarily use the human body and textile as the transmission medium, has caught our interest.

As the model shown in Fig. 1. In TBAN, there are N biosensor nodes and a HUB on the human body. The sensors are distributed

Table 1
List of the major notations used in this paper.

Symbol	Description
$\mathcal{L}$	Set of sensors
T	Set of unit time slots
$\mathcal{Z}$	Set of posture states
S_i^m	The amount of data transmitted (bit)
N_i^m	The amount of data processed (bit)
η	Path loss factor
ρ	Duty cycle
E_{elec}	Energy consumption of electronic circuit
E_{amp}	Energy consumption of amplifier circuit
β_h	Human body loss
α	Effective switched capacitance constant
f_i	CPU frequency
C	Node's task computation intensity
X_{σ^m}	Shadowing component
σ_m	Standard deviation in different posture
R_i^m	Data rate of sensor i in state m
d_i	Distance between sensor i and HUB
d_0	Reference distance
π_m	Probability of different postures

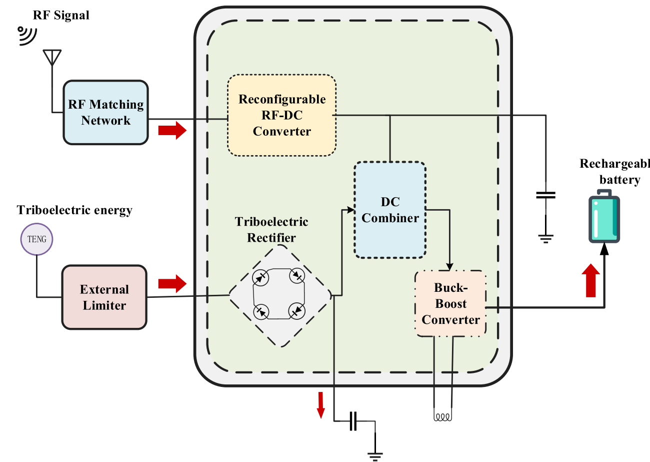

Fig. 2. Block diagram of triboelectric and RF hybrid energy.

in various parts while HUB is located at the waist of the human body. We assume that the data transmission and communication is performed in a single-hop mode between the scattered nodes and HUB. Each node is equipped with a rechargeable battery, transceiver, processing, sensor, and EH modules. They can be treated as an edge node. While HUB is in charge of collecting all the information from the sensors and handling the interaction with the AP. The HUB is assumed to have high processing capacity and no energy shortage problem. Furthermore, variations in the posture state have relatively small impact on the HUB. For energy supply, we refer to the EH belts mentioned in [25]. As stated in Section 3.3, it is proposed that these harvesting belts be worn in various body locations to gather as much energy as possible.

3.2. Mobility model

In order to simulate the behavior of realistic nodes, mobility models are utilized to describe the stochastic patterns of their movement. The propagation of wireless signal undergoes fading due to diffraction, reflection, energy absorption and body-induced shadowing effects. The path loss values and the structure of the node network vary with different motional states. Besides, the issue of imbalanced energy consumption caused by mobility cannot be neglected.

Five common postures of users we considered in daily life are standing, sitting, lying, walking, and running. These different activities not only affect energy consumption and collection, but make a major difference in the QoS of data transmission as well. Consequently, a crucial feature that cannot be disregarded is the frequency of motion disturbances. We simulate the aforementioned motions using the Markov models from [37] to model daily human activities. Standing, sitting and lying are considered as stationary states, while walking and running are taken as dynamic states. The state of the human body in five different postures shown in Fig. 1.

Changes in the energy collecting rate and the QoS of the data are relatively minor while a person is in a stationary state. Yet, when a person is in motion, the collected and consumed energy changes greatly.

3.3. Energy harvesting model

With the rapid development of wearable healthcare applications today, the use of EH technology to power devices has become a hot research topic. A key component in determining the ENO of the system is the availability and sufficiency of the gathered energy.

Among the numerous energy sources available for collection. RF energy is a simple, widespread and controllable energy source. It is clean and widely available around us, as well as unaffected by human activity and weather changes.

In wearable devices, mechanical energy serves as a reliable supply. It can be generated during daily life. The vast majority of this energy, though, is ignored and wasted. Triboelectric nanogenerator (TENG) is a newly developed EH technology. Notably, even in static stats, very small deformations of human body can generate effective triboelectric charges. Its key element is two friction surfaces with different properties. When two friction surfaces undergo relative displacement, the mechanical energy of human motion can be converted into electrical energy.

The power needs of smart wearable devices are typically not met by a single source of energy collection. In addition, the reliability of such systems is more fragile because most energy sources are not continuously available. By using hybrid energy generators to integrate different energy sources, allowing several energy sources can be used simultaneously or separately. Furthermore, compared with the limitation of a single energy source, gathering hybrid energy can be more effective in enhancing energy efficiency, and can extend the life of TBAN. In this study, a hybrid energy source is developed by combining RF energy and tribological electrical energy. The block diagram of acquisition of mixed energy is shown in Fig. 2. We use $H_{RF,i}$ and $H_{tr,i}^m$ to represent the gathered RF energy and triboelectric energy, respectively. When user is in a same environment for a long time, the collected RF energy energy varies slightly. We regard it as a constant for simplicity. The collected triboelectric energy is closely correlated with user's actions. Thus, the collected energy can be expressed as:

$$H_i^m = H_{RF,i} + H_{tr,i}^m. \tag{1}$$

It is worth mentioning that the captured energy cannot exceed the maximum capacity of the battery.

3.4. Energy consumption model

As mentioned in the previous section, the scattered nodes consume different amounts of energy across various states. This is because the quality of the communication link and the communication distance can be affected by various postures and movement states. In the active state, the node performs data transmission, data computing, data sensing and receiving. While sensors only sense data in sleep state. Since the energy consumption of the node in the sleep state has a small fluctuation and this part of the energy cannot be ignored, we set it as a constant for simplicity.

The energy of the sensor node's active state is composed of data transmission, data computation, and data reception. It can be expressed as: $E^{m}_{active,i} = E^{m}_{tran,i} + E^{m}_{con,i} + E_{RE}$. The energy consumption of data transmission is mainly determined by the transmission distance, the amount of transmitted data and the energy of the receiving circuit, which as follows [38]:

$$E^{m}_{tran,i} = S^{m}_{i} \cdot \left(E_{elec} + \beta_h E_{amp} d^{\eta}_{i,m}\right), \tag{2}$$

where E_{elec}, E_{amp} stand for the transmit circuit energy and amplify circuit energy, separately. The amount of transmitted data in posture m is denoted by S^{m}_{i}. η is the path loss factor and d^{m}_{i} denotes the distances between ith node in state m, β_h means human body loss.

The input data size N^{m}_{i}, CPU frequency f_i of sensor i and computational intensity C are the three key factors that affect how much energy the sensor consumes. Hence, the computational energy consumption can be estimated as [39]:

$$E^{m}_{con,i} = \alpha f_i^2 \left(N^{m}_{i} \cdot C\right), \tag{3}$$

here, α is effective switched capacitance depending on the node chip architecture [38].

According to the formula given above, we can calculate the total energy of node as follows, in which ρ means duty cycle:

$$E_{total} = \sum_{i}^{N} \sum_{m}^{M} \pi_m \left(\rho \cdot E^{m}_{active,i} + (1-\rho) E_{sleep}\right). \tag{4}$$

3.5. The QoS model

Given the specificity of TBAN application scenarios, accurate and timely data transmission is particularly essential. The shadowing effect and the network's dynamic topology both have an impact on how reliably data is transmitted. It has to be said that complexity of QoS increases due to the mobility of nodes and frequent changes in topology.

3.5.1. Time delay

Timely transmission of data is essential to monitor users' health status. The purpose of TBAN is to promptly monitor the user's vital signs without disrupting their life. Given high sensitivity of some vital signs in emergency situations, it is important that such information is transmitted to surveillance center in a timely manner. If the medical center cannot receive real-time data to make appropriate diagnosis, there may be serious consequences. When a person moves, the network topology changes dynamically and propagation delay varies accordingly. It can be calculated as: $T^{m}_{i} = T^{m}_{con,i} + T^{m}_{tran,i}$, where $T^{m}_{con,i}$, $T^{m}_{tran,i}$ represent computation delay and transmission delay of node i in mth posture state, respectively. The calculation formula is given as [15,16,40]:

$$T^{m}_{con,i} = \frac{N^{m}_{i} \cdot C}{f_i}, \tag{5}$$

$$T^{m}_{tran,i} = \frac{S^{m}_{i}}{R^{m}_{i}}, \tag{6}$$

3.5.2. Data rate

The sensor nodes distributed on body sense different physiological data. Each dispersed sensor has various monitoring needs and a correspondingly different data rates. The channel capacity sets a restriction the amount of data that can be transmitted per unit time from the node to HUB. In the case of the ith node in state m transmit to HUB, the data rate R^{m}_{i} is within a certain range. It can be expressed as:

$$R_{\min} \leqslant R^{m}_{i} = B \log_2 \left(1 + SNR^{m}_{i}\right) \leqslant R_{\max}, \tag{7}$$

In the above equitation, B is the bandwidth of the channel. $R_{\min}$ and $R_{\max}$ denote the minimum and maximum required data rate of sensor i, respectively. SNR represents the signal-to-noise ratio of the link between node and HUB, and it can obtain as [41]:

$$SNR^{m}_{i} = P^{tran}_{m} - PL^{m}_{i} - X_{\sigma_m} - N_0, \tag{8}$$

PL^{m}_{i} denotes path loss of channel in states m and X_{σ_m} is shadowing component, we can obtain: $PL^{m}_{i} = PL_0 + 10\eta \log_{10} \frac{d_i}{d_0} + \sigma_m$. P^{tran}_{m} is the transmission power standard deviation in different posture is indicated by σ_m.

3.5.3. Data transmission reliability

Personal privacy is a concern that is closely tied to collected data and is very essential to consumers. Once data lost in transmission, it immediately affects the user's life, health, and safety. Therefore, We need to pay attention to the reliability of device, one of the performance metric of which is packet error rate (PER) [29]. It can be calculated as:

$$PER^{m}_{i} = 1 - \left(1 - BER^{m}_{i}\right)^{N}, \tag{9}$$

where N is packet size in bits. The constraint of PER can be expressed as: $PER^{m}_{i} \leqslant PER_{max}$. Denoting BER^{m}_{i} as bit error rate (BER), given by:

$$BER^{m}_{i} = \frac{1}{2} \exp\left(-\left(SNR^{m}_{i}\right)^{0.7}\right). \tag{10}$$

4. Problem formulation

The object of this paper is to achieve ENO by adjusting the duty cycle to balance energy acquisition and consumption in TBAN under different postures. A combination of RF and triboelectric energy is harvested by each decentralized node. The amount of tribological energy varies according to the state of motion. The energy consumption is increased by dynamic topological disconnections and link quality variations. In mild body movements, the energy consumed is relatively low. Additionally, different degree of body movement affects the amount of frictional energy collected. A wide range of motion results in an increase in the quantity of tribological electrical energy that can be captured.

Base on the correlation between energy consumption and energy harvesting in different posture. Duty cycle regulation is crucial because it allows a trade-off between energy consumption and acquisition thus achieving ENO goals. The battery powers the node if the energy available for acquisition is inadequate to maintain data continuity. When the battery power falls below a certain threshold, the node automatically switches to a sleep state to maintain the long-term use. Moreover, the ENO of TBAN is achieved on the basis of satisfying the QoS of the device. The problem can be stated as:

$$\begin{aligned} &\min \ \left(B_{ini} + H_{total} - E_{total}\right). \ \ \forall i \in \mathcal{L}, m \in \mathcal{Z} \\ &s.t \ \ c_1: PL^{m}_{i} = PL_0 + 10\eta \log_{10} \frac{d_i}{d_0} + \sigma_m \\ &\quad\ \ c_2: PER^{m}_{i} \leqslant PER \\ &\quad\ \ c_3: R^{\min}_{i} \leqslant R^{m}_{i} \leqslant R^{\max}_{i} \\ &\quad\ \ c_4: T^{m}_{i} \leqslant T^{\max}_{i} \end{aligned} \tag{11}$$

The probability of various postures is represented by π_m. H^m_{total} and E^m_{total} are total energy harvested and energy consumed in different postures, respectively. We expect the battery level of the node to be in stable and sufficient during operation. Eq. (11) is an optimization problem with several constraints. c_1 is the path loss calculation model. c_2 indicates the range of PER. c_3 and c_4 show the data rate and time delay limits mentioned above, respectively. The TBAN model we proposed provides a balance between energy consumption and acquisition by adjusting the duty cycle of the sensor.

5. RL solution analysis

Traditional decision-making optimization methods are mainly designed for static optimization problems, which is lack of interaction with dynamic environments. Even some heuristic algorithms, such as particle swarm methods, cannot accurately reflect the environment for model-free dynamic planning problems. In contrast, RL has been designed to study the optimal sequential decision-making process of agents in uncertain environments. Since RL derives the best policies through experience rather than mathematical models. All it requires is agents to identify the relative optimum based on reward values through continuous interaction with the environment. Healthcare systems are heterogeneous and highly dynamic environments. Because of RL's real-time predictive and fast processing capabilities. It has gained great interest in healthcare systems. Hence, in this section, we base on two algorithms, Q-learning and DQN, to perform simulations.

5.1. Q-learning and DQN based RL model

We can formulate the implementation of ENO in TBAN as an MDP problem for the aforementioned optimization problem. Q-learning can be adopted to solve this type of issue. Generally, the MDP problem can be described as a tuple (**S**, **A**, **P**, **R**), in which **S** is the set of states and **A** is action space. **P** is the transfer probability from one state to another after executing the action. And **R** is reward function [28]. The aim of MDP is to find an optimal policy to make reward maximum. RL is an experience-driven machine learning technique. The agent can obtain information of current state in interaction with the environment. Agent makes an experience through a constant interactive trial-and-error process to improve future choices. It performs proper action through an appropriate strategy, and then moves to next state. This process is repeated until the agent's policy is close to the optimal policy [35].

To address energy and QoS problem in this paper. The state space can be expressed as $\mathbf{S} = (\mathrm{S}_1, \mathrm{S}_2, \mathrm{S}_3)$. Where $\mathrm{S}_1, \mathrm{S}_2, \mathrm{S}_3$ are the battery level, the collected energy and the posture of the human body respectively. The action space is duty cycle of each node. The signal that is sent to the agent following each time slot's actions is known as the reward function. It defined in this paper is the negative of the weighted sum of energy consumed, delay and PER, which can be formulated as: reward $= -(\omega_1 \cdot \mathrm{E_{total}} + \omega_2 \cdot \mathrm{T_{total}} + \omega_3 \cdot \mathrm{PER})$. Where ω_1, ω_2 and ω_3 are weighting coefficient.

Q-learning is an off-policy model-free RL algorithm. It stores Q-values in a Q-table, where rows represent states, columns stand for actions, and cells represent expected total rewards [42]. For direct learning models with smaller state spaces, Q-learning is completely effective. The size of the Q-table, however, continuously grows as the number of states and actions does, which lowers the efficiency. It is challenging to obtain the optimal strategy in a reasonable time with such a look-up table. Furthermore, for continuous states and actions, Q-learning is not able to produce satisfactory result.

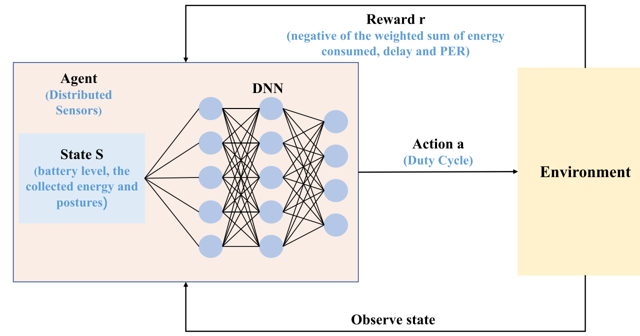

Fig. 3. DQN flowchart with a combination of TBAN networks.

Algorithm 1 DQN-based ENO problem solving

Input: PL_0, σ, η, E_{sleep}, B_{ini}, m

Initialize replay memory, action-value function Q with random weight $\boldsymbol{\theta}$ and target action-value function $\hat{\mathrm{Q}}$ with $\hat{\boldsymbol{\theta}}$
for *episode* $= 1$ to M **do**
  Initialize a random process $\mathbb{N}$ for action exploration
  Receive initial observation state $\boldsymbol{s}_1$
  for $i = 1, T$ **do**
    select a random action a_t with the probability ϵ
    Otherwise select the action $a_t = argmaxQ^*(s_t, a_t, \omega)$
    Perform action a_t. Calculate energy consumption E_{total} and QoS (time delay, data rate and PER)
    Update the posture state according to the Markov model and update the collected energy H_{total}
    if $B_{ini} + H_{total} - E_{total} < Threshold$ **then**
      Set sensor node to ***sleep*** state
    else
      Reasonably adjust the duty cycle ρ based on battery power and task volume
    end if
    Store transition $(\boldsymbol{s_t}, \boldsymbol{a_t}, \boldsymbol{r_t}, \boldsymbol{s}_{t+1}, \boldsymbol{t})$
    Sample random minibatch of transition $(\boldsymbol{s_i}, \boldsymbol{a_i}, \boldsymbol{r_i}, \boldsymbol{s}_{i+1}, \boldsymbol{i})$
    if episode terminate at step $i+1$ **then**
      $\boldsymbol{y_i} = \boldsymbol{r_i}$
    else
      $\boldsymbol{y_i} = \boldsymbol{r_i} + \gamma \max_{\boldsymbol{a}} \hat{\mathbf{Q}}\left(\boldsymbol{s_i}, \boldsymbol{a_i}, \hat{\theta}\right)$
    end if
    perform a gradient descent step on $\boldsymbol{y_i} - \mathbf{Q}(\boldsymbol{s_i}, \boldsymbol{a_i}, \boldsymbol{\theta})^2$ with respect to the network parameter $\boldsymbol{\theta}$
    Every C steps reset $\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}$
  end for
end for

To address the limitations of using tables in Q-learning. DQN turns Q-tables into Q-networks by combining Q-Learning and neural networks. To fulfill the function, a deep neural network (DNN) is utilized. It can overcome the shortcomings of Q-learning in large state spaces. DQN takes state **S** as input and the output is a vector that contains the values of all the actions. The parameters are trained until convergence. The block diagram of the network is shown as Fig. 3. Moreover, an experience pool is also introduced by DQN, where it is kept after being acquired through exploration or action. It is able to execute repeated learning with the experience pool. The pseudo-code for problem-solving using DQN in this paper is as 1.

Table 2
The simulation parameters used in the paper.

Parameter	Description	value
E_{amp}	Energy consumption of amplifier circuit	1.97 nJ/bit
E_{RE}	Energy consumption of receiver circuit	36.1 nJ/bit
B_{ini}	The initial battery level of the node	300 mAh
α	Effective switched capacitance constant	10^{-28}
B	Channel bandwidth	1 MHz
N	The number of bits in a packet	800 bit
f_i	CPU frequency	1 GHz
C	Node's task computation task intensity	1000
d_0	Reference distance	0.1 m
t	Time slot	1.5 s

5.2. Complexity analysis

How well Q-learning converges is largely determined by the trade-off between exploration and exploitation. The time complexity of Q-Learning can be evaluated by analyzing the maximum number of iterations. The Q-values of the states are recomputed on each iteration. It takes $\mathbf{S} * \mathbf{A}$ times to calculate the state space $\mathbf{S}$ and action space $\mathbf{A}$ in our ENO problem. The complexity increases exponentially as the state and action space expand. Moreover, the iteration must proceed if the Q value does not converge after two calculations, which increases complexity [43].

According to Algorithm 1 we can observe that the time complexity of DQN is mainly related to *episodes* and t. When these two numerical values are large enough, the other computation time in the loop can be negligible. DQN-based models use DNNs to compress the state space and speed up the convergence in Q-Learning. DNNs are nonlinear approximators for each q-value calculation [44]. When the action state space is large enough, the DQN-based model can converge fast with the assistance of DNN, whereas the Q-Learning-based model must invest more time in learning.

6. Simulation result

The results obtained by both algorithms were compared with the un-optimized result to evaluate the feasibility of implementing ENO in TBAN.

6.1. Configurations

As shown in Fig. 1, the model contains some biosensor nodes and one HUB node, as well as several energy harvesting belts. According to article [45–47], the distance from ith sensor node and HUB, denoted by d_i, is uniformly selected in the range of [0.2, 0.8] m. The time frame length is set to 1.5 s. We assume that within a time frame, the posture will hold steady throughout time. When human is in a stationary state (sitting, standing and lying down), the communication between the node and the HUB is regarded as line-of-sight (LOS), and when active state (walking and running) is regarded as non-line-of-sight (NLOS). For LOS TBAN, the value of human body loss factor β_h is randomly selected in the range [3,4], and varies in [5,7.4] for NLOS TBAN. Reasonable control of the duty cycle of the node is the core of the implementation of ENO, which ranges between [0, 1]. When $\rho = 0$, node is in a sleep state, while $\rho = 1$, the node is in the active state during a entire time slot. And in the algorithm experiment, we set the learning rate α of Q-Learning and DQN to 0.9, and the discount factor γ to 0.1. Furthermore, the boundary value of the data rate is set to $R_{min} = 10^4$ (bit/s) and $R_{max} = 10^7$ (bit/s), separately. The Table 2 lists some other important parameters.

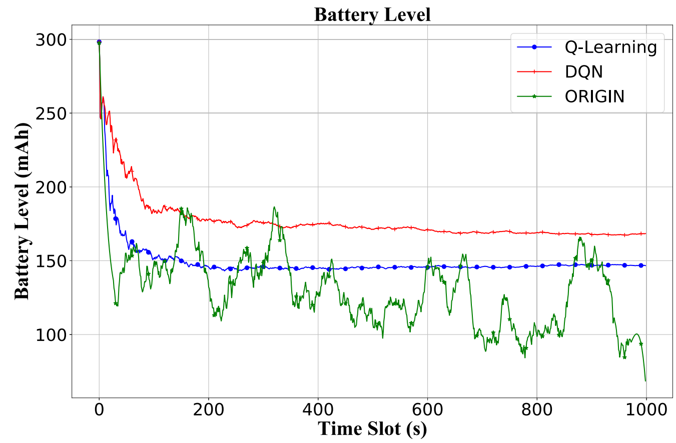

Fig. 4. Battery power comparison.

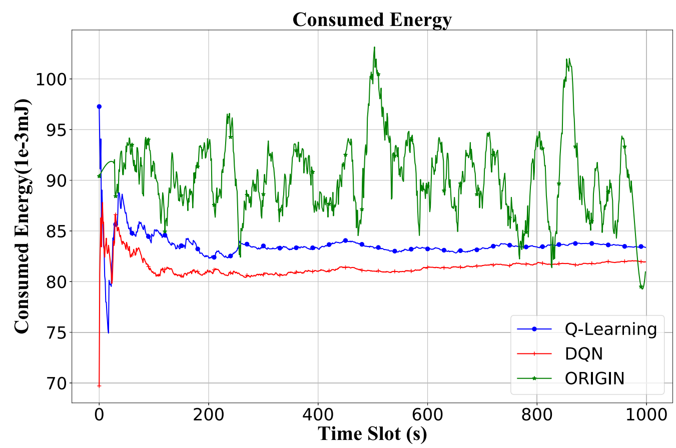

Fig. 5. Energy consumption comparison.

6.2. Simulation result

This section compares the optimization performance of algorithms based on DQN and Q-Learning in the proposed system. The origin data is used as comparison. Depending on energy usage and sensor data collection, both algorithms that based Q-Learning and DQN can reasonably adjust the duty cycle.

Fig. 4 shows the battery levels over 1000 time slots. The graph makes it clear that the maximum battery power in the initial state is 300 mAh. After 1000 time slots, the node has very little power left if no optimization is done. Even though the node can get energy through EH technology, the overall battery power is still in a state of decline. Because extra energy is only available when there is enough energy from outside, which is inseparable from the change in posture. In the case of optimized result, it can be seen that during the first 200 time slots, both Q-Learning and DQN are in a decline trend which because both of them are in the training process. After about 300 time slots, both algorithms converge and the battery power can basically remain in balance. It is apparent from the figure that DQN can maintain a higher level in terms of battery optimization, the DQN-based algorithm performs about 14% better than the Q-learning-based algorithm. It may because the battery power and gathered energy are continuously varying rather than finite discrete values in real applications. For this situation, Q-Learning may not be able to find the best value function.

The comparison of the energy consumption is shown in Fig. 5. In the case of unoptimized, the energy consumption of the nodes

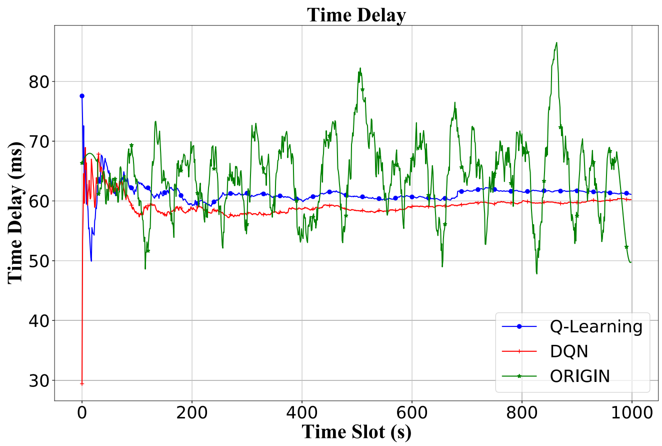

Fig. 6. Latency comparison.

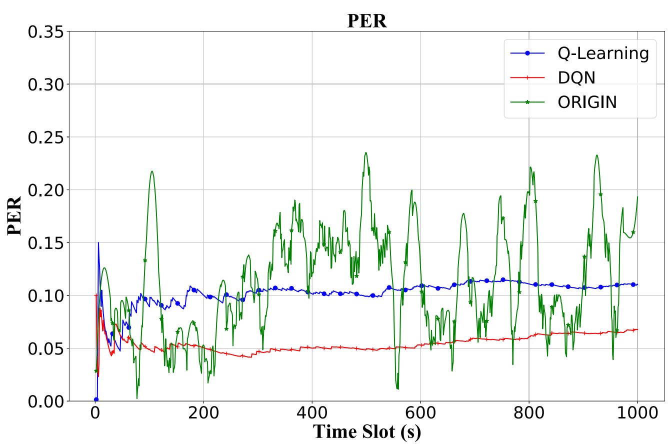

Fig. 7. PER comparison.

fluctuates throughout the time slot. This is exactly in contrast to Q-Learning and DQN, where the energy consumption of both algorithms eventually stabilizes. Moreover, it is apparent that Q-Learning uses a significant amount of energy. DQN uses Q-networks rather than Q-tables. To enhance network performance, It is used to extract features from environment. The outcomes of the latency comparison, a crucial component to take into account in TBAN, are shown in Fig. 6. Different link qualities caused by various motion states greatly affect the time delay. Consequently, the original delay fluctuates wildly. As mentioned above, we employ latency, energy consumption and PER as rewards for both algorithms. These two algorithms do exploration and optimization in a sensible manner. Finally, the delay can reach convergence. The accurate transmission of data is crucial and Fig. 7 presents the PER within 1000 time slots. It is an important indicator to demonstrate the reliability of TBAN. Once an excessive amount of data loss occurs, it has an unpredictable impact on the user. Compared to the fluctuation of the original data, the PER of both algorithms tends to stabilize after about 250 time slots. For this evaluation, DQN-based performance outperforms Q-learning-based by about 56% for PER improvement which means the data transmission can be more reliable and efficient.

7. Conclusion

In this paper, we concentrate on the two main challenges faced by TBAN in practical applications, namely energy and QoS issues. In order to tackle these issues, EH techniques and duty cycle strategies are adopted to improve the performance of the devices and extend the battery life. In this paper, the distinctions between TBAN and other networks are analyzed. In TBAN, human muscles and postural architecture have a great influence on data propagation. Energy consumption and acquisition as well as QoS are intimately tied to posture. The advantages of hybrid energy compared to the uncertainty of a single energy source are also mentioned. Moreover, the fitness of the adopted triboelectric energy and the energy of RF in TBAN is analyzed, separately. Five typical gestures in the daily activities of users were selected for analysis. In each of the different states, we evaluated the energy consumption, latency and PER of the device.

In order to fulfill the device's long-term use and practical application goals. We incorporate the concept of ENO into TBAN. Depending on the circumstances, varying amounts of energy are collected and used. And both are closely related to the change of movement. By switching between sleep-activity states, a balance of energy can be achieved. So as to realize the ENO operation. We employ Q-learning and DQN algorithms to verify the feasibility of the proposed ideas. From the results, both algorithms eventually converge and achieve good performance. In addition, it is clear that DQN performs better in both of battery and QoS. The figure makes it quite obvious that DQN is outperforming by 14% and 56% in battery level and PER, separately.

CRediT authorship contribution statement

Lei Zhang: Conceptualization, Methodology, Supervision, Writing – review & editing. **Panyue Lin:** Simulation, Validation, Writing – original draft.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Lei Zhang reports financial support was provided by National Natural Science Foundation of China. Lei Zhang reports a relationship with National Natural Science Foundation of China that includes: funding grants.

Data availability

No data was used for the research described in the article.

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