MER-WearNet: Medical-Emergency Response Wearable Networking Powered by UAV-Assisted Computing Offloading and WPT

Yingying Jiang, Yujun Ma, Jia Liu, *Member, IEEE*, Long Hu, Min Chen, *Fellow, IEEE*, and Iztok Humar, *Senior Member, IEEE*

***Abstract*—The global outbreak of the 2019-nCoV pneumonia has led to illness and loss of life for a large number of people. Many countries built medical-emergency facilities in remote areas to isolate infected people in an attempt to contain the spread of the virus. Various wearable devices based on smart new fabrics can collect life-relevant data from patients on a continuous basis. However, the computing capacity and battery energy of wearable devices are limited. Prolonging the life cycle of the wearable medical-emergency system for as long as possible, while guaranteeing the effectiveness of the monitoring tasks for the users, is a great challenge. Therefore, Medical-Emergency Response Wearable Networking Powered by UAV-assisted (unmanned aerial vehicle) computing offloading and wireless power transfer (WPT), known as MER-WearNet, is presented in this paper. Due to the ultra-low delay demand in the medical emergency scenario, the proposed scheme uses UAV to charge the wearable devices wirelessly, so that the wearable devices can obtain more energy and ensure the efficient completion of the computing offloading in the shortest possible time. The successive convex optimization (SCP) is used to solve the joint optimization model. Finally, simulation experiments verify the effectiveness of the proposed scheme.**

***Index Terms*—Medical emergency, UAV, WPT, wearable network.**

I. Introduction

THE epidemic disease report of the World Health Organization (WHO) on May 20, 2020, included nearly 4.8 million confirmed cases and more than 310 000 deaths from 2019-nCoV pneumonia globally, with these numbers continuing to rise [1]. In the epidemic disease report of the WHO on April 11, 2020, 22 073 medical workers were confirmed as being infected by 2019-nCoV [2]. Since the outbreak of the pandemic, countries around the world have successively gone into lockdowns, leading to global economy shrinking by about 1% [3]. The sudden outbreak of the 2019-nCoV pneumonia caused serious problems to medical systems and the economy in all countries. To prevent the further spread of 2019-nCoV, some countries urgently built isolation hospitals in remote places, with patients being treated and cured in these temporary isolation hospitals. However, the question arises, about how life indicators can be monitored continuously for 24 hours a day with models of the vital signs being built. With the application of 5 G, the Internet of Things, chips with low power consumption and the motivation of industrial design, various wearable devices based on new smart fabrics play an increasingly important role in health monitoring. These devices become important entries and application terminals for the Internet of Things in times of 5 G and will be pivotal in the medical-emergency response to the 2019-nCoV pneumonia [4], [5]. Smart wearable devices integrating AI and wearable technology can collect the life indicators from patients automatically, so that the doctor's diagnosis and treatment can be synced to the patient's side. Additionally, the infection rate of medical workers will be lowered by decreasing the contacts with patients. Multiple wearable devices jointly monitor the user's various health data, such as monitoring the user's body temperature, heart rate, electrocardiogram (ECG), blood pressure, blood oxygen, electroencephalogram (EEG), etc. By analyzing multiple physiological indicators collected by smart wearable devices, the patient's health status can be obtained in real time. However, the computing capacity, battery energy and life cycle of smart wearable devices are limited [6]. The challenges to guaranteeing the high-efficiency charging of wearable devices in medical-emergency response are as follows:

1) Real-time charging: Incomplete network facilities in temporary medical-emergency locations cause difficulties in guaranteeing real-time charging to various wearable devices in large numbers. In addition, the analysis of the severity degree for patients should be updated in real time based on changes in the physical signs. The charging of wearable devices should also meet the

Manuscript received July 30, 2020; revised January 28, 2021; accepted February 9, 2021. Date of publication March 17, 2021; date of current version January 4, 2022. This work was supported by the National Key Research and Development Program of China under Grant 2017YFE0123600, in part by the National Natural Science Foundation of China under Grant 61802139, and also in part by the Technology Innovation Project of Hubei Province of China under Grant 2019AHB061. Dr. Humar would like to acknowledge the financial support from the Slovenian Research Agency (research core funding No. P2-0246). Recommended for acceptance by Prof. Limei Peng.
(Corresponding authors: Yujun Ma, Long Hu, and Min Chen.)

Yingying Jiang, Yujun Ma, Jia Liu, Long Hu, and Min Chen are with the School of Computer Science, and Technology, Huazhong University of Science, and Technology, Wuhan 430074, China (e-mail: yingyingjiang@hust.edu.cn; yujun.hust@gmail.com; liujia0330@hust.edu.cn; longhu@hust.edu.cn; minchen2012@hust.edu.cn).

Iztok Humar is with the Faculty of Electrical Engineering, University of Ljubljana, Ljubljana 1000, Slovenia (e-mail: iztok.humar@fe.uni-lj.si).
Digital Object Identifier 10.1109/TNSE.2021.3066598

2327-4697 © 2021 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.
See https://www.ieee.org/publications/rights/index.html for more information.

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.

requirement of a short delay in the medical-emergency response.

2) Long-term monitoring: Due to the particular conditions of the patients at medical-emergency locations, the continuous monitoring of patients' health is required. Therefore, the power supply of smart wearable devices must not to be interrupted, and they must be charged prior to any power failure.
3) Comfort of patients: During the pandemic, the patients are in poor physical health. If the batteries of the wearable devices are frequently replaced, this will further interfere with the patients' care. Therefore, the requirement of maintaining high comfort levels for patients must be considered.

Thanks to the rapid development of wireless power transfer (WPT) technology, wireless charging can be used for smart wearable devices, thereby prolonging battery life and making frequent battery changes unnecessary [7], [8]. In comparison with other energy-harvesting technologies, such as wind and solar energy, WPT utilizes radio-frequency signals to charge smart wearable devices with a low power consumption and supply controllable and stable energy [9]. On the other hand, the wireless communication link assisted by UAV has attracted a great deal of attention [10], [11]. During the pandemic, infected patients tend to be kept in isolation in remote places for medical emergencies. Therefore, the UAV can be used as the carrier of WPT that can charge wearable devices and guarantee their long-term and effective health monitoring [12]. In addition to being the carrier of the wireless-charging technology, it is also the carrier of edge computing devices [13], [14], analyzing the physiological data of patients in real time, building models of vital signs and assessing the severity of the patients' symptoms, which greatly increases the energy-conversion efficiency of wireless charging and the communication performance of the medical-emergency response.

To address the limits of wearable-device charging and computing power in the medical-emergency response scenario, this article presents the Medical-Emergency Response Wearable Networking powered by UAV-assisted computing offloading and WPT (MER-WearNet). A wireless-charging transmitter carried on the UAV was used to charge smart wearable devices in real time. When multiple smart wearable devices have obtained enough energy, due to their own limited computing capabilities, they need to upload the collected data to the UAV edge server for providing real-time patient health analysis. According to the distance between smart wearable devices and UAV, the current network environment and the service demand of computing offloading, it is necessary to determine the optimal charging time allocation, the computing offloading sequence, and dynamically adjust the optimal hovering position of UAV in the computing offload phase. In summary, the main contributions of this paper are as follows:

- This paper proposes a novel MER-WearNet schema, namely wearable network for medical emergency response. The wireless charging of UAV is used to ensure the long-term continuous health monitoring of smart wearable devices, and the joint optimization model of charging time allocation, computing offloading sequence decision and hovering positions of UAV is established.
- We model the computing offloading sequence of smart wearable devices as the traveling salesman problem (TSP) and solves it based on genetic algorithm, and then solves the charging time and the optimal hovering positions of the UAV based on successful convex optimization.
- The effectiveness of the proposed scheme is verified by simulation experiments. The experimental results show that the proposed scheme can make the energy obtained by smart wearable devices through WPT meet the requirements of computing task offloading, and greatly reduce the delay of medical emergency response.

The reminder of this paper is arranged as follows. Section 2 summarizes the application scenarios of intelligent wearable devices in the medical field, as well as the related work of UAV WPT and computing offload. Section 3 introduces the proposed smart wearable network architecture and the joint optimization model of charging time allocation, computing offloading sequence and hovering positions of UAV. Section 4 solves the joint optimization model. Section 5 conducts simulation experiments. Finally, Section 6 summarizes our work.

II. Related Work

Smart wearable devices are widely used in medical healthcare, such as smart clothing and wearable effective robot proposed by Chen *et al.* [15], [16], which can respectively monitor physiological parameters such as ECG, blood pressure, blood oxygen and psychological parameters such as EEG, voice and tactile pressure. Shi *et al.* [17] proposed a weight calculation method for heterogeneous wearable sensors to reduce the interference caused by abnormal sensors in wearable devices and improve the accuracy of input data. There are still some works focused on the design of networking protocols in wearable networks, such as Liao *et al.* [18] proposed a cooperative routing protocol based on incremental relay to extend the lifetime of wearable networks. Kim *et al.* [19] proposed an adaptive control algorithm for the WiFi coexistence environment based on ZigBee to ensure the delay requirements of wearable sensors. Above work is mainly used for the transmission of structured physiological data, and can not support large-scale multi-dimensional data transmission. In [20], the author uses coordinator based MEC server to offload tasks to improve the computing power of wearable devices. However, this paper assumes that the mobility of patients is based on the nomadic mobility model, and the transition probability of users in different locations in real life does not always follow the existing prediction model.

Regarding offloading computing tasks to the UAV-driven edge cloud, many research teams have carried out promising work. Zhou *et al.* [9] studied the problem of computing rate maximization in UAV enabled MEC wireless powered system with causal constraints of energy acquisition and UAV speed constraints under partial and binary offloading mode, and gave the near optimal solution of CPU frequency, offloading

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.

time and transmission power. Yang *et al.* [10] studied the problem of minimizing the sum of power consumption by jointly optimizing user connections, power control, computing power allocation and UAV path planning in a multi-UAV MEC network, and proposed an iterative three sub-problem solution algorithm. Bai *et al.* [21] proposed an energy efficiency calculation offloading algorithm for UAV-MEC system based on physical layer security, and found the best solution for active and passive eavesdroppers. In the UAV cooperative communication system, for the amplify and forward (AF) and decode and forward (DF) protocol, Yin *et al.* [22] optimize the UAV power profile, power splitting ratio profile and trajectory to maximize the end-to-end throughput.

Due to the remarkable characteristics of flexibility, mobility and freedom from spatial constraints, the development of WPT technology provides a new energy supply scheme for battery driven terminal equipment [23]. At present, a lot of work has focused on improving the communication energy efficiency of IoT equipment by combining UAV and WPT technology. Xu *et al.* [24], [25] studied how to maximize the minimum energy received by sensor nodes through trajectory design in the limited charging time of UAV. In [26], the author proposes a successive hover-and fly scheme to search the optimal hover point and hover time based on genetic algorithm. The goal is to maximize the minimum energy harvested by all devices. In [27], the author maximizes the throughput of the network by jointly optimizing the trajectory design and wireless resource allocation of UAV. Du *et al.* [28] proposed a new TDMA workflow model, and established a joint optimization model of IOT device connection, computing resource allocation, UAV hover time, wireless charging time and service order, so as to minimize the total energy consumption of UAV. In [29], the author first uses WPT technology to charge sensor nodes, and periodically sends data to cluster heads, and then uses UAV to send data to sink node for further processing and analysis. The author uses Lagrange dual method and heuristic algorithm to reduce the computational complexity and obtain the optimal time allocation scheme. In [30], the author uses deep Q-learning algorithm to manage the resources of UAV assisted WPT network. Baek *et al.* [31] uses the Lagrange multiplier method and the proposed geometry-based update algorithm to jointly solve the hover position and hover time of the UAV, thereby maximizing the minimum energy remaining after the sensor node receives energy and consumes energy for data transmission.

Although UAV-enabled computing offloading and WPT have been well studied in above works, very few work has focused on solving the problems of charging, data collection and computing tasks offloading faced by smart wearable devices in the wearable network for medical emergencies. Our work is based on the TSP model and successive convex optimization in the work of [32]. Different from the work of [32], we introduce the process of wireless charging before wearable devices offloading computation tasks to the UAV. Therefore, the minimum delay of the system needs to be added with the charging time, and the energy constraint of wearable devices is based on the energy harvested in the previous charging process.

III. System Model and Problem Formulation

With the help of UAV's mobility, flexibility and better computing power, UAV is used to charge multiple smart wearable devices worn by patients in infectious disease isolation places, and then carry out data transmission. When the data collection is completed, the UAV carries out multimodal data analysis to provide reliable patient health analysis results. This process mainly includes three stages: the wireless charging stage of UAV for smart wearable devices, the data transmission stage of smart wearable devices (computing task offloading stage), and the multimodal data fusion and analysis stage in UAV edge server, as shown in Fig. 1. The main notation is shown in Table I.

A. UAV Charging Model With WPT

We consider the scenario of a UAV with N smart wearable devices. The set of smart wearable devices is $\{w_n, n \in \{1, 2, \ldots, N\}\}$. The space between smart wearable device and UAV is three-dimensional. When charging, the UAV can charge multiple intelligent wearable devices at the same time, and the location of the UAV is recorded as $l_{UAV}(0) = (x(0), y(0), H)$, the position of smart wearable device w_n is $l_n = (x_n, y_n, 0)$. The height H of UAV is assumed to be fixed, and H is the minimum height for UAV not to collide with buildings, trees and other obstacles. The communication link between UAV and smart wearable devices adopts Line-of-Sight (LOS) mode. During charging, the distance between w_n and UAV is expressed as:

$$d_{w,n} = \sqrt{(x(0) - x_n)^2 + (y(0) - y_n)^2} \tag{1}$$

The channel gain during charging is as follows:

$$h_{w,n} = \frac{\beta_0}{d_{w,n}^2 + H^2} = \frac{\beta_0}{(x(0) - x_n)^2 + (y(0) - y_n)^2 + H^2} \tag{2}$$

β_0 is the power attenuation gain when the distance between UAV and wearable devices is 1 m. During the charging time t_0, the energy collected by the wearable device w_n is:

$$E_{harvest,n} = \mu p_0 h_{w,n} t_0 \tag{3}$$

Where μ is the WPT energy conversion coefficient, p_0 is the communication power when UAV charges smart wearable devices.

B. Computing Offloading of Wearable Devices

After the charging is completed, the smart wearable device needs to transmit collected data to UAV, perform multimodal physiological data analysis and complete the offloading of the computing task. We adopt the fly-hover mode in [32], that is, when the smart wearable device w_n is uploading data, the UAV needs to fly to the best hovering point corresponding to w_n. The UAV will continue to fly to the next hovering point for data transmission with the next wearable device after completing the computing task offloading of w_n. The set of

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.

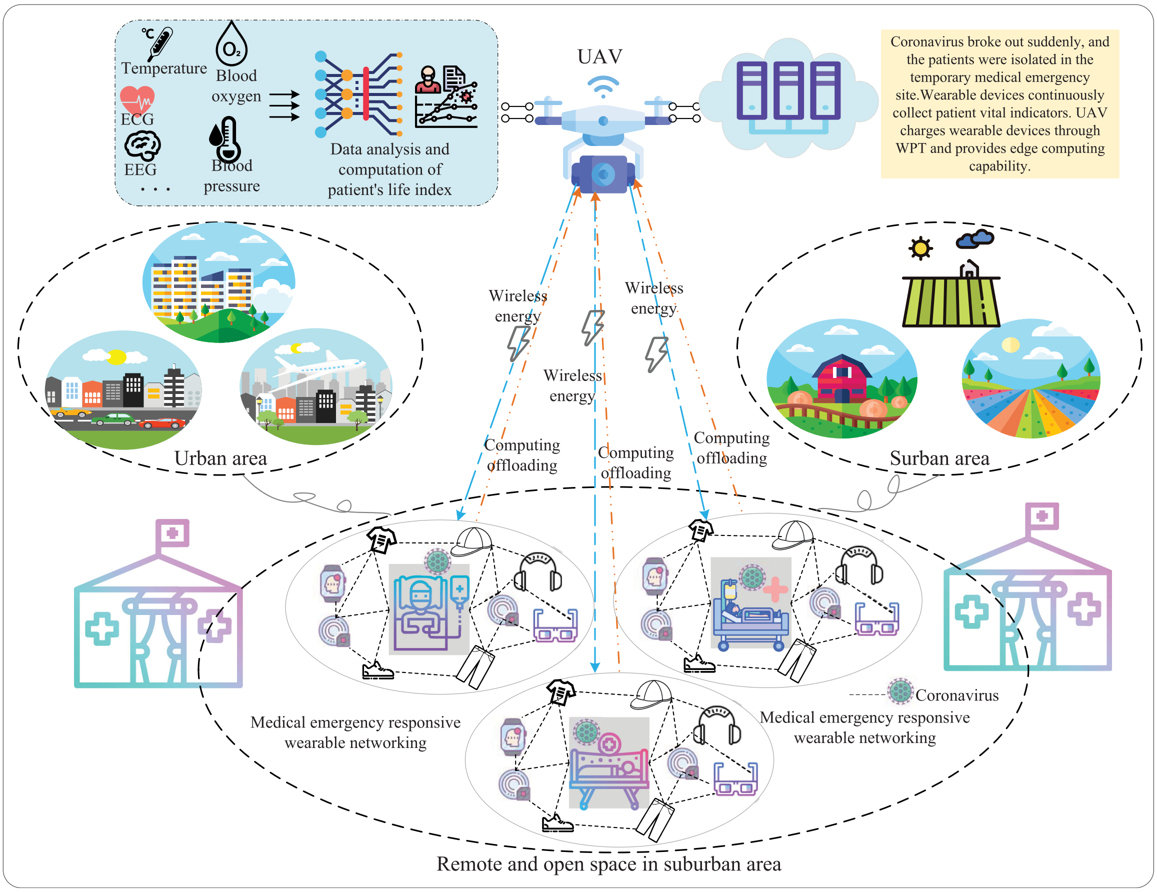


Fig. 1. System architecture of MER-WearNet.

TABLE I
NOTATION TABLE

Notation	Description
p_0	Charging power
t_0	Charging time
$E_{harvest,n}$	Harvested energy of w_n
$h_{w,n}/h_{c,n}$	The channel gain of WPT stage or computing offloading stage
p_n	Data uploading power of wearable devices
$r(n)$	Data transmission rate between wearable devices and UAV
Φ	Computing offloading sequence of wearable devices
B	Transmission bandwidth
$t_{h,n}$	The data uploading time of the wearable device, also the hovering time of the UAV
$s(n)$	Data transmission amount of wearable devices
$s_{n,min}$	Minimum data transmission requirements
$E_{con,n}$	Energy consumption of data transmission
$d_{\phi(n),\phi(n+1)}$	The flight distance of UAV between two hovering points
t_{fly}	UAV flying time
v	UAV flying speed

computing offloading sequence is expressed as $\Phi = \{\widetilde{O}_1, \widetilde{O}_2, \ldots, \widetilde{O}_N\}$, let $\phi(n) = \widetilde{O}_n$, which represents the index of the smart wearable device. Then, the hovering position of UAV is $\{l_{UAV}(\phi(1)), l_{UAV}(\phi(2)), \ldots, l_{UAV}(\phi(n))\}$. $l_{UAV}(\phi(n)) = (x(\phi(n)), y(\phi(n)), H)$ is the best hovering position of the UAV when the smart wearable device $w_{\phi(n)}$ offloads computing task. The channel gain of the smart wearable device $w_{\phi(n)}$ is as follows:

$$\begin{aligned} h_{c,\phi(n)} &= \frac{\beta_0}{d^2_{c,\phi(n)} + H^2} \\ &= \frac{\beta_0}{\left(x(\phi(n)) - x_{\phi(n)}\right)^2 + \left(y(\phi(n)) - y_{\phi(n)}\right)^2 + H^2} \end{aligned} \tag{4}$$

The signal to interference noise ratio (SINR) is:

$$\gamma(\phi(n)) = \frac{p_{\phi(n)} h_{c,\phi(n)}}{\sigma^2} \tag{5}$$

Where $p_{\phi(n)}$ is the transmission power of the wearable device $w_{\phi(n)}$, and σ^2 is the white Gaussian noise. According to Shannon's theorem, the data transmission rate of wearable device $w_{\phi(n)}$ is:

$$r(\phi(n)) = B\log_2(1 + \gamma(\phi(n))) \tag{6}$$

Among them, B is the data transmission bandwidth when computing offloading. For wearable device $w_{\phi(n)}$, if the hovering time of UAV at corresponding hovering point $l_{UAV}(\phi(n))$ is $t_{h,\phi(n)}$, then the data transmission amount of $w_{\phi(n)}$ during this period is:

$$s(\phi(n)) = r(\phi(n)) t_{h,\phi(n)} = B\log_2(1 + \gamma(\phi(n))) t_{h,\phi(n)} \tag{7}$$

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.

Because in the medical emergency response scenario, smart wearable devices need to complete the offloading of computing tasks in the shortest possible time, so each wearable device needs to meet a certain amount of data transmission requirements $s_{\phi(\mathrm{n}),min}$ during the hovering time of the UAV, which is:

$$B\log_2(1+\gamma(\phi(n)))t_{h,\phi(n)} \geq s_{\phi(n),min} \tag{8}$$

Wearable devices consume a certain amount of energy during data transmission. In the transmission time $t_{h,\phi(n)}$, the energy consumed by $w_{\phi(n)}$ can be expressed as:

$$E_{con,\phi(n)} = p_{\phi(n)} t_{h,\phi(n)} \tag{9}$$

Since the energy collected by the wearable device $w_{\phi(n)}$ during the charging process is $E_{harvest,\phi(n)}$, and the energy consumed by data transmission cannot exceed the collected energy. Therefore, there are the following constraints:

$$p_{\phi(n)} t_{h,\phi(n)} \leq \mu p_0 h_{w,\phi(n)} t_0 \tag{10}$$

C. UAV Flying Time

The flight distance of UAV from hovering position $l_{UAV}(\phi(n))$ to the next hovering position $l_{UAV}(\phi(n+1))$ is as follows:

$$d_{\phi(n),\phi(n+1)} = \sqrt{(x(\phi(n+1)) - x(\phi(n)))^2 + (y(\phi(n+1)) - y(\phi(n)))^2} \tag{11}$$

The flight time of UAV is calculated as follows:

$$t_{fly} = \sum_{n=0}^{N-1} \frac{d_{\phi(n),\phi(n+1)}}{v} \tag{12}$$

D. Problem Formulation

In the case of medical emergency, it is necessary to complete data transmission in the shortest possible time in order to get the patient's health status analysis as soon as possible. Therefore, the goal of this paper is to minimize the total time for smart wearable devices to complete charging and computing tasks offloading. The optimization problem in this paper can be summed up as P1:

$$\begin{aligned} P1: \quad & \min_{t_0,\Phi,x(\phi(n)),y(\phi(n))} T = t_0 + \sum_{n=1}^{N} t_{h,\phi(n)} + t_{fly} \\ \text{s.t.} \quad & C1: v \leq v_{\max} \\ & C2: p_{\phi(n)} t_{h,\phi(n)} \leq \mu p_0 h_{w,\phi(n)} t_0, \forall n \in \{1,2,\ldots,N\} \\ & C3: B\log_2(1+\gamma(\phi(n)))t_{h,\phi(n)} \geq s_{\phi(n),\min}, \\ & \quad \forall n \in \{1,2,\ldots,N\} \end{aligned}$$

The constraint condition C1 indicates that the flight speed of UAV between hovering points corresponding to each wearable device does not exceed the maximum speed, while C2 and C3 are the requirements of energy constraint and data transmission amount respectively.

IV. Problem Solution

The variables to be solved for problem P1 include charging time t_0, computing offloading sequence Φ, and the hovering position of UAV in each wearable device. Because the position variable of UAV involved in constraint C3 is a non-convex and non-concave function in the denominator of log function, and the hovering sequence of UAV is also unknown, P1 is difficult to solve. Therefore, we first determine the hovering sequence of UAV, that is, the computing tasks' offloading sequence of wearable devices, and then solve the charging time and hovering position.

A. Determining the Computing Offloading Sequence of Wearable Devices

If the hovering position of UAV is known, problem P1 can be decomposed into two subproblems: the minimization of flight time, the minimization of the sum of charging time and hovering time, which can be attributed to P2.1 and P2.2 respectively. Problem P2.1 can be expressed as:

$$\begin{aligned} P2.1: \quad & \min_{\Phi} t_{fly} = \sum_{n=0}^{N-1} \frac{d_{\phi(n),\phi(n+1)}}{v} \\ \text{s.t.} \quad & C1: v \leq v_{\max} \end{aligned}$$

It is obvious that UAV uses the maximum speed to fly between the hovering points to minimize the flight time. Then the main solution of P2.1 is that the UAV has the smallest flying distance between N hovering points, which requires determining the hovering sequence Φ. Referring to [32], the UAV flight distance minimization problem can be solved by solving TSP to determine the computing offloading sequence of wearable devices. Assuming that the N hovering positions of the UAV are just above each wearable device, we use the genetic algorithm to solve TSP of P2.1. Set the population size as M, the population of each generation in the evolution process is expressed as $\mathbb{Z}^k$, and k is the number of generations. Genetic algorithm for TSP includes initialization of population, calculation of fitness, selection of parent chromosomes, crossover and mutation. The specific process is as follows:

(1) Initialize the Population: M paths are generated randomly, and M chromosomes are obtained. Each path corresponds to a computing offloading sequence of wearable devices. Each path is composed of the location of N wearable devices and the location of UAV when charging.

(2) Calculate the Fitness Value: We set the fitness function to the reciprocal of the sum of distances in P2.1, which is $f_m^k = \frac{1}{\sum_{n=0}^{N-1} d_{\phi(n),\phi(n+1)}}$. f_m^k represents the fitness function value of the m-th chromosome in the k-th generation population.

(3) Select Parent Chromosomes: The roulette algorithm is used to select two chromosomes from the current population

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.

as parent chromosomes. Calculate the cumulative probability of each chromosome fitness function value, and then the parent chromosomes are determined according to the cumulative probability range of the generated random number. The single probability of each chromosome is calculated as: $pr_m^k = \frac{f_m^k}{\sum_{m=1}^{M} f_m^k}$, and the cumulative probability is calculated as: $cpr_m^k = cpr_{m-1}^k + pr_m^k$. The two selected chromosomes are recorded as C_1^k, C_2^k.

(4) Crossver: Determine whether to perform the crossover operation according to the crossover probability α. Two intersections e_1 and e_2 are generated randomly, and the wearable device index numbers of chromosome C_1^k and C_2^k from e_1 to e_2 are exchanged. If there are duplicate wearable devices in the chromosomes after crossover, perform the deduplication operation again to obtain two new son chromosomes.

(5) Mutation: After crossover, we decide whether to mutate the two son chromosomes according to the mutation probability ϵ. Randomly generate two mutation points m_1, m_2, and reverse the positions of the two daughter chromosomes from m_1 to m_2.

The process of (2)–(5) is repeated until M new populations are generated, and then the next generation cycle is carried out until the set maximum generation number. Select the chromosome with the largest fitness function value f_m^k in all generations, then we can determine the hovering sequence Φ^* of UAV.

P2.2 is the minimization of the sum of charging time and hovering time. When the hovering position of UAV is determined, P2.2 has nothing to do with hovering sequence. Since we assume that the UAV hovers just above each wearable device, the distance between UAV and wearable device at each hovering point is calculated to be 0. The problem P2.2 can be expressed as:

$$
\begin{aligned}
P2.2: \quad & \min_{t_0, t_{h,n}} T_1 = t_0 + \sum_{n=1}^{N} t_{h,n} \\
\text{s.t.} \quad & C2: p_n t_{h,n} \le \mu p_0 h_{w,n} t_0, \forall n \in \{1, 2, \ldots, N\} \\
& C3: B\log_2\left(1 + \frac{p_n \beta_0}{\sigma^2 H^2}\right) t_{h,n} \ge s_{n,min}, \\
& \forall n \in \{1, 2, \ldots, N\}
\end{aligned}
$$

The variables to be solved in P2.2 include the charging time t_0 and the hover time $t_{h,n}$ at each wearable device. The problem can be solved by linear programming (LP). When the hovering position of the UAV is known, P2.1 and P2.2 determine the computing offloading sequence and charging time of wearable devices, and then the overall minimum time of the two stages can be determined. The solving process of P2.1 and P2.2 is attributed to Algorithm 1.

Algorithm 1. Time minimization based on genetic algorithm and linear programming

Input:
The location of smart wearable device l_n, and the location $l_{UAV}(0)$ of the UAV in the WPT phase;
Genetic algorithm related parameters: population size M, crossover probability α, mutation probability ϵ;
Output:
Charging time t_0, computing offloading sequence Φ^*, minimized overall time T;
Initialize the population and randomly generate M sequences;
for $k = 1, 2, \ldots, MaxGeneration$ **do**
  for $m = 1, 3, 5, \ldots, M$ **do**
    Calculate the fitness function value and cumulative probability of M chromosomes respectively;
    Select two chromosomes C_1^k, C_2^k from $\mathbb{Z}^k$ according to the cumulative probability;
    Perform a crossover operation on C_1^k, C_2^k according to the crossover probability, and perform a deduplication operation on the wearable device that is repeated after the crossover to generate two new chromosomes;
    According to the mutation probability, two mutation points are randomly generated, and the mutation position is reversed;
  end for
end for
Select the chromosome corresponding to the largest f_m^k from all populations, determine the sequencer Φ^*, and obtain the minimum flight time t_{fly};
Solve the LP problem in P2.2, and get the sum of the minimum charging time and hovering time T_1;
Calculate the minimum total time $T = T_1 + t_{fly}$.

B. Optimal Charging Time Allocation and Hovering Position Solution

After the computing offloading sequence is determined by genetic algorithm, P1 is still difficult to solve because the constraint C3 is a non-convex and non-concave function. According to [32], [33], we introduce the slack variable $\{\omega(\phi^*(\mathrm{n}))\}$, and then obtain the lower bound $\hat{r}$ of the data transmission rate r through the first-order Taylor expansion. In the i-th iteration, $\widehat{r}_i$ is convex with respect to $\left(x(\phi^*(n)) - x_{\phi^*(n)}\right)^2 + \left(y(\phi^*(n)) - y_{\phi^*(n)}\right)^2$. $\widehat{r}_i$ is obtained by the following transformation:

$$
\begin{aligned}
& B\log_2(1 + \gamma(\phi^*(n))) \\
& \ge -\mathbb{A}_i(\phi^*(n))\Big(\left(x(\phi^*(n)) - x_{\phi^*(n)}\right)^2 \\
& \quad + \left(y(\phi^*(n)) - y_{\phi^*(n)}\right)^2 - \left(x_i(\phi^*(n)) - x_{\phi^*(n)}\right)^2 \\
& \quad - \left(y_i(\phi^*(n)) - y_{\phi^*(n)}\right)^2\Big) + \mathbb{B}_i(\phi^*(n)) \\
& \triangleq r_i(\widehat{\phi^*(n)})
\end{aligned} \tag{13}
$$

Where,

$$
\begin{aligned}
& \mathbb{A}_i(\phi^*(n)) = \\
& \frac{B\left(p_{\phi^*(n)}\beta_0/\sigma^2\right)\log_2 e}{\left(H^2 + \left(x_i(\phi^*(n)) - x_{\phi^*(n)}\right)^2 + \left(y_i(\phi^*(n)) - y_{\phi^*(n)}\right)^2 + p_{\phi^*(n)}\beta_0/\sigma^2\right)} \\
& \cdot \frac{1}{\left(H^2 + \left(x_i(\phi^*(n)) - x_{\phi^*(n)}\right)^2 + \left(y_i(\phi^*(n)) - y_{\phi^*(n)}\right)^2\right.}
\end{aligned} \tag{14}
$$

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.

and

$$\mathbb{B}_i(\phi^*(n)) = B\cdot \log_2\left(1+\frac{p_{\phi^*(n)}\beta_0/\sigma^2}{H^2+\left(x_i(\phi^*(n))-x_{\phi^*(n)}\right)^2+\left(y_i(\phi^*(n))-y_{\phi^*(n)}\right)^2}\right) \tag{15}$$

Then P1 is transformed into P3:

$$\begin{aligned} P3: &\min_{t_0,x(\phi^*(n)),y(\phi^*(n)),\omega(\phi^*(n))} T = t_0+\sum_{n=1}^{N} t_{h,\phi^*(n)}+\sum_{n=0}^{N-1}\frac{d_{\phi^*(n),\phi^*(n+1)}}{v_{\max}} \\ \text{s.t. } & C2: p_{\phi^*(n)}t_{h,\phi^*(n)} \le \mu p_0 h_{w,\phi^*(n)} t_0, \forall n\in\{1,2,\ldots,N\} \\ & C3: \omega(\phi^*(n))t_{h,\phi^*(n)} \ge s_{\phi^*(n),min}, \forall n\in\{1,2,\ldots,N\} \\ & C4: r_i(\widehat{\phi^*(n)}) \ge \omega(\phi^*(n)), \forall n\in\{1,2,\ldots,N\} \end{aligned}$$

After introducing the slack variable $\omega(\phi^*(n))$ in P3, the left $\omega(\phi^*(n))t_{h,\phi^*(n)}$ of constraint C3 is still non-convex. To solve the problem, referring to [34], we replace $\omega(\phi^*(n))t_{h,\phi^*(n)}$ with $\frac{(\omega(\phi^*(n))+t_{h,\phi^*(n)})^2-(\omega(\phi^*(n))-t_{h,\phi^*(n)})^2}{4}$. Then apply the first-order Taylor expansion to $(\omega(\phi^*(n))+t_{h,\phi^*(n)})^2$. In the i-th iteration, the inequality constraint C3 in P3 is transformed into the following formula:

$$\begin{aligned} &\frac{\left(\omega_i(\phi^*(n))+t_{i,h,\phi^*(n)}\right)^2}{4}+\frac{\left(\omega(\phi^*(n))+t_{h,\phi^*(n)}-\omega_i(\phi^*(n))-t_{i,h,\phi^*(n)}\right)}{2} \\ &\cdot\frac{\left(\omega_i(\phi^*(n))+t_{i,h,\phi^*(n)}\right)}{2} \\ &-\frac{\left(\omega(\phi^*(n))-t_{h,\phi^*(n)}\right)^2}{4}-s_{\phi^*(n),\min}\ge 0, \\ &\forall n\in\{1,2,\ldots,N\} \end{aligned} \tag{16}$$

Then P3 can be transformed into P4:

$$\begin{aligned} P4: &\min_{t_0,x(\phi^*(n)),y(\phi^*(n)),\omega(\phi^*(n))} T = t_0+\sum_{n=1}^{N} t_{h,\phi^*(n)}+\sum_{n=0}^{N-1}\frac{d_{\phi^*(n),\phi^*(n+1)}}{v_{\max}} \\ \text{s.t. } & C2 \quad and \quad C4 \\ & (16) \end{aligned}$$

During each iteration, P4 can be solved with the standard convex optimization toolkit CVX [35]. In the initial iteration, the hover position of the UAV is set to be directly above each wearable device. After finding the optimal UAV hovering position $x^*(\phi^*(n)), y^*(\phi^*(n))$ in each iteration, $x_i(\phi^*(n))$ and $y_i(\phi^*(n))$ in the next iteration is replaced with $x^*(\phi^*(n)), y^*(\phi^*(n))$ until the algorithm converges to the optimal value and no longer changes. The successive convex optimization is summarized as Algorithm 2.

Algorithm 2. SCP-based hovering position and charging time solutiong

Input:
Data transmission requirements $S_{n,\min}$ for smart wearable devices; Charging power p_0, UAV position $l_{UAV}(0)$ in WPT;
Output:
Charging time t_0, N hovering positions $\{(x(\phi^*(n)), y(\phi^*(n))\}$, minimum time T;

1: According to Algorithm 1, determine the computing offloading sequence Φ^* of wearable devices;
2: Initialize the position of UAV at N hovering points $x_1(\phi^*(n)) = x_{\phi^*(n)}, y_1(\phi^*(n)) = y_{\phi^*(n)}$;
3: **while** $i \le max\_iteration$ **do**
4: Use the CVX toolkit to solve the convex optimization problem in P4, and get the hover position $x^*(\phi^*(n)), y^*(\phi^*(n))$ and the charging time t_0^*;
5: Updated $x_{i+1}(\phi^*(n)) = x^*(\phi^*(n))$, $y_{i+1}(\phi^*(n)) = y^*(\phi^*(n))$;
6: Update $\mathbb{A}_{i+1}(\phi^*(n)), \mathbb{B}_i(\phi^*(n)), (r_i(\widehat{\phi^*(n)}))$ according to formula (14), (15) and (13);
7: update $i = i+1$;
8: **end while**

TABLE II
SIMULATING SETTING

Parameters	Value
The height of UAV	10m
Channel power attenuation gain β_0 with a distance of 1m	-30dB
UAV max flying speed v_{max}	5 m/s
Energy harvesting coefficient μ	0.8
Charging power p_0	1W
Transmission power	0.0011W
Transmission bandwidth	20MHz
White Gaussian noise power	10^{-9}W

V. EXPERIMENT

A. Simulation Setting

We assume that multiple smart wearable devices are randomly distributed in an area of $10\,m \times 10\,m$. Unless otherwise specified, the number of smart wearable devices in this paper is 15. When charging, the UAV is in the center of the area, the height of the UAV is 10 m, and the maximum flight speed is 5 m/s. The energy conversion efficiency μ during charging is 0.8, the charging power p_0 is 1 W, the channel gain β_0 when the distance is 1 m is -30 dB, and the white Gaussian noise σ^2 is $10^{-9}W$. When wearable devices offload computing tasks, the power p_n of data uploading is 0.0011 w, the bandwidth B is 20 MHz, and the requirement of data transmission is 14Mbits. The specific parameter settings are shown in Table II.

B. Performance Analysis

Fig. 2 shows the evolution process of the shortest flight distance corresponding to the number of different wearable devices when the UAV hovers just above the wearable devices. With the increase of the number of wearable devices, the shortest flight distance of UAV converges more and more slowly.

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.

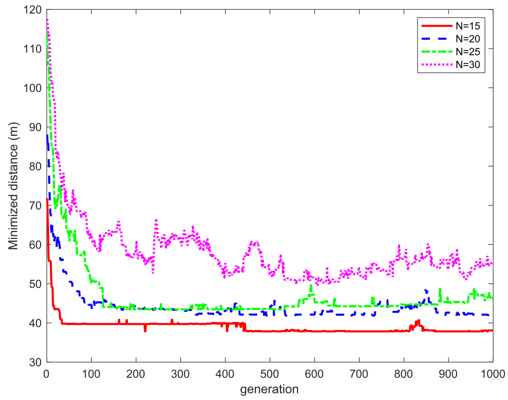
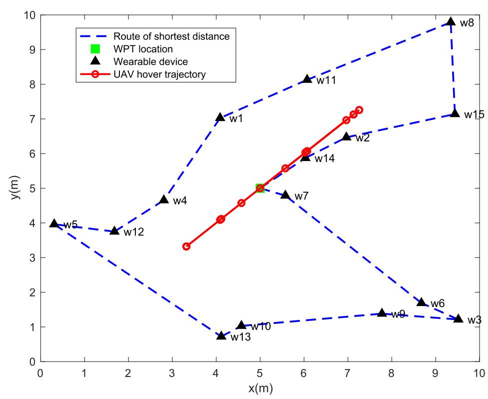
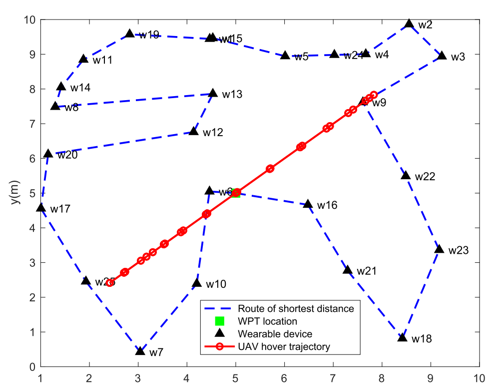


Fig. 2. Iterative process of UAV shortest flight distance in Algorithm 1.



(a) N=15



(b) N=25

Fig. 3. The initial shortest flight path and final hovering position of UAV.

Figs. 3(a) and 3(b) show the shortest flight path of UAV hovering just above the wearable devices when the number of wearable devices is 15 and 25 respectively, and the final hovering path obtained by SCP algorithm. In fact, by analyzing the red path in Fig. 3, it is found that N hovering points of UAV constitute a straight line. In this case, no matter what the hovering sequence of UAV is, the sum of the flight distances of UAV at each hovering point is the same, which leads to that the total time has nothing to do with the computing offloading sequence of wearable devices. Therefore, the computing offloading sequence can be given randomly, and then the hovering

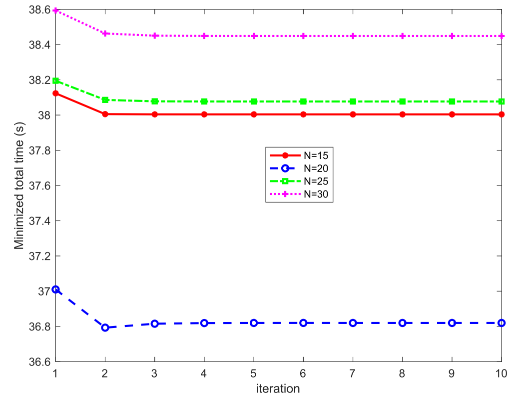


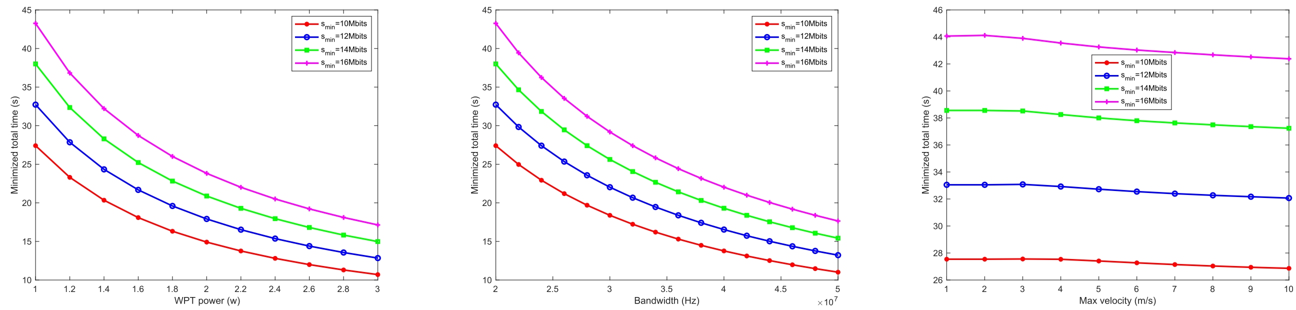
Fig. 4. Convergence process of minimum time under different number of wearable devices.

position, charging time allocation and total time can be obtained directly by using Algorithm 2.

Fig. 4 shows the iterative process of solving problem P4 based on SCP algorithm to get the total time. We can find that in the second or third iteration, the algorithm can converge to the optimal value. The different number of wearable devices does not have much effect on the total time. Although the total time of 25 and 30 wearable devices is larger, the total time of $N = 20$ is smaller than the total time of $N = 15$. Therefore, in the network architecture mentioned in this article, even if the number of wearable devices is increased, the overall delay of the system will not necessarily increase accordingly. In the case of medical emergency, if the number of patients or wearable devices is increased, UAV can still transmit enough energy for these devices, so that these wearable devices can ensure effective data acquisition and transmission, and ensure that the analysis results of patients' vital signs are not affected. given randomly, and then the hovering position, charging time allocation and total time can be obtained directly by using Algorithm 2.

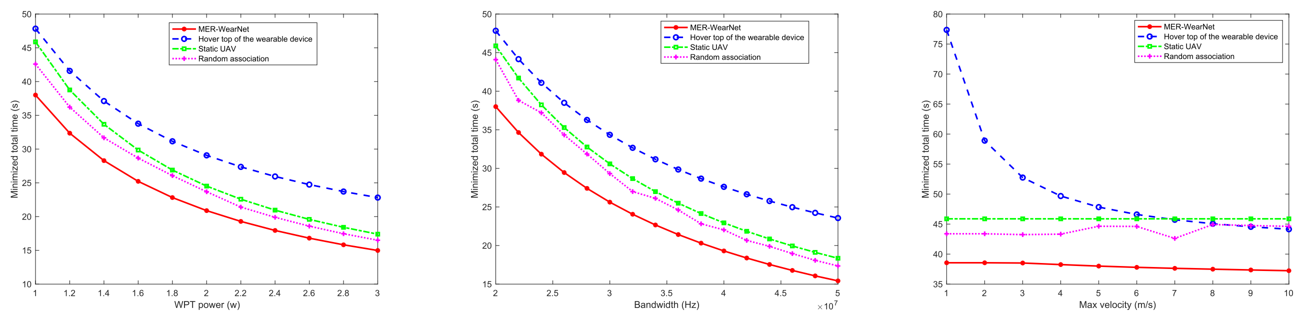
Fig. 5 shows the impact of minimum data transmission requirements on the overall service time. Fig. 5(a) shows the change of total system time with the increase of charging power in WPT stage and different data transmission requirements. It can be seen that under the four data transmission requirements, the larger the charging power is, the smaller the total time is. The total time required by the system will also increase with the demand for data transmission. This is because the higher the charging power, the wearable device can collect enough energy in a shorter time to complete the data transmission requirements, that is, the charging time is shorter, so the overall time is shorter. The higher the requirement of data transmission, the more transmission time is needed, and more charging time is needed to obtain more energy to ensure the data transmission, so the total time is more. In Fig. 5(b), with the increase of transmission bandwidth, the transmission time required to complete the data transmission is reduced, so the total time is reduced. In Fig. 5 (c), with the increase of flight speed, the flight time of UAV decreases, resulting in the decrease of total time. However, compared to the impact of charging power and transmission

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.



(a) Different charging power (b) Different bandwidth (c) Maximum flight speed of UAV

Fig. 5. The impact of data transmission requirements on the total time.



(a) Under the change of charging power (b) Under the change of transmission bandwidth (c) Under the change of maximum flight speed

Fig. 6. Comparison of the total time obtained by different schemas.

bandwidth on the total time, the flight speed has a slower impact on the total time, and the rate at which the total time decreases is slower.

Fig. 6 shows the impact of different schemes on the overall system time. We compare the proposed MER-WearNet scheme with the three schemes, namely, the scheme of UAV hovering directly above the wearable device in Algorithm 1, the static UAV scheme, and randomly assigning association schema after obtaining the hovering trajectory of UAV according to Algorithm 2. In the static UAV scheme, it is assumed that the UAV is always in the center of the region. As can be seen from Fig. 6, with the increase of charging power, transmission bandwidth and maximum flight speed, the total time of MER-WearNet proposed in this paper is smaller than that of the other three schemes. In Algorithm 1, when the UAV hovering position is directly above the wearable device, although the transmission distance decreases, the data transmission rate increases and the transmission time decreases, but the charging time and flight time increase more, so the total time required is the most. In the static UAV scheme, the UAV is always in the charging position, which leads to the decrease of UAV flight distance and flight time, but the data transmission time is still larger than that of MER-WearNet. When the hovering position of UAV is determined, it takes more time to randomly allocate the association between UAV and wearable device than computing offloading sequence corresponding to the shortest distance determined by genetic algorithm in MER-WearNet. In Fig. 6(c), with the increase of flight speed, since the flight distance of static UAV is 0, the total time will not change with the flight speed. In the random association schema, although the flight distance is the same as that of MER-WearNet, since the connection method between the UAV and the wearable device is random, the data transmission time and charging time are random. The total time of MER-WearNet decreases as the flight speed increases.

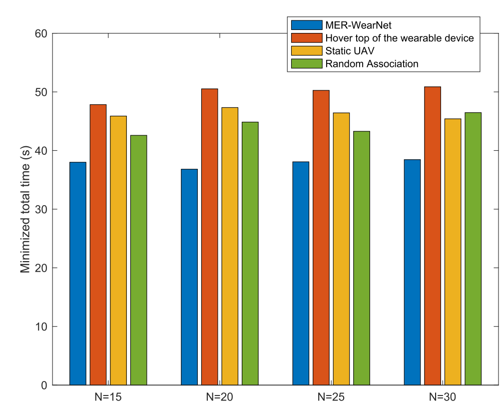


Fig. 7. The impact of the number of smart wearable devices on the results.

Fig. 7 is the total time comparison of the four schemes under different number of wearable devices. Under the four schemes, the larger the number of wearable devices does not necessarily increase the total time, but the total time of MER-WearNet is the smallest. Fig.refharvestenergy shows the energy harvested by 15 smart wearable devices. It can be seen that the energy collected by each device is above 0.14 mW.

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.

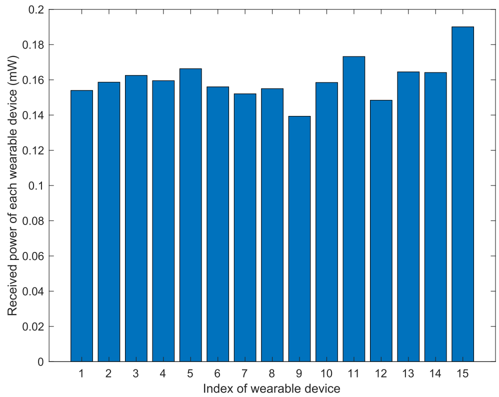


Fig. 8. Energy harvested by 15 smart wearable devices.

VI. Conclusion

In this paper, WPT technology and UAV mobile edge technology are combined to solve the bottleneck problem of limited battery energy and computing power of intelligent wearable devices, and extend the life cycle of wearable network. An MER-WearNet scheme was proposed, which uses WPT technology to solve the power supply problem of wearable devices worn by patients in medical emergency scenarios, and establishes a joint optimization model of charging time allocation, wearable computing offloading sequence and hovering position of UAV. Then it is solved based on genetic algorithm and SCP. The simulation results show that the proposed MER-WearNet scheme can effectively reduce the total time of the system and meet the delay requirements in medical emergency scenarios.

References

[1] World Health Organization, "Coronavirus disease (COVID-19) situation report-121," 2019. Accessed: 20 May 2020. [Online]. Available: https://apps.who.int/iris/handle/10665/332156

[2] World Health Organization, "Coronavirus disease (COVID-2019) situation report 82," 2019. Accessed: 11 Apr. 2020. [Online]. Available: https://apps.who.int/iris/handle/10665/331780

[3] Monthly Briefing on the world economic situation and prospects. Retrieved No. 136, 1 Apr. 2020. [Online]. Available: https://www.un.org/development/desa/dpad/publication/world-economic-situation-and-prospects-april-2020-briefing-no-136

[4] M. Chen *et al.*, "Living with I-fabric: Smart living powered by intelligent fabric and deep analytics," *IEEE Netw.*, vol. 34, no. 5, pp. 156–163, Sep./Oct. 2020.

[5] N. Jiang, Y. Deng, A. Nallanathan, and J. A. Chambers, "Reinforcement learning for real-time optimization in NB-IoT networks," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 6, pp. 1424–1440, Jun. 2019.

[6] M. Chen,"NDNC-BAN: Supporting rich media healthcare services via named data networking in cloud-assisted wireless body area networks," *Inform. Sci.*, vol. 284, no. 10, pp. 142–156, Nov. 2014.

[7] L. Huang, S. Bi, and Y.-J. A. Zhang, "Deep reinforcement learning for online computation offloading in wireless powered mobile-edge computing networks,"*IEEE Trans. Mobile Comput.*, vol. 19, no. 11, pp. 2581–2593, Nov. 2020.

[8] S. Bi, C. K. Ho, and R. Zhang, "Wireless powered communication: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 53, no. 4, pp. 117–125, Apr. 2015.

[9] F. Zhou, Y. Wu, R. Q. Hu, and Y. Qian, "Computation rate maximization in UAV-Enabled wireless-powered mobile-edge computing systems," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 9, pp. 1927–1941, Sep. 2018.

[10] Z. Yang, C. Pan, K. Wang, and M. Shikh-Bahaei, "Energy efficient resource allocation in UAV-Enabled mobile edge computing networks," *IEEE Trans. Wireless Commun.*, vol. 18, no. 9, pp. 4576–4589, Sep. 2019.

[11] Y. Zeng, R. Zhang, and T. J. Lim, "Wireless communications with unmanned aerial vehicles: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 54, no. 5, pp. 36–42, May 2016.

[12] H. Wang, J. Wang, G. Ding, L. Wang, T. A. Tsiftsis, and P. K. Sharma, "Resource allocation for energy harvesting-powered D2D communication underlaying UAV-Assisted networks," *IEEE Trans. Green Commun. Netw.*, vol. 2, no. 1, pp. 14–24, Mar. 2018.

[13] N. Cheng *et al.*, "Space/Aerial-assisted computing offloading for IoT applications: A. learning-based approach," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 5, pp. 1117–1129, May 2019.

[14] M. Chen, Y. Hao, K. Lin, L. Hu, and Z. Yuan, "Label-less learning for traffic control in an edge network,"*IEEE Netw.*, vol. 32, no. 6, pp. 8–14, 2018.

[15] M. Chen, Y. Ma, Y. Li, D. Wu, Y. Zhang, and C. Youn, "Wearable 2.0: Enabling human-cloud integration in next generation healthcare systems," *IEEE Commun. Mag.*, vol. 55, no. 1, pp. 54–61, Jan. 2017.

[16] M. Chen, J. Zhou, G. Tao, J. Yang, and L. Hu, "Wearable affective robot," *IEEE Access*, vol. 6, pp. 64766–64776, 2018.

[17] H. Shi, W. Gao, Y. Liu, B. Wang, and H. Zhao "An adaptive multi-homogeneous sensor weight calculation method for body sensor networks," *IEEE Access*, vol. 7, pp. 121629–121644, 2019.

[18] Y. Liao, M. S. Leeson, M. D. Higgins, and C. Bai, "An incremental relay based cooperative routing protocol for wireless in-body sensor networks," *Proc. IEEE 12th Int. Conf. Wireless Mobile Comput., Netw. Commun.* 2016, pp. 1–6.

[19] Y. Kim, S. S. Lee, and S. K. Lee, "Coexistence of ZigBee-based WBAN and WiFi for health telemonitoring systems," *IEEE J. Biomed. Health Inform.*, vol. 20, no. 1, pp. 222–230, Jan. 2016.

[20] Y. Liao, Y. Han, Q. Yu, Q. Ai, Q. Liu, and M. S. Leeson, "Wireless body area network mobility-aware task offloading scheme," *IEEE Access*, vol. 6, pp. 61366–61376, 2018.

[21] T. Bai, J. Wang, Y. Ren, and L. Hanzo, "Energy-efficient computation offloading for secure UAV-edge-computing systems," *IEEE Trans. Veh. Technol.*, vol. 68, no. 6, pp. 6074–6087, Jun. 2019.

[22] S. Yin, J. Tan, and L. Li, "UAV-assisted cooperative communications with wireless information and power transfer," 2017, *arXiv:1710.00174*.

[23] Z. Zhang, H. Pang, A. Georgiadis, and C. Cecati, "Wireless power transfer-an overview," *IEEE Trans. Ind. Electron.*, vol. 66, no. 2, pp. 1044–1058, Feb. 2019.

[24] J. Xu, Y. Zeng, and R. Zhang, "UAV-enabled wireless power transfer: Trajectory design and energy region characterization," *Proc. IEEE Globecom Workshops*, 2017, pp. 1–7.

[25] J. Xu, Y. Zeng, and R. Zhang, "UAV-enabled wireless power transfer: Trajectory design and energy optimization," *IEEE Trans. Wireless Commun.*, vol. 17, no. 8, pp. 5092–5106, Aug. 2018.

[26] T. Yang, Y. Hu, X. Yuan, and R. Mathar, "Genetic algorithm based UAV trajectory design in wireless power transfer systems,"*Proc. IEEE Wireless Commun. Netw. Conf.*, 2019, pp. 1–6.

[27] L. Xie, J. Xu, and R. Zhang, "Throughput maximization for UAV-enabled wireless powered communication networks," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1690–1703, Apr. 2019.

[28] Y. Du, K. Yang, K. Wang, G. Zhang, Y. Zhao, and D. Chen, "Joint resources and workflow scheduling in UAV-enabled wirelessly-powered MEC for IoT systems," *IEEE Trans. Veh. Technol.*, vol. 68, no. 10, pp. 10187–10200, Oct. 2019.

[29] T. D. P. Perera, S. Panic, D. N. K. Jayakody, P. Muthuchidambaranathan, and J. Li, "A WPT-Enabled UAV-Assisted condition monitoring scheme for wireless sensor networks," *IEEE Trans. Intell. Transp. Syst.*, to be published, doi: 10.1109/TITS.2020.3018493.

[30] K. Li, W. Ni, E. Tovar, and A. Jamalipour, "Deep q-learning based resource management in UAV-assisted wireless powered IoT networks," in *Proc. ICC IEEE Int. Conf. Commun.*, 2020, pp. 1–6.

[31] J. Baek, S. I. Han, and Y. Han, "Optimal UAV route in wireless charging sensor networks," *IEEE Internet Things J.*, vol. 72, no. 2, pp. 1327–1335, Feb. 2020.

[32] C, Zhan and Y. Zeng, "Completion time minimization for multi-UAV-enabled data collection," *IEEE Trans. Wirel. Commun.*, vol. 18, no. 10, pp. 4859–4872, Oct. 2019.

[33] Y. Zeng and R. Zhang, "Energy-efficient UAV communication with trajectory optimization," *IEEE Trans. Wireless Commun.*, vol. 16, no. 6, pp. 3747–3760, Jun. 2017.

[34] M. Samir, S. Sharafeddine, C. M. Assi, T. M. Nguyen, and A. Ghrayeb, "UAV trajectory planning for data collection from time-constrained IoT devices," *IEEE Trans. Wireless Commun.*, vol. 19, no. 1, pp. 34–46, Jan. 2020.

[35] M. Grant and S. Boyd, "CVX: Matlab software for disciplined convex programming," Mar. 2014, *version 2.1*, [Online]. Available: http://cvxr.com/cvx

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.

Yingying Jiang received the bachelor's degree from the School of Information and Safety Engineering, Zhongnan University of Economics and Law, Wuhan, China, in June 2017. She is currently working toward the Ph.D. degree with the Embedded and Pervasive Computing Lab, School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan, China. Her research interests include healthcare big data and cognitive learning.

Yujun Ma received the Ph.D. degree from the School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan, China, in 2016. From 2018 to 2019, he was a Visiting Associate Professor with the Department of Electrical and Computer Engineering, The University of British Columbia, Vancouver, BC, Canada. His current research interests include the Internet of Things, edge computing, body sensor networks, healthcare big data, and mobile cloud computing.

Jia Liu (Member, IEEE) received the bachelor's degree from the School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu, China, in June 2020. She is currently working toward the master's degree with the Embedded and Pervasive Computing Lab, School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan, China. Her research interests include knowledge graph and healthcare big data.

Long Hu is an associate professor in School of Computer Science and Technology at Huazhong University of Science and Technology (HUST). He is the vice-director of Embedded and Pervasive Computing (EPIC) Lab at HUST. He was a visiting scholar in the Department of Electrical and Computer Engineering at the University of British Columbia. He is the Publication Chair for 4th International Conference on Cloud Computing (CloudComp 2013). Currently, his research includes 5G Mobile Communication System, Big Data Mining, Marine-Ship Communication, Internet of Things, and Multimedia Transmission over Wireless Network, etc.

Min Chen (Fellow, IEEE) is a full professor in School of Computer Science and Technology at Huazhong University of Science and Technology (HUST) since Feb. 2012. He is the director of Embedded and Pervasive Computing (EPIC) Lab, and the director of Data Engieering Institute at HUST. He is the founding Chair of IEEE Computer Society (CS) Special Technical Communities (STC) on Big Data. He was an assistant professor in School of Computer Science and Engineering at Seoul National University (SNU). He worked as a Post-Doctoral Fellow in Department of Electrical and Computer Engineering at University of British Columbia (UBC) for three years. Before joining UBC, he was a Post-Doctoral Fellow at SNU for one and half years. He has 300+ publications, including 200+ SCI papers, 100+ IEEE Trans./Journal papers, 34 ESI highly cited papers and 12 ESI hot papers. He has published 12 books, including Cognitive Computing and Deep Learning (2018) with China Machine Press and Big Data Analytics for Cloud/IoT and Cognitive Computing (2017) with Wiley. His Google Scholar Citations reached 27,800+ with an h-index of 82 and i10-index of 249. His top paper was cited 3,200+ times. He was selected as Highly Cited Researcher at 2018, 2019 and 2020. He got IEEE Communications Society Fred W. Ellersick Prize in 2017, and the IEEE Jack Neubauer Memorial Award in 2019. His research focuses on cognitive computing, 5G Networks, wearable computing, big data analytics, robotics, machine learning, deep learning, emotion detection, and mobile edge computing, etc.

Iztok Humar (Senior Member, IEEE) received the B.Sc., M.Sc., and Ph.D. degrees in telecommunications with the Faculty of Electrical Engineering, University of Ljubljana, Ljubljana, Slovenia, in 2000, 2003, and 2007, respectively. He also received the Ph.D. degree in information management with the Faculty of Economics, University of Ljubljana, in 2009. In 2010, he was a three-month Visiting Professor and Researcher with the Huazhong University of Science and Technology, Wuhan, China. He is currently a Professor with the Faculty of Electrical Engineering, where he lecturers on design, modeling, and management of communication networks on graduate and postgraduate study. He was a Supervisor of many undergraduate students and some postgraduate students. His main research interests include the energy efficiency of wireless networks, cognitive computing for communications with applications and modeling of network loads, and traffic for QoS or QoE. He is a Senior member of IEEE Communication Society from 2009 and a Member of Electrical Association of Slovenia. He was the IEEE Communication Society of Slovenia Chapter Chair for 10 years.

Authorized licensed use limited to: The Chinese University of Hong Kong CUHK(Shenzhen). Downloaded on January 14,2022 at 01:32:29 UTC from IEEE Xplore. Restrictions apply.