Accelerated genetic algorithm for bandwidth allocation in view of EMI for wireless healthcare

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Abstract—To enhance the capacity of patients supported by wireless in-hospital monitoring systems, a bandwidth allocation scheme for the transmission of medical data in the wireless local area network (WLAN) is proposed. The problem of bandwidth allocation, subject to limited wireless bandwidth, quality of service (QoS) requirements of medical data transmission, as well as electromagnetic interference, is modeled as a non-polynomial (NP) optimization problem. To save the computation time of this NP problem, we propose an accelerated genetic algorithm by dynamically adjusting both the inheritance probability and the mutation probability, and then compare it with other off-the-shelf genetic algorithms. Our study shows that our proposed algorithm can save computation time and attain the same result of bandwidth allocation in comparison with other algorithms.

Index Terms—Wireless healthcare monitoring, electromagnetic interference, NP optimization problem, genetic algorithm.

I. INTRODUCTION

Recent advances in wireless local area (WLAN) networks have enabled the inventive application of wireless healthcare monitoring in hospitals. Such a wireless monitoring system (illustrated in Fig. 1 and described in detail later) can help healthcare staff gather and analyze up-to-date information about patients, for instance those who need to stay in emergency rooms (ER) for treatment. Despite recent development in WLAN, its wide application on in-hospital healthcare monitoring still faces several challenges. One of these challenges is the limited wireless resources, including both the limited bandwidth and limited memory size of patient devices, to support the healthcare monitoring of quite a few patients. Another challenge is the different quality of service (QoS) requirements of medical data (e.g., alarm about a patient in emergent status vs. routine monitoring data). Finally, electromagnetic interference (EMI) on medical equipments would restrict the transmit power of patient devices or healthcare staff devices. All these challenges will naturally reduce the network patient capacity in a wireless healthcare monitoring system, which we define as the number of patients that one WLAN deployment can support.

To enhance the network patient capacity supported by the WLAN for healthcare monitoring, we employ the bandwidth allocation scheme proposed in our paper [1]. Based on this scheme, the problem to maximize the network patient capacity is modeled as a non-polynomial (NP) optimization problem, subject to limited wireless resources, various QoS requirements of medical data as well as EMI constraints. We have shown elsewhere [2] that some off-the-shelf genetic algorithms can solve this NP problem well by enabling their genetic convergence to the global optimum, but most of them are time consuming. To reduce the computation time, we propose an accelerated genetic algorithm by dynamically adjusting both the inheritance probability and the mutation probability. In comparison with other genetic algorithms, our algorithm can save up to 30% of computation time with respect to other accelerated genetic methods [3] while maintaining the same quality of convergence.

The paper is organized in the following: In section II, we introduce the architecture of our monitoring system and EMI on medical equipments. In section III, we propose the problem of bandwidth allocation as well as the algorithms to solve it. In section IV, we discuss the simulation results. In section V, we conclude this paper.

II. CONTEXT AND RELATED WORK

In this section, we first clarify the architecture of our monitoring system by taking monitoring patients with heart attack as an example. Then, we introduce the constraints of transmit power of a patient device due to the EMI on medical equipments.

A. Architecture of our health monitoring system

Based on their coverage, healthcare monitoring systems can mainly be classified into two types: in-hospital monitoring systems [4]–[6] and remote monitoring systems [7]–[9]. In-hospital monitoring systems serve inpatients who usually require intensive watching. Once abnormal conditions occur, the healthcare staff must be alerted in time since a delay of even a few seconds may sometimes mean a loss of life. Remote monitoring systems mainly serve the elderly or chronic patients, and emergent cases do not occur frequently.

In this paper, we focus on the monitoring of patients in an in-hospital monitoring system. To clarify the architecture of an in-hospital monitoring system, we take the monitoring of patients with heart diseases as an example (The architecture of monitoring heart diseases is shown in Fig. 1). Once arriving to the emergency department, a patient with heart attack would be required to wear a Holter device at his waist, shoulder or neck. The Holter device would collect the Electrocardiography signal.
(ECG) of this patient and regularly send the ECG to doctors for diagnosis as well as to a data server for filing. (The information about ECG is listed in Table I). Within this monitoring system, we use the IEEE 802.11n based WLAN, the most recently published IEEE standard for WLAN, for data transmission and communication. IEEE 802.11n employs both the technologies of MIMO and OFDM, so the amount of bandwidth in WLAN equals the number of subcarriers. We would interleave these two terms bandwidth and subcarrier in the following.

As shown in Fig.1, a WLAN is responsible for the transmission of traffic between patient devices and the doctor’s office. Due to the limited memory size of patient computing devices, medical data should be transmitted from patient devices to the doctor's office; building on the status of patients, the data from different patient devices may have different delay requirements and should be given different priorities. In addition, patients and healthcare staff may communicate via video conferences when abnormal status is detected. Finally, some messages on patient information also need to be sent between patient devices and the healthcare staff; building on the status of patients, the data from patient devices to the doctor’s office; building on the status of patients, the data from different patient devices may have different delay requirements and should be given different priorities. In addition, patients and healthcare staff may communicate via video conferences when abnormal status is detected. Finally, some messages on patient information also need to be sent between patient devices and the doctor’s office. Building on the status of patients, the data from different patient devices may have different delay requirements and should be given different priorities. In addition, patients and healthcare staff may communicate via video conferences when abnormal status is detected.

For a patient device, the potential interference or noise may be from the healthcare staff devices, other patient devices and the background noise of this patient device. The summation of all the potential interference or noise should be less than the tolerable level of interference. Mathematically, for a patient device $x$, we have

$$\frac{P_t(x)}{L(D_x(x))\gamma(x)} \geq \sum_{A=1}^{A_x} \frac{P_A(x)}{L(D_A(x))} + \sum_{z=1, z \neq x}^{X_t} \frac{P_t(z)}{L(D_z(x))} + N(x)$$

(1)

where $L(d)$ is the total indoor propagation path loss when the distance is $d$; $P_t(x)$ is transmit power of the patient device $x$; $D_x(x)$ is the distance between the transmitter and the receiver of the device $x$; $\gamma(x)$ is the SINR threshold of the device $x$; $P_A(x)$ is transmit power of a healthcare staff device $A$; $D_A(x)$ is the distance between the healthcare staff device and the receiver of the patient device $x$; $P_t(z)$ is transmit power of a patient device $z$ ($z \neq x$); $D_z(x)$ is the distance between the transmitter of the device $z$ and the receiver of the patient device $x$; $N(x)$ is the background noise of the device $x$; $X_t$ and $A_x$ are the number of patient devices and healthcare staff devices being turned on.

To analyze the cases of EMI on medical equipments, we should employ a basic relationship between radiated power $P(W)$ and electric field $E(V/m)$, that is, $E = \frac{Z\sqrt{P}}{D}$. $Z(\Omega)$ is the impedance of free space; $D(m)$ is the distance between the transmit and receive ends. The relationship between radiated power $P(W)$ and electric field $E(V/m)$ is rec-
ommended by IEC [11] as $E = 7\sqrt{P}/D$ and $E = 23\sqrt{P}/D$ for a non-life-support equipment and a life-support equipment, respectively. For a medical equipment, the summation of all potential interference should be less than the tolerable level of interference.

$$\sum_{A=1}^{A_1} \frac{\sqrt{P_{NLS}(A)}}{D_{NLS}(A)} + \sum_{x=1}^{X_1} \frac{\sqrt{P_i(x)}}{D_x(p)} \leq E_{NLS}(p)$$  \hspace{1cm} (2)$$

$$\sum_{A=1}^{A_1} \frac{3\sqrt{P_{LS}(A)}}{D_{LS}(A)} + \sum_{x=1}^{X_1} \frac{3\sqrt{P_i(x)}}{D_x(q)} \leq E_{LS}(q)$$  \hspace{1cm} (3)$$

where $P_{NLS}(A)$ and $P_{LS}(A)$ are the maximal potential transmit power of a healthcare staff $A$ to satisfy the EMI requirement of a non-life-support equipment and a life-support equipment, respectively; $D_{NLS}(A)$ and $D_{LS}(A)$ are the distances from the healthcare staff device to the non-life-support equipment $A$ and the life-supporting equipment $A$, respectively; $E_{NLS}(p)$ and $E_{LS}(q)$ are the acceptable EMI levels for a non-life-support equipment $p$ and a life-support equipment $q$, respectively; $P_i(x)$ is transmit power of a patient device $x$; $D_x(p)$ and $D_x(q)$ are the distances between the transmitter of the device $x$ and the non-life-support $p$ or the life-support equipment $q$; $X_1$ and $A_1$ are the number of patient devices and healthcare staff devices being turned on.

In a real hospital environment, patient devices, life-support medical equipments and non-life-support medical equipments may operate at the same time. Therefore, the maximal potential transmit power of a healthcare staff device or a patient device should satisfy equation (1), equation (2) and equation (3).

III. OPTIMAL BANDWIDTH ALLOCATION IN VIEW OF EMI

In this section, we would discuss the issue of bandwidth allocation in view of EMI on medical equipments. Firstly, we discuss the constrains of transmit power in our research. Then, we discuss the issue of optimal bandwidth allocation.

A. Transmit power constraints in our research

In a real hospital environment, patient devices, healthcare staff devices, life-support medical equipments and non-life-support medical equipments may operate at the same time. Therefore, the maximal potential transmit power of a healthcare staff device or a patient device should satisfy both equation (2) and equation (3) to avoid intolerable EMI on medical equipments. We denote the maximal transmit power at time slot $k$ for patient device $i$ as $P_{max}(i)$; then, the transmit power at time slot $k$ for patient device $i$, $P_i(k)$ should be less than or equal to $P_{max}(i)$. In addition, medical data have different priorities according to patient status, and the medical data with a higher priority have a more demanding requirement of transmission delay. Usually, the patient status can be classified into ‘high-degree (H)’, ‘low-degree (L)’ and ‘normal (N)’, which represent the emergency degree of patient status.

B. Optimal bandwidth allocation

Medical data have different priorities according to patient status, and the medical data with a higher priority have a more demanding requirement of transmission delay. Usually, the patient status can be classified into ‘high-degree (H)’, ‘low-degree (L)’ and ‘normal (N)’, which represent the emergency degree of patient status [12]. Based on the scheme for the transmission of medical data, we discuss the method to maximize the capacity of patients supported by the WLAN given the total amount of bandwidth in this WLAN. Detailed steps to model this problem have been reported in [2], and are summarized here for the sake of completeness.

Let $N_u$ be the number of patients, $N_T$ be the total number of time slots during monitoring, $S^{(k)}$ be the number of special subcarriers in the $k$th ($k = 1, 2, \cdots N_T$) time slot, $M_i^{(k)}[\text{bits}]$ be the amount of data in the memory of the $i$th patient device in the $k$th time slot, $B_i^{(k)}[\text{Hz}]$ be the bandwidth allocated to the $i$th device in the $k$th time slot, $B_i^{(k)}[\text{Hz}] = \sum_{i=1}^{N_u} B_i^{(k)}$, $\eta_i^{(k)}[\text{bps/Hz}]$ be the bandwidth efficiency of the $i$th device in the $k$th time slot, $a_i^{(k)}[\text{bps}]$ be the data arrival rate of the $i$th device in the $k$th time slot, $M_i^{\text{max}}[\text{bits}]$ be the memory size of the $i$th device, $B_i^{(k)}[\text{Hz}]$ be the bandwidth for applications in the $k$th time slot, $T_i[s]$ be the duration of one time slot, $B_{total}[\text{Hz}]$ be the total amount of bandwidth; $B_i^{(k)}[\text{Hz}]$ be the bandwidth of one subcarrier, $\Delta T_1[i]$, $\Delta T_2[i]$ and $\Delta T_3[i]$ be the tolerable delay for data transmission as the patient status is ‘H’, ‘L’ and ‘N’, respectively. For simplicity, we assume $\Delta T_3 = \infty$, that is, the transmission of data corresponding to status ‘N’ has no delay requirement. Then, the problem of maximizing the patient capacity can be modeled as a dynamic programming problem, and this dynamic programming problem in the $k$th ($k = 1, 2, \cdots N_T$) time slot can be denoted as

$$\begin{align*}
\text{Max} \quad N_u \\
\text{s.t.} \quad & M_i^{(k)} = \text{Max} \left\{ \left( \eta_i^{(k)} \Delta T_i \right) + M_i^{\text{max}}(i) \right\} \\
& M_i^{(k)} \leq M_i^{\text{max}}(i) \\
& \sum_{i=1}^{N_u} B_i^{(k)} + B_a^{(k)} = S^{(k)} \Delta B + \sum_{i=1}^{N_u} B_i^{(k)}(i-1) \\
& \sum_{i=1}^{N_u} B_i^{(k)} + B_a^{(k)} \leq B_{total} \\
& a_i^{(k)}T_i \leq \eta_i^{(k)}B_i^{(k)} \Delta T_1 (i \in \text{H}) \\
& a_i^{(k)}T_i \leq \eta_i^{(k)}B_i^{(k)} \Delta T_2 (i \in \text{L}) \\
& P_i^{(k)} \leq P_{max}(i) \\
& r_i^{(k)} = \frac{P_i^{(k)} h_i^{(k)} \sigma^2}{B_i^{(k)}} \\
\end{align*}$$

(4)

where $\eta_i^{(k)}$ is the bandwidth efficiency for patient device $i$ at time slot $k$, and it is represented by equation (5) [13]; $P_i^{(k)}[\text{W}]$ is the transmit power of patient device $i$ at time slot $k$; $\sigma^2[\text{W/Hz}]$ is the noise spectral density; $r_i^{(k)}$ is the signal to noise ratio (SNR) for patient device $i$ at time slot $k$; $h_i^{(k)}$ is the channel fading for patient device $i$ at time slot $k$; the channel fading in a hospital environment can be assumed as flat-fading [14], so for a particular patient device, the channel fading of each subcarrier can be represented by a common value. In
addition, as shown in equation (5), the bandwidth efficiency of each subcarrier can also be represented by a common value.

In equation (4), the objective of this dynamic programming is to find the maximal $N_u$. The first constraint represents that the amount of data in the memory equals that in the last time slot plus the data accumulated in this time slot; Of course, the amount of data in the memory should be non-negative. The second constraint ensures that the amount of data in the memory should be less than the memory size. The third constraint means that the total bandwidth consists of the bandwidth employed for applications (video conferences) and that employed for transmitting medical data. In addition, the total bandwidth in the $k$th time slot is equal to the total bandwidth in the $(k-1)$th time slot plus the bandwidth of special subcarriers in the $k$th time slot. The fourth constraint ensures that the total bandwidth utilized in the WLAN should be less than the given bandwidth of a WLAN. The fifth and the sixth constraints mean that the data in state 'H' and 'L' should satisfy delay requirements. The seventh and eighth constraints show the limit of transmit power and its corresponding signal-to-noise ratio.

We transform the problem of maximizing the capacity of patients, shown in equation (4), into the problem of minimizing the number of required subcarriers given the number of patients $N_u$. Mathematically, the dynamic programming problem in the $k$th $(k=1, 2 \cdots N_T)$ time slot can be denoted as

$$
\begin{align*}
Min & \quad S^{(k)} \\
\text{s.t.} & \quad Max \left\{ (a_i^{(k)} - \eta_i^{(k)} B_i^{(k)}) T_e + M_i^{(k-1)-1}, 0 \right\} \leq M_i^{(k)} \\
& \quad \sum_{i=1}^{N_u} B_i^{(k)} + B_a^{(k)} = S^{(k)} \Delta B + B^{(k-1)} \\
& \quad \sum_{i=1}^{N_u} B_i^{(k)} + B_a^{(k)} \leq B_{\text{total}} \\
& \quad \eta_i^{(k)} T_e \leq \eta_i^{(k)} B_i^{(k)} \Delta T_1 \quad (i \in H) \\
& \quad \eta_i^{(k)} T_e \leq \eta_i^{(k)} B_i^{(k)} \Delta T_2 \quad (i \in L) \\
& \quad P_i^{(k)} \leq P_{\text{max}}^{(k)} (i) \\
& \quad r_i^{(k)} = P_i^{(k)} \left[ a_i^{(k)} \right]^2 / \left( B_i^{(k)} \sigma^2 \right) \\
\end{align*}
$$

In equation (6), the objective is to minimize $S^{(k)}$ in each slot, which would lead to the minimization of $\sum_{k=1}^{N_T} S^{(k)}$. For each given $N_u$, we can calculate the minimal number of subcarriers for data transmission. Then, we increase $N_u$, and the number of required subcarriers would also increase; the maximal number of patients supported by the WLAN can be obtained as the number of required subcarriers increase to $B_{\text{total}} / \Delta B$. For this NP problem shown as equation (6), a modification of a canonical genetic algorithm (GA) can attain its optimum, which is detailed in our conference paper [2]. However, this algorithm is time consuming to attain the solution. In the following, we would discuss some accelerated GA to save the computation time by dynamically adjusting some parameters of the canonical genetic algorithm [2].

C. Adaptive algorithm for convergence acceleration

The idea of adapting mutation probability to accelerate convergence has been employed in [15]–[19], but the approaches of these studies are shown not to converge to the global optimum [20]. To ensure convergence to the global optimum, Liu et al. in [3] propose an adaptive algorithm by reserving the best individual in each generation and show that the solution of this algorithm converges to the global optimum by finite Markov processes. Specifically, Liu et al. in [3] adaptively use the probability of mutation $P_m$ as a function of fitness function $f$, shown as

$$
P_m = \begin{cases} 
k_1(f_{\text{max}} - f) / (f_{\text{max}} - \overline{f}) & f \geq \overline{f} \\
k_2 & \text{otherwise} \end{cases}
$$

where $\overline{f}$ is the average of fitness function $f$ in a particular generation; $f_{\text{max}}$ is the maximum of fitness function $f$ in this generation; $k_1$ and $k_2$ are coefficients fixed at the initialization.

The idea of best individual reservation in [3] can guarantee global convergence, and we will reuse this idea in our study. In addition, we attempt to speed up the convergence in the algorithm [3] by adjusting both the probability of inheritance $P_c$ and the probability of mutation $P_m$; these probabilities determine the speed of convergence given fitness functions. Either too large or too small $P_c$ and $P_m$ would lower the convergence speed. Specifically, a small $P_m$ and a large $P_c$ may reduce the diversity of genes (gene represents the traits passing to offsprings), and the best individual would occur after quite a few generations due to the lack of gene diversity. On the other hand, a large $P_m$ and a small $P_c$ may lose excellent genes to generate the best individual, and the convergence time would also increase in this case. For fixed $P_m$ and $P_c$, the genetic algorithm would have the risk of both lacking gene diversity and losing excellent genes. Both of these risks would slow down the global convergence. To reduce these risks, we attempt to adjust both the parameters $P_m$ and $P_c$.

Instead of only adjusting $P_m$ as a function of fitness function $f$ in [3], we also adjust $P_c$ by expressing it as a function of fitness function $f$

$$
P_c = \begin{cases} 
k_3 (f - f_{\text{min}}) / (\overline{f} - f_{\text{min}}) & f \geq \overline{f} \\
k_4 & \text{otherwise} \end{cases}
$$

where $\overline{f}$ is the average of fitness function $f$ in a particular generation; $f_{\text{min}}$ is the minimum of fitness function $f$ in this generation; $k_3$ and $k_4$ are two coefficients determining the $P_c$.

Building on equation (7) and equation (8), our accelerated genetic algorithm can be expressed as Algorithm 1.

IV. SIMULATION AND DISCUSSION

The parameters in the simulation are as follows: $N = 10000$; $\Delta B = 0.8 \text{Mbps}$; $a_i^{(k)} = 800 \text{kbps}$; $T_e = 0.1 \text{s}$; $\Delta T_1 = 0.5 T_e$; $\Delta T_2 = T_e$; $B_a^{(k)} / \Delta B \sim B(N_0, p)$, where $B(\cdot)$ represents a binomial distribution and $p$ represents the probability of a subcarrier being occupied for video conferences. In Algorithm 1, $N_0 = 30$ and $p_f = 0.05$. In addition, we need to choose
\[
\bar{\eta}_i^{(k)} = \left[ \sum_{p=1}^{m} \exp \{ p / r_i^{(k)} \} \sum_{l=1}^{(n+m-2p)p} (n+m-2p)^p \right]_{i}
\]  

0 ≤ k₁ ≤ k₂ ≤ 1 to guarantee that P_m decreases with the values of a fitness function. At the same time, we need to choose 0 ≤ k₃ ≤ k₄ ≤ 1 to guarantee that P_c increases with the values of a fitness function. For simplicity, we set k₁ = k₂ = k₃ = k₄ = 1.

Firstly, we discuss the convergence time with the adaptive algorithm proposed in this paper, the adaptive algorithm proposed in [3], and the non-adaptive algorithm proposed in [2]. This non-adaptive algorithm is viewed as a benchmark for adaptive algorithms. Cartwright et al. in [21] show that these GA would converge to the global optimum with a probability of 1 assuming that the number of generations increases to infinite; this assumption does not hold in reality. In reality, after a finite number of generations, this algorithm must stop, and the result may have an error in comparison with the exact global optimum. Given the result R and the exact optimum E, the relative error of this result is defined as |R − E|/E. Thus, we discuss the computation time of these algorithms given an acceptable relative error. As shown in Fig.3, both our proposed algorithm and the adaptive algorithm proposed in [3] can save convergence time in comparison with the non-adaptive algorithm proposed in [2], which uses both the fixed probability of mutation and the fixed probability of inheritance. Additionally, our proposed algorithm needs less convergence time than the algorithm proposed in [3], especially when tolerable relative errors are small. This result is not surprising. The process of inheritance mainly influences the algorithm after quite a few generations, since only the inheritance of good genes can generate the best individual and these good genes usually occur after a few generations. A solution with larger tolerable errors can be attained in earlier generations, so adaptive selection of inheritance probability has little effect on the convergence time in this case.

Secondly, we compare the network patient capacity with different algorithms. Fig.4 shows that all three algorithms can attain the same result, since they are all globally convergent. Fig.4 also shows that a small probability p corresponds to a larger capacity of patients. In addition, without considering EMI, the number of patients supported by the system would be overestimated. For a hospital, once the probability p is estimated by statistics, the capacity of patients supported by the WLAN can be estimated with our algorithm; this information on network patient capacity is necessary for the design of wireless healthcare monitoring systems.

V. CONCLUSION

In this paper, we propose an generic algorithm to accelerate the process of bandwidth allocation to enhance the capacity of patients, in consideration of both QoS requirements of medical data transmission and EMI on medical equipments. Firstly, maximizing the capacity of patients is modeled as a NP optimization problem. Then, to solve this programming problem and save computation time, we propose an adaptive genetic algorithm by adjusting the inheritance probability and the mutation probability, both of which depend on the values of individuals’ fitness function. Finally, we compare the computation time of our proposed algorithm and that of some off-the-shelf algorithms. The result shows that dynamically adjusting the inheritance probability and the mutation probability in the genetic algorithm can save computation time to attain the global optimum. Our work can provide some references for the design of wireless healthcare monitoring system in a hospital.
Input: The optimization problem with the objective to minimize $S^{(k)}$

Output: The global optimum with the GA method, $\mathbf{B}^{(k)} = [B_1^{(k)}, B_2^{(k)}, \ldots, B_{N_N}^{(k)}]$

1. We randomly select $N_0$ of $\mathbf{B}^{(k)}$ from the set of $\mathbf{B}^{(k)}$ that satisfy all the constraints; we denote them as $\mathbf{B}^{(k)}_{(1)}, \mathbf{B}^{(k)}_{(2)}, \ldots, \mathbf{B}^{(k)}_{(N_0)}$.

2. $\mathbf{B}^{(k)}_{(j)} (j = 1, 2, \ldots, N_0)$ are ordered for an ascending order of objective function $\sum_{i=1}^{N_N} B_i^{(k)}$, and we denote ordered $\mathbf{B}^{(k)}_{(j)}$ as $\mathbf{B}^{(k)}_{(1)}, \mathbf{B}^{(k)}_{(2)}, \ldots, \mathbf{B}^{(k)}_{(N_0)}$.

3. Set the fitness function as $f_j = \text{fitness} (\mathbf{B}^{(k)}_{(j)}) = p_f (1 - p_f)^j - 1 (j = 1, 2, \ldots, N_0)$, where $0 \leq p_f \leq 1$.

4. Calculate the probability $p_j = f_j / \sum_{j=1}^{N_0} f_j$, and we reselect $N_0$ of $\mathbf{B}^{(k)}_{(j)}$ from the set of $\mathbf{B}^{(k)}_{(1)}, \mathbf{B}^{(k)}_{(2)}, \ldots, \mathbf{B}^{(k)}_{(N_0)}$, with the probability of $p_j$ to select $\mathbf{B}^{(k)}_{(j)}$. The same $\mathbf{B}^{(k)}_{(j)}$ is allowed to be selected multiple times, and we denote the reselected group as $\mathbf{B}^{(k)}_{(1)}, \mathbf{B}^{(k)}_{(2)}, \ldots, \mathbf{B}^{(k)}_{(N_0)}$.

5. Building on equation (8), we can attain the probability of inheritance $P_e$ and then generate the next generation of $\mathbf{B}^{(k)}$ according to $\mathbf{B}^{(k)}_{(i)} = C \mathbf{B}^{(k)}_{(i)} + (1 - C) \mathbf{B}^{(k)}_{(j)}$, where $\mathbf{B}^{(k)}_{(i)}$ denotes the next generation of $\mathbf{B}^{(k)}_{(i)}$, and $C$ is randomly selected between 0 and 1. We randomly select a pair of $\mathbf{B}^{(k)}$ for inheritance. If $\mathbf{B}^{(k)}_{(i)}$ can satisfy all constraints of equation (4), then, we keep it in the next generation; otherwise, we reselect the pair of $\mathbf{B}^{(k)}_{(j)}$ for inheritance until we get $N_0$ of $\mathbf{B}^{(k)}_{(i)}$.

6. Building on equation (7), we can attain the probability of mutation $P_m$. The process of mutation is $\mathbf{B}^{(k)}_{(i)} = \mathbf{B}^{(k)}_{(i)} + M^{(k)} d^{(k)}_{(i)}$, where $M^{(k)}$ is a randomly selected step size and $d^{(k)}_{(i)}$ is a randomly selected direction of the $N_0$-dimension space formed by vectors $\mathbf{B}^{(k)}_{(i)}$. If $\mathbf{B}^{(k)}_{(i)}$ satisfy all the constraints of equation (4), then, we keep it in this generation; Otherwise, we would regenerate $M^{(k)}$ and $d^{(k)}_{(i)}$ until we get a $\mathbf{B}^{(k)}_{(i)}$ that satisfy all the constraints of equation (4).

7. Reserve $\mathbf{B}^{(k)}_{(i)}$ that maximizes the objective function up to $k$th generation;

8. Repeat all the steps above $G$ times, and output the solution that maximizes the objective function up to $G$th generation.

Algorithm 1: Proposed accelerated genetic algorithm for bandwidth allocation.

ACKNOWLEDGMENT

This work was partially supported by the Natural Sciences and Engineering Research Council (NSERC) and industrial and government partners, through the Healthcare Support through Information Technology Enhancements (hSITE) Strategic Research Network, and was partially supported by Quebec MDEIE PSR-SiIrI program.

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