Optimal Haptic Communications over Nanonetworks for E-Health Systems

Li Feng, Amjad Ali, Muddesar Iqbal, Ali Kashif Bashir, Syed Asad Hussain, and Sangheon Pack

***Abstract*—Tactile Internet-based nanonetwork is an emerging field that promises a new range of e-health applications, in which human operators can efficiently operate and control devices at the nanoscale for remote-patient treatment. Haptic feedback is inevitable for establishing a link between the operator and unknown in-body environment. However, haptic communications over the terahertz band may incur significant path loss due to molecular absorption. In this paper, we propose an optimization framework for haptic communications over nanonetworks, in which in-body nano-devices transmit haptic information to an operator via the terahertz band. By considering the properties of the terahertz band, we employ Brownian motion to describe the mobility of the nano-devices and develop a time-variant terahertz channel model. Furthermore, based on the developed channel model, we construct a stochastic optimization problem for improving haptic communications under the constraints of system stability, energy consumption, and latency. To solve the formulated non-convex stochastic problem, an improved time-varying particle swarm optimization algorithm is presented, which can deal with the constraints of the problem efficiently by reducing the convergence time significantly. The simulation results validate the theoretical analysis of the proposed system.**

***Key words*: Tactile Internet, 5G, haptic communication, stochastic optimization, energy harvesting, nanonetwork, e-health**

I. Introduction

Year 2020 is envisioned as the "golden age" of wireless technology, in which daily life tasks are expected to be increasingly performed remotely [1]. For example, human can interact with a machine intuitively and naturally if the feedback from the machine is adapted according to the human reaction time, e.g., about 100 ms, 10 ms, and 1ms are required for the auditory, visual, and manual interaction, respectively [10]. Realizing these reaction times can enable human-to-machine interaction, in which human beings not only can see and hear things far away, but also can touch and feel. Hence, transmitting accurately equivalent to human touch via networks is the vision to close the data cycle, which is aimed to be realized by the Tactile Internet. The Tactile Internet will enable haptic communications and provide the medium for transporting touch and actuation in real-time, i.e., the ability to exert the haptic control through the Internet. It is expected that the Tactile Internet has tremendous potential for creating a new range of applications and opportunities that can change human life and economy. M. Dohler and G. Fettweis revealed in their preliminary market survey that the Tactile Internet has the potential for extending the worldwide market up to US$ 20 trillion, and this increase is approximately 20% of the worldwide gross domestic product today [2].

Haptic communications will be the prime application running on the Tactile Internet [3], [4]. Moreover, the relationship between the haptic communications and Tactile Internet will be that of service and medium, respectively (e.g., the relationship between VoIP and the Internet) [3]. Typically, haptic communication is composed of two distinct types of feedbacks: kinesthetic feedback (providing information of force, torque, position, velocity, etc.), and tactile feedback (providing information about surface texture, friction, etc.). The nanotechnology has emerged as a new frontier in science & technology that can extend the haptic communications over the Tactile Internet into e-health systems at the nano-scale. Nanotechnology can enable the human operator to extend their eyes and hands into the nano-world. Particularly, the nanotechnology can manipulate the devices in the nano-world, transfer information from the nano-word to the micro-word, and travel in the nano-environment. Thus, in nanonetwork-based haptic communications, a human operator can controls the nano-machines inside a body for disease treatment, such as providing drugs for some cancerous cells or operating microsurgery. However, the design efforts for both the Tactile Internet and haptic communications are at their beginning stages. Therefore, investigating the potential of nanonetworks for haptic communications would be a significant step toward realizing the concept of the Tactile Internet.

Due to the fact that the component behavior in a nano-system is very complex; therefore, the in-body operational environment is hostile for humans. Moreover, some force/biofeedback is required to detect and transfer the haptic feedback from the in-body nano-system toward the operator. With this eventually, the operator can touch, feel, and manipulate the in-body nano-devices immersively and interactively [6]. However, to provide real-time human-to-machine (H2M) interaction remotely, the system must have a very low transmission latency; otherwise,

This research was supported by the National Research Foundation (NRF) of Korea Grant funded by the Korean Government (MSIP) (No. 2017R1E1A1A01073742).

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the operator will experience cyber-sickness. Therefore, in this paper, we mainly focus on sustainable and efficient haptic communications over nanonetworks to satisfy the high capacity and low latency requirements. The terahertz (THz) band is vital for supporting haptic communications in nano-devices. The THz band that ranges from 0.1 THz to 10 THz is capable of supporting extremely high-bandwidth communications with extremely low latency [5]. However, because of molecular absorption, the THz band may incur a significant path loss, which may further lead to fluctuations in the channel capacity [7]. Moreover, the mobility of the nano-devices can significantly affect the communication paths. In addition, the nano-devices implanted in the human body typically have a limited battery power owing to their physical dimensions. Therefore, a resource allocation scheme that ensures timely and stable communications for real-time haptic feedback and control delivery is highly required. To this end, the distinguishing contribution of this study is the investigation of the problem of radio resource allocation for haptic communications in a nanonetwork under the constraints of the system stability, energy consumption, and latency.

In the proposed scheme, first, we employ a Brownian motion model to describe the mobility of the nano-device and develop a time-variant channel model by exploiting the properties of the THz band. Then, by considering the dynamic channel and energy resources of the nano-devices, we propose a stochastic optimization framework for improving the haptic communications. To solve the non-convex stochastic problem, we convert the proposed optimization into three sub-optimization problems, namely, 1) energy harvesting, 2) packet-dropping, and 3) resource allocation. These optimization problems are formulated via linear programming and mixed integer non-linear programming (MINLP). To solve the formulated non-convex stochastic problem, an improved time-varying particle swarm optimization (iPSO) algorithm is presented, which can deal with the constraints of the problem efficiently by reducing the convergence time significantly.

The remainder of this paper is organized as follows: Section II presents the related works. The system model and problem formulation are described in Sections III and IV, respectively. Section V, discusses the proposed stochastic optimization framework, whereas Section VI describes the proposed iPSO algorithms. Section VII shows the simulation results for evaluating the performance of the proposed scheme. Finally, the conclusions are drawn in Section VIII.

II. Related Works

Resource allocation, frequency selection, and power allocation are some of the key research interests for ensuring timely and reliable information transmission [8], [9]. A resource management scheme was introduced for 5G-based Tactile Internet-enabled haptic communication in [10]. To meet the stringent latency requirement for Tactile Internet-enabled networks, a predictive resource allocation algorithm including the dynamic wavelength and bandwidth allocation was proposed in [11]. To optimize the overall network transmission rate, frequency selection strategies for the nanoscale devices were introduced in the nanonetworks in the THz band [12]. To improve the channel capacity, an optimal power allocation scheme was proposed in [13]. However, in this scheme, the properties of the channel (e.g., the time-varying chemical composition and change in the distance over the communication path) were ignored, which significantly affect the achievable data rate. By considering the variant channel in the THz band, a frequency-hopping scheme was proposed in [14] for time-varying chemical compositions. However, in this scheme, the motion of nano-devices was not considered.

To address the energy bottlenecks in wireless networks, energy harvesting techniques are considered as promising solutions for providing wireless power to network devices with a limited battery life [15]. Nevertheless, conventional energy harvesting mechanisms, (e.g., solar energy, wind power, and underwater turbulence) cannot be directly applied in nanonetworks because of the technological limitations [16]. Therefore, new energy harvesting schemes are required for nano-devices. A model for energy harvesting was introduced in [17] for analyzing the network capacity of electromagnetic nanonetworks in the THz band. Recently, performance maximization has been typically formulated and solved as a convex optimization problem [18]. However, a practical data transmission system is typically a non-convex utility function. Prior to such non-convex optimization problems, a continuous convex approximation method was introduced in [19] for energy efficient resource optimization. Concurrently, the branch-and-bound technique was adopted in [20] to deal with the power minimization problem for wireless networks. A discrete partial swarm optimization algorithm was introduced in [27] to deal with the optimal deployment problem in a non-convex region. Edge or fog computing could be promising techniques for reducing transmission time during computational offloading in latency-sensitive applications for 5G [22]. However, a lots of research issues (i.e., resource sharing, access with legacy devices, network coexistence among different radio access technologies, propagation and environmental issues, cost and power issues, and network coexistence among different radio access technologies) need to be addressed [21], [23], [24], [25].

To the best of our knowledge, none of the presented schemes deal with the resource allocation for efficient haptic communications in a nanonetwork under the constraints of the system stability, energy consumption, and latency. Owing to the complexity of the system, it is difficult to find a convex problem for approximating the proposed non-convex problem. Our proposed iPSO algorithm belongs to the range of evolutionary solutions based on the imitation of the foraging behavior of a flock of birds learning and grouping the best experiences [26].

III. System Model

A. Network Model

The functional architecture for the haptic communication over nanonetworks for e-health system adopted in this paper is mainly divided into three parts: master domain, network domain, and control domain, as shown in Fig. 1. The master

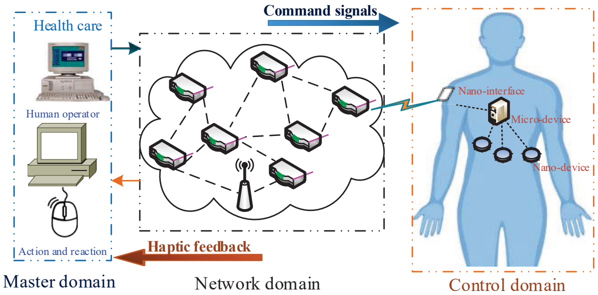


Fig. 1: Remote manipulation at nanoscale for e-health applications.

domain includes the human operator and the haptic device, which enables the human operator to touch, feel, and control objects in remote environment. The network domain provides the communication medium between the master and the slave domains. The control/slave domain is the in-body nano-devices, that are controlled by the main haptic device via a command signals transferred via a network. Moreover, the devices in the control domain provide the haptic feedback to the master domain via a network domain for the human operator to learn about the remote environment.

In our network model, we consider total N biofeedback nano-devices and a single micro-device in a specific tissue of the in-body environment. Note that the control and haptic feedback are exchanged in the form of information/haptic packets. We assume that the nano-devices (in the control domain) detect and transfer the haptic packets about the in-body environment to the micro-device over a single hop. The micro-device is also placed in-body and capable of performing complex tasks. It further forwards the received haptic packets to a higher layer (e.g., nano-interface). Then, the nano-devices can access the wireless network (in the network domain) via a nano-interface, and the haptic information can be transmitted from the in-body nanonetwork to the operator (in the master domain). Accordingly, an operator can touch, feel, and manipulate the in-body nano-machines with an immersive and interactive environment, this phenomenon is shown in Fig. 1.

To execute the haptic communications, each nano-device is composed of a power block and communication block along with the relevant transmission process and storage units. Owing to the size limitation of the nano-devices, both the power and communication blocks are finite [28]. In order to ensure smooth system operation, each nano-device can harvest energy to power itself. Moreover, due to small form factors, these nano-devices operate in the THz band, and the transmission bandwidth for the each THz band is further divided into M narrow frequencies of equal width, Δf. Furthermore, different nano-devices can operate over different sub-frequency bands. Hence, there is no interference between the in-body nano-devices. Let $\mathcal{M}$ be a set of frequencies and nano-device n transmit its radio signal at any discrete frequency f_m, $m \in \mathcal{M}$. The energy resources of the nano-devices will change during their energy harvesting and haptic transmission processes; meanwhile, the channel characteristics for nano-devices-based haptic transmission may vary with their motions. We assume that the time axis is divided into discrete time intervals of equal duration indexed by, t, $t = \{0, 1, 2, \cdots\}$. In each time slot t, a nano-device harvests energy first, and then perform sensing and transmit or/and receive haptic packets by using the harvested energy.

B. Mobility Model

In our study, $\vec{d}_n^{\mathbb{I},t}$ represents the haptic distance between a micro-device and nano-device n over a time slot t. Similar to [36], [37], we assume an unbounded fluid environment with constant viscosity and temperature, in which a nano-device travels via a Brownian motion with the drift in the in-body environment; therefore, we employ the Langevin equation for describing the mobility of a nano-device. The dynamic transmission distance of nano-device n is calculated as

$$\frac{d\vec{d}_n^{\mathbb{I},t}}{dt} = \frac{\beta_{n,\mathbb{I}}^{L}}{\alpha_{n,\mathbb{I}}^{L}} \frac{d\vec{W}_n(t)}{dt}, \tag{1}$$

where d is a differential operator. $\alpha_{n,\mathbb{I}}^{L}$, and $\beta_{n,\mathbb{I}}^{L}$ are the positive constants describing the resistance of the nano-device to the motion and noise, respectively. $\vec{W}_n(t)$ denotes the vector Wiener process. The dynamic data communication distance between nano-device n and the micro-device over a discrete time slot t is given by

$$\vec{d}_n^{\mathbb{I},t+1} = \vec{d}_n^{\mathbb{I},t} + \frac{\beta_{n,\mathbb{I}}^{L}}{\alpha_{n,\mathbb{I}}^{L}} \vec{\mathcal{G}}(\tau). \tag{2}$$

Where τ is the duration of a time slot and $\vec{\mathcal{G}}(\tau) = \vec{W}(t+1) - \vec{W}(t)$ is a random Gaussian process.

C. THz Channel Model

Haptic communications over the THz band may incur significant path loss due to molecular absorption. Motivated by the literature [36], [37], [38], we assume that the in-body temperature and pressure are constants. The binary variable, $x_{n,m}^t$, is an indicator function describing the operating frequency band of nano-device n. Specifically, $x_{n,m}^t = 1$ shows that nano-device n can transmit its radio signal to frequency band f_m in time slot t. Ignoring the time selectivity of THz band, the path loss in decibels for nano-device n in frequency band f_m, $PL^t(x_{n,m}^t, \vec{d}_n^{\mathbb{I},t})$, is given by [29]

$$\begin{aligned} PL^t(x_{n,m}^t, \vec{d}_n^{\mathbb{I},t})[dB] = 20log(\frac{4\pi \vec{d}_n^{\mathbb{I},t} x_{n,m}^t f_m}{c})[dB] \\ +10K^m_{t,x_{n,m}^t,\vec{d}_n^{\mathbb{I},t}} log(e)[dB], \end{aligned} \tag{3}$$

where $K^m_{t,x_{n,m}^t,\vec{d}_n^{\mathbb{I},t}} = 4\pi K_m \vec{d}_n^{\mathbb{I},t} x_{n,m}^t f_m$ is the molecular absorption coefficient, which is a function of extinction K_m, c is the speed of light, and $x_{n,m}^t f_m$ is the operating frequency of nano-device n. The first term in Eq. (3) is the data spread path loss, and the second term denotes molecular absorption loss of nano-device n in decibels. The noise for nano-device n in the THz band primarily due to the molecular absorption noise can be obtained from

$$N_{abs}^n(t, x_{n,m}^t, \vec{d}_n^{\mathbb{I},t}) = k_B T_0 (1 - e^{-K^n_{t,x_{n,m}^t,\vec{d}_n^{\mathbb{I},t}}}), \tag{4}$$

where k_B is the Boltzmann constant and T_0 is the reference fluid temperature, 311 K, for the human body. $S_{n,m}^t$ denotes the power spectral density of the transmitted radio signal at time slot t. Then, the signal to noise ratio (SNR) of nano-device n on frequency band f_m over distance $\vec{d}_n^{\mathbb{1},t}$ is calculated as

$$\begin{aligned} SNR_n^m(t, x_{n,m}^t, \vec{d}_n^{\mathbb{1},t}) &= \frac{S_{n,m}^t}{PL^t(x_{n,m}^t, \vec{d}_n^{\mathbb{1},t}) N_{abs}^n(t, x_{n,m}^t, \vec{d}_n^{\mathbb{1},t})} \\ &= \frac{S_{n,m}^t}{\Psi(t, \vec{d}_n^{\mathbb{1},t}, x_{n,m}^t)}, \end{aligned} \tag{5}$$

where $\Psi(t, \vec{d}_n^{\mathbb{1},t}, x_{n,m}^t) = (\frac{4\pi \vec{d}_n^{\mathbb{1},t} x_{n,m}^t f_m}{c})^2 k_B T_0 (e^{4\pi K_n^t \vec{d}_n^{\mathbb{1},t} x_{n,m}^t f_m} - 1)$. As discussed above, each nano-device operates over an orthogonal frequency, and therefore, frequency overlapping is not allowed. Then, we have the following constraint:

$$\sum_{n=1}^{N} x_{n,m}^t \leq 1, x_{n,m}^t \in \{0,1\}, \forall m \in \mathcal{M}. \tag{6}$$

Without the loss of generality, by using the Shannon formula, the transmission rate of a nano-device n to the micro-device over time slot t is given by

$$r_n^m(t) = \triangle f \log\left(1 + SNR_n^m(t, x_{n,m}^t, \vec{d}_n^{\mathbb{1},t})\right), \forall t > 0, n \in \mathcal{N}, \tag{7}$$

where $\triangle f$ is the width of each frequency band and $\mathcal{N}$ is the set of in-body nano-devices that perform temperature-dependent movements by a Brownian motion using a drift. To achieve a real-time haptic feedback, the transmission latency should not exceed the given threshold in terms of the upper bound, $B_{\max}$. We denote the packet-dropping rate of nano-device n at time slot t as D_n^t. The packet-dropping rate of nano-device n shall satisfy the following constraint:

$$0 \leq D_n^t \leq \mathcal{D}_n, \tag{8}$$

where $\mathcal{D}_n$ is the maximal rate for packet dropping. The dynamics of the data queue backlog of the communication block of nano-device n ($\forall t > 0, n \in \mathcal{N}$) over different time slots can be described as

$$Q_n^{t+1} = \max[Q_n^t - \sum_m r_n^m(t) - D_n^t, 0] + \zeta_n^t. \tag{9}$$

Owing to the time-varying variables (i.e., nano-device mobility, $\vec{d}_n^{\mathbb{1}}$, dropping rate D_n^t, and flow rate ζ_n^t), the data queue backlogs change over time. In haptic information transmissions, the command and feedback signals are exchanged between different domains, which may lead to a close-loop control system involving the human operator, the communication network, and the remote environment. Therefore, in such global control systems, the system stability is considered as a natural constraint. Note ζ_n^t is a stochastic process that indicates the number of sensed haptic packets by nano-device n at time slot t. As, the system stability is considered as a natural constraint in our system. Therefore, to ensure the system stability and further to limit the average transmission latency for haptic communications, the average length of information block for nano-device n is bounded in the long term [39], which given as below

$$\lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} Q_n^t \leq 0, \forall n \in N. \tag{10}$$

D. Energy Consumption and Supply Model

Generally, nano-devices possess processing and communication capabilities; therefore, the availability of the information on the energy requirements and energy harvesting mechanisms jointly at the nanoscale is highly important for designing optimized architectures [16]. Let $E_{Tr}^n(t)$ and $E_r^n(t)$ be the energy required by nano-device n to transmit and receive the haptic packets during time slot t, respectively. We assume that the energy required to deal with the haptic communication of nano-device n is $E_{Tr}^n(t) = \kappa\tau \sum_m x_{n,m}^t S_{n,m}^t$, where κ is the transmission factor, if it is allocated the frequency band and power. The energy consumption for nano-device n for receiving packets is $E_r^n(t) = R_p^t \tau$ where $R_p^t \tau = \varepsilon \zeta_n^t$ and ε is the power consumption for the unit data packet, which is assume to be constant over the time slot t. Then, the total energy consumption $P_i^{Total,t}$ of nano-device n during time slot t is given by

$$P_n^{Total,t} = E_r^n(t) + E_{Tr}^n(t) = \kappa\tau \sum_m x_{n,m}^t S_{n,m}^t + R_p^t \tau. \tag{11}$$

By denoting the amount of harvesting energy for nano-device n as $\mathcal{H}_{cap^n}^t$, the available energy resource to a nano-device n at time slot $t+1$ can be expressed as

$$\begin{aligned} E_n(t+1) &= E_n(t) + \mathcal{H}_{cap^n}^t - P_n^{Total,t} \\ &= E_i(t) + \mathcal{H}_{cap^n}^t - \kappa\tau \sum_m x_{n,m}^t S_{n,m}^t - R_p^t \tau. \end{aligned} \tag{12}$$

In practice, the maximum harvesting power for nano-device n is given as follows:

$$0 \leq \mathcal{H}_{cap^n}^t \leq o_n. \tag{13}$$

where o_n denotes the maximum power that nano-device n can harvest. Moreover, the transmit power available at each nano-device is limited; therefore, the total transmit power at nano-device n should satisfy the following constraint:

$$\sum_n \sum_m x_{n,m}^t S_{n,m}^t \leq P_{\max}. \tag{14}$$

In addition, nano-device n is assumed to be equipped with a power block having limited capacity $\mathcal{E}_n^{max}$. In time slot t, the total energy volume stored in the power block is limited by the battery capacity. Thus, the following inequality must be satisfied:

$$E_n^t + \mathcal{H}_{cap^n}^t \leq \mathcal{E}_n^{max}, \forall n \in N. \tag{15}$$

To ensure appropriate operation of nano-device n, the average energy in the power block should not be less than a certain threshold given as

$$\lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} E_n^t \geq \varphi_n, \forall n \in \mathcal{N}, \tag{16}$$

where φ_n is the predefined energy threshold. A higher φ_n implies a more long-term average energy in the power block.

IV. Problem Formulation

In this section, we discuss our optimization problem and its formulation. The THz channel capacities can be expressed as a summation of the capacities of all the narrow sub-channels. Then, the THz channel capacity in time slot t is given as follows:

$$C_{THz}^{n}(\mathbf{H}^t, \mathbf{x}^t, \mathbf{S}^t) = \sum_{m} \triangle f \log_2(1+\frac{S_{n,m}^t}{\Psi(t, d_n^{\mathbb{1},t}, x_{n,m}^t)}), \quad (17)$$

where $\mathbf{H}^t = \{\mathcal{H}_{cap^n}^t\}_{n\in\mathcal{N}}$, $\mathbf{x}^t = \{x_{n,m}^t\}_{n\in\mathcal{N},m\in\mathcal{M}}$, $\mathbf{S}^t = \{S_{n,m}^t\}_{n\in\mathcal{N},m\in\mathcal{M}}$ and $\log_2$ is the binary logarithm.

In our study, for efficient remote manipulation, we improve the haptic communication performance to obtain a high capacity and low packet-dropping rates for transmitting more detected haptic feedback in the long term. Therefore, we adopt a quality of information (QoI) metric to quantify the efficiency of the haptic communication at the nano-scale, which is a multi-dimensional parameter that can be defined for an application to give more meaningful measures about the value of information [41]. The information in QoI is defined by a collection of multiple quality descriptors (i.e., accuracy, reliability, relevancy, timeliness, and usability). In this paper, QoI is particularly evaluated by virtue of the average data rates including the channel capacity and packet-dropping rates. Then, the average QoI of a nanonetwork can be expressed as

$$\begin{aligned}\overline{QoI}(\mathbf{H}^t, \mathbf{D}^t, \mathbf{x}^t, \mathbf{S}^t) &= \sum_{n} \omega_n \mathcal{F}\left(\bar{C}_{THz}^{n} - \bar{D}^n\right) \\ &= \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}[QoI^t(\mathbf{H}^t, \mathbf{D}^t, \mathbf{x}^t, \mathbf{S}^t)].\end{aligned} \quad (18)$$

Where $\mathbb{E}[\cdot]$ is the average and ω_n is the weight. $\bar{C}_{THz}^{n}$ and $\bar{D}^n$ are the average channel capacity and packet-dropping rate for any nano-device n, respectively. The objective is to perform the energy harvesting, packet-dropping, frequency selection, and power control of the nano-devices to maximize the average QoI value of the system under the time-variant channels and constraints of system stability, nano-devices communication latency, and limited power blocks. Consequently, the average QoI maximization problem is formulated as

$$\begin{aligned}\textbf{P1:} \max_{\mathbf{x}^t, \mathbf{D}^t, \mathbf{S}^t, \mathbf{H}^t} \quad & \overline{QoI}(\mathbf{H}^t, \mathbf{D}^t, \mathbf{x}^t, \mathbf{S}^t) = \quad (19) \\ & \lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} \mathbb{E}[QoI^t(\mathbf{H}^t, \mathbf{D}^t, \mathbf{x}^t, \mathbf{S}^t)] \\ \text{s.t.} \quad & \text{Eqs. (6), (8), (10), (13), (14), (15), and (16),} \\ & \text{Bounded latency of each packet is } B^{\max}. \text{ (C1)}\end{aligned}$$

In the optimization problem **P1**, the constraint (C1) is the latency constraint indicating that each haptic packet must be transmitted or dropped within latency $B^{\max}$. Problem **P1** can be viewed as a stochastic programming problem. The solution is to propose a dynamic haptic communication optimization algorithm, such that all the constraints are satisfied and average QoI is maximized.

V. Problem Reformulation by Stochastic Optimization Theory

The optimization problem, such as problem **P1**, involves the long-term averaging of both the objective function and constraints, which cannot be directly solved by the traditional optimization techniques. Therefore, we convert it into potentially solvable problems with the help of Lyapunov optimization theory [31]. To apply the Lyapunov optimization theory, we first transform the long-term energy constraint described in Eq. (16) in problem **P1** into a virtual energy queue, which is given as

$$Y_n^{t+1} = \max\{Y_n^t - E_n^{t+1} + \varphi_n, 0\}. \quad (20)$$

The virtual energy queue is an indicator to determine how well a constraint is satisfied in the previous slots.

Definition 1. *A discrete queue is the mean rate stable as given in [30] based on the satisfaction of the following constraint:*

$$\lim_{t\to\infty} \frac{1}{t}\mathbb{E}[\mathcal{Q}_n^t] \leq 0, \quad (21)$$

where $\mathcal{Q}_n^t$ denotes the discrete queue.

Then, we can easily prove that if virtual energy queue Y_n^t is rate stable, such as $\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1} Y_n^t \leq 0$, $\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1} E_n^t \geq \varphi_n$. In addition, to deal with the constraint (C1) in problem **P1**, we introduce another virtual queue for the latency requirement of the system, called ς-persistent queue. It ensures worst-case latency $B_{\max}$ for each haptic packet, as given in [32]. Specifically, we define virtual queue Z_n^t for nano-device n with an updated equation as follows:

$$\begin{aligned}Z_n^{t+1} &= \max\{Z_n^t - D_n^t - \mathbf{1}_{\{Q_n^t>0\}} r_n^{\max}, 0\} \\ &+\mathbf{1}_{\{Q_n^t>0\}}(\varsigma_n - \sum_{m} r_n^m(t)).\end{aligned} \quad (22)$$

where ς_n is a predefined constant whose range is $0 < \varsigma_n \leq \min\{\mathcal{D}_n, r_n^{\max}\}$. $r_n^{\max}$ denotes the maximum transmit rate of nano-device n, and $\mathbf{1}_{\{Q_n^t>0\}}$ is an indicator function. According to [33], any algorithm that ensures the mean rate stable of Q_n^t and Z_n^t also esnures worst-case latency $B_{\max}$ for each packet, and the relationship between them can be expressed as

$$B_{\max} \leq \lceil \frac{(Q_n^{\max} + Z_n^{\max})}{\varsigma_n} \rceil, \quad (23)$$

where $\lceil l \rceil$ denotes the smallest integer that is greater than or equal to l, and $Q_n^{\max}$ and $Z_n^{\max}$ are the maximal values of Q_n^t and Z_n^t, respectively. Hence, by controlling the arrival and departure processes of the queues appropriately via the Lyapunov *drift-plus-penalty method, we can maximize the average QoI of the network as well ensure that the queues including Y_n^t, Q_n^t, and E_n^t are mean rate stable.* Let $\mathbf{\Theta}^t$ denote the matrix containing queues $\{Q_n^t\}_{n\in\mathcal{N}}$, $\{Y_n^t\}_{n\in\mathcal{N}}$, and $\{Z_n^t\}_{n\in\mathcal{N}}$. We define the quadratic Lyapunov function in time slot t as below:

$$L(\mathbf{\Theta}^t) = \frac{1}{2}\left(\sum_{n=1}^{N}[Q_n^t]^2 + \sum_{n=1}^{N}[Y_n^t]^2 + \sum_{n=1}^{N}[Z_n^t]^2\right). \quad (24)$$

A small value of $L(\mathbf{\Theta}^t)$ implies low latency for haptic communication and low spare capacity in nano-device batteries.

$$\max_{\mathbf{H}^t,\mathbf{D}^t,\mathbf{x}^t,\mathbf{S}^t} \left\{\begin{array}{c} V\sum_n\sum_m \omega_n \triangle f\log_2(1+\frac{S^t_{n,m}}{\Psi(t,\vec{d}_n^{1,t},x^t_{n,m})}) - V\sum_n \omega_n D^t_n + \sum_n (Q^t_n + Z^t_n \mathbf{1}_{\{Q^t_n>0\}})\sum_m r^m_n(t) \\ -\sum_n \tau(Y^t_n+\varphi_n - E^t_n)\sum_m x^t_{n,m}S^t_{n,m} + (Q^t_n+Z^t_n)D^t_n + \sum_n (E^t_n - Y^t_n - \varphi_n)\mathcal{H}^t_{cap^n}\end{array}\right\}$$
$$\text{s.t. Eqs. (6), (8), (13), (14) and (15).} \tag{28}$$

Based on Lyapunov function $L(\mathbf{\Theta}^t)$, the conditional expected Lyapunov drift in time slot t is defined as:

$$\Delta(\mathbf{\Theta}^t) :\triangleq \mathbb{E}[L(\mathbf{\Theta}^{t+1})|\mathbf{\Theta}^t] - \mathbb{E}[L(\mathbf{\Theta}^t)]. \tag{25}$$

In Eq. (25), $\Delta(\mathbf{\Theta}^t)$ measures the increase in $L(\mathbf{\Theta}^t)$ in each time slot t. Following from the Lyapunov optimization framework, we can add penalty term $-V\mathbb{E}[QoI^t(\mathbf{H}^t,\mathbf{D}^t,\mathbf{x}^t,\mathbf{S}^t)]$ into Eq. (25) to obtain the following *drift-plus-penalty* term:

$$\Delta_V(\mathbf{\Theta}^t) = \Delta(\mathbf{\Theta}^t) - V\mathbb{E}[QoI^t(\mathbf{H}^t,\mathbf{D}^t,\mathbf{x}^t,\mathbf{S}^t)|\mathbf{\Theta}^t]. \tag{26}$$

Here, $V>0$ is a control parameter. As can be seen from Eq. (26), by minimizing $\Delta_V(\mathbf{\Theta}^t)$, we can jointly minimize Lyapunov drift $\Delta(\mathbf{\Theta}^t)$ and maximize utility $QoI^t(\mathbf{H}^t,\mathbf{D}^t,\mathbf{x}^t,\mathbf{S}^t)$. To simplify the optimization problem, we first derive the upper bound of $\Delta_V(\mathbf{\Theta}^t)$ in **Theorem 1**, and then minimize the upper bound to solve problem **P1**.

Theorem 1. *For any feasible decision that can be implemented in time slot* t*, we have,*

$$\Delta_V(\mathbf{\Theta}^t) \leq \Xi - V\mathbb{E}[QoI^t(\mathbf{H}^t,\mathbf{D}^t\mathbf{x}^t,\mathbf{S}^t)|\mathbf{\Theta}^t] - \sum_n \left\{\begin{array}{c} (E^t_n - Y^t_n - \varphi_n)\mathcal{H}^t_{cap^n} - (Q^t_n + Z^t_n\mathbf{1}_{\{Q^t_n>0\}})\sum_m r^m_n(t) \\ +(Y^t_n+\varphi_n - E^t_n)\tau\sum_m x^t_{n,m}S^t_{n,m} - (Q^t_n+Z^t_n)D^t_n,\end{array}\right\} \tag{27}$$

where $\sum_n = \sum_{n=1}^N$, $\sum_n\sum_m = \sum_{n=1}^N\sum_{m=1}^M$ *and* $\vartheta^t_n = p^t_r\tau + PS_n + PC_n$. Ξ *is the upper bound on the terms* $Q^t_n(Z^t_n\mathbf{1}_{\{Q^t_n>0\}} - D^t_n) + \frac{1}{2}(Z^t_n\mathbf{1}_{\{Q^t_n>0\}} - D^t_n)^2 + \frac{1}{2}(\sum_m r^m_n(t))^2 + D^t_n\sum_m r^m_n(t) + Y^t_n[\varphi_n + \vartheta^t_n - E^t_n] + (\varphi_n)^2 + (E^t_n)^2 + (\mathcal{H}^t_{cap^n})^2 + (\tau\sum_m x^t_{n,m}S^t_{n,m})^2 + (\vartheta^t_n)^2 + \varphi_n\vartheta^t_n - \varphi_n E^t_n - \Xi^t_n E^t_n + \vartheta^t_n\tau\sum_m x^t_{n,m}S^t_{n,m} - \mathcal{H}^t_{cap^n}\tau\sum_m x^t_{n,m}S^t_{n,m}$.

Our dynamic capacity optimization policy is designed to observe the energy queue $\mathbf{E}^t = \{E^t_n, n\in\mathcal{N}\}$, $\vec{\mathbf{d}}^t = \{\vec{d}_n^{1,t}, n\in\mathcal{N}\}$, and then to make the decision variables to minimize the right-hand-side (RHS) of Eq. (27) for the current time slot, which is shown in Eq. (28).

From Eq. (28), the first part and the constraints Eqs. (6) and (14) just depend on the resource allocation variables $\mathbf{x}^t, \mathbf{S}^t$ whereas the second part is dependent of the packet-dropping variable $\mathbf{D}^t$. Similarly, the third part and the constraints Eqs. (13) and (15) depend on the energy harvesting variable $\mathbf{H}^t$. Therefore, the energy harvesting decision ($\mathbf{H}^t$), packet-dropping decision ($\mathbf{D}^t$), and resource allocation decision ($\mathbf{x}^t,\mathbf{S}^t$) are independent of each other at any time slot t. Thus, the above optimization problem can divided into three independent sub-problems: 1) energy harvesting problem, 2) packet dropping problem, and 3) resource allocation problem.

A. Energy Harvesting Problem

To obtain the optimal energy harvesting for nano-device n in time slot t, we optimize the following function:

$$\max_{\mathbf{H}^t} \sum_n (Y^t_n + \varphi_n - E^t_n)\mathcal{H}^t_{cap^n} \quad \text{s.t. Eqs. (13) and (15).} \tag{29}$$

Since Eq. (29) is a linear equation, if $(Y^t_n + \varphi_n - E^t_n) \geq 0$, nano-device n can harvest maximal energy to recharge its battery for optimizing Eq. (29). Otherwise, the residual energy of nano-device n is sufficient, and it does not need to harvest energy. Therefore, we get,

$$\mathcal{H}^t_{cap^n} = \left\{\begin{array}{ll} \min[o_n, \mathcal{E}^{\max}_n - E^t_n] & \text{if } E^t_n \leq Y^t_n + \varphi_n, \\ 0 & \text{otherwise.}\end{array}\right. \tag{30}$$

B. Packet Dropping Problem

To obtain the optimal packet dropping rate for nano-device n in time slot t, we have the following optimization problem:

$$\max_{\mathbf{D}^t} \sum_n (Q^t_n + Z^t_n - V\omega_n)D^t_n \quad \text{s.t. Eq. (8).} \tag{31}$$

Since Eq. (31) is also a linear equation, So, we get,

$$D^t_n = \left\{\begin{array}{ll} \mathcal{D}_n & \text{if } Q^t_n + Z^t_n \geq V\omega_n, \\ 0 & \text{otherwise.}\end{array}\right. \tag{32}$$

C. Resource Allocation Problem

From Eq. (28), the resource allocation problem for nano-devices in time slot t can be rewritten as

$$\max_{\mathbf{x}^t,\mathbf{S}^t} \sum_n \left\{\begin{array}{c} (V\omega_n + Q^t_n + Z^t_n\mathbf{1}_{\{Q^t_n>0\}})\sum_m \triangle f\log_2(1+\frac{S^t_{n,m}}{\Psi(t,\vec{d}_n^{1,t},x^t_{n,m})}) \\ -\tau(Y^t_n+\varphi_n - E^t_n)\sum_m x^t_{n,m}S^t_{n,m})\end{array}\right\} \quad \text{s.t. Eqs. (6) and (14),} \tag{33}$$

Eq. (33) is dependent of variables $\mathbf{x}^t$ and $\mathbf{S}^t$. Hence, Eq. (33) is a mixed-integer non-linear programming (MINLP) problem, which is typically difficult to solve. Two approximate methods were proposed for the sub-optimal solution of MINLP, namely, 1) the continuous convex approximation [17] and 2) the branch-and-bound method [18]. In this study, because of the complexity of the system, it is difficult to convert Eq. (33) into a convex optimization problem. Therefore, a heuristic method is proposed to derive a sub-optimal solution of Eq. (33) with an acceptable complexity.

VI. Proposed iPSO Algorithm

The employed heuristic algorithm is based on the swarm intelligence technique, which is suitable for solving complex optimization problems. However, there are some drawbacks for directly employing the traditional particle swarm optimization (PSO) algorithm (TPA) in Eq. (33). For example, first, in a TPA algorithm, a penalty function is employed to deal with the constraints of the problem. Thus, the algorithm performance is significantly affected by the value of the penalty parameters. Moreover, the dimensionality of the variable for a particle is $(2N) \times M$. Thus, a swarm may lose its diversity in some dimensions, and the TPA may suffer from the issue of dimensionality, which majorly deteriorates its performance. Detailed description on the TPA can be found in [44] which may help the interested readers to better understand its working in detail. To overcome these drawbacks, we first exploit the relationship between power control $S^t_{n,m}$ and frequency selection $x^t_{n,m}$ based on the property of the objective function in Eq. (33). Subsequently, we construct a new optimization problem only for variables $\mathbf{x}^t$ and propose an iPSO algorithm for problem **P1**.

A. Frequency Selection vs. Power Control

By using the primal-dual decomposition method given in [34], we first relax, $x^t_{n,m}$ in Eq. (33) in continuous interval $[0,1]$, which is denoted by $\breve{x}^t_{n,m}$. We further introduce a new variable, $\breve{S}^t_{n,m} = \breve{x}^t_{n,m} S^t_{n,m}$. Then, we can rewrite Eq. (33) as,

$$\begin{aligned}\max_{\breve{\mathbf{S}}^t} & \sum_n (V\omega_n + Z^t_n \mathbf{1}_{\{Q^t_n>0\}} + Q^t_n) \sum_m \triangle f \log_2 (1 + \frac{\breve{S}^t_{n,m}/\breve{x}^t_{n,m}}{\Psi(t, \vec{d}^{1,t}_n, x^t_{n,m})}) \\ & - \tau \sum_n \sum_m (Y^t_n - \varphi_n - E^t_n) \breve{S}^t_{n,m} \\ \text{s.t.} & \sum_m \breve{x}^t_{n,m} \le 1, 0 \le \breve{x}^t_{n,m} \le 1, \quad \text{(C2)} \\ & \sum_m \breve{S}^t_{n,m} \le P^n_{\max}, \forall t \ge 0. \qquad \text{(C3)}\end{aligned} \tag{34}$$

Since the feasible set of constraints in Eq. (34) is a convex set and Eq. (34) is a convex optimization problem for variable $\breve{S}^t_{n,m}$. Thus, based on the gradient descent (GD) method [35], we can derive the relationship between variables $\breve{S}^t_{n,m}$ and $\breve{x}^t_{n,m}$ by solving Eq. (34), which is given below.

$$\breve{S}^t_{n,m} = \left(\frac{(V\omega_n + Z^t_n \mathbf{1}_{\{Q^t_n>0\}} + Q^t_n)\triangle f}{u + \tau(Y^t_n + \varphi_n - E^t_n)} - \Psi(\breve{x}^t_{n,m}) \right) \breve{x}^t_{n,m}, \tag{35}$$

where u is the Lagrange multiplier.

Substituting Eq. (35) into Eq. (34), we obtain Eq. (36) for binary variable $x^m_{n,k}$. This is a typical nonlinear 0–1 integer programming problem. Note that in Eq. (36), the overlapping of frequencies is avoided (i.e., $\sum_{n=1}^N x^t_{n,m} \le 1$, $\forall m \in \mathcal{M}$). Thus, a frequency band can by allocated to only one nano-device. Therefore, we rewrite frequency allocation $\mathbf{x}_t$ as a new variable, $\mathbf{a}_t = [\{a^t_m\}_{m\in M}]$. Element a^t_m takes a value from set $[0, N]$, and it denotes that frequency f_m is allocated to the nano-device. The notation, $\mathbf{a}_t$, naturally prevents the overlapping of the frequencies. Accordingly, we can convent Eq. (36) into an unconstrained optimization problem, and employ an iPSO method to determine the sub-optimal frequency allocation. In the proposed iPSO algorithm, J denotes the number of particles in a swarm. The solution to the problem is represented by the position of each particle O_j, $j \in J$. With the increase in the iterations, all the particles gradually move toward the optimal position. Fitness is used to evaluate the quality of the position of a particle. Specifically, in the ith iteration, the position and velocity of the jth particle in the swarm can be denoted as follows:

$$\mathbf{a}^{j,i}_t = \left[\{a^{t\ j,i}_m\}_{m\in\mathcal{M}} \right], \ and \ \tilde{\mathbf{V}}^{j,i}_t = \left[\{\tilde{V}^{j,i}_m\}_{m\in\mathcal{M}} \right].$$

The previous best positions for the jth particle and all the particles in the ith iteration, respectively, are as below:

$$p\mathbf{a}^{j,i}_t = \left[\{pa^{t\ j,i}_m\}_{m\in\mathcal{M}} \right], \ and \ g\mathbf{a}^i_t = \left[\{ga^{t\ \ i}_{n,m}\}_{m\in\mathcal{M}} \right].$$

The new velocity of each particle can be found as follows:

$$\tilde{\mathbf{V}}^{j,i+1}_t = \varpi_{j,i} \tilde{\mathbf{V}}^{j,i+1}_t + c_1 r_1 (p\mathbf{a}^{j,i}_t - \mathbf{a}^{j,i}_t) + c_2 r_2 (g\mathbf{a}^i_t - \mathbf{a}^{j,i}_t). \tag{37}$$

where c_1 and c_2 are the constants called acceleration coefficients, and r_1 and r_2 are two independent random numbers uniformly distributed in range $[0,1]$. $\varpi_{j,i}$ is the inertia factor given as below:

$$\varpi_{j,i} = \varpi_{\max} - \frac{i(\varpi_{\max} - \varpi_{\min})}{\widetilde{inter}^{\max}}, \tag{38}$$

where $\varpi_{\max}$ is the maximum inertia weight, $\varpi_{\min}$ is the minimum inertia weight, and $\widetilde{inter}^{\max}$ is the maximum number of iterations. Then, position $\mathbf{x}^{j,i}_t$ for particle O_j in the ith iteration is updated as follows:

$$a^{t\ j,i+1}_n = \begin{cases} \lfloor \mathbf{x}^{j,i}_t + \tilde{\mathbf{V}}^{j,i+1}_m \rfloor & \text{if } mod(\mathbf{x}^{j,i}_t + \tilde{\mathbf{V}}^{j,i+1}_n) > rand^{j,i}_m, \\ \lfloor \mathbf{x}^{j,i}_t + \tilde{\mathbf{V}}^{j,i+1}_m \rfloor + 1 & \text{otherwise}, \end{cases} \tag{39}$$

where $\lfloor l \rfloor$ is the maximal integer, which is less than l. The fitness function is constructed in Eq. (40). With the help of optimal variable $g\mathbf{a}_t$, optimal frequency allocation $\mathbf{x}_t$ can be achieved. Then, by exploiting the relationship between the variables in Eq. (35), we can further obtain optimal power control $S^t_{n,m}$ for the ith iteration, which is as follows:

$$S^t_{n,m} = \begin{cases} 0 & \text{if } x^t_{n,m} = 0, \\ \frac{(V\omega_n + Z^t_n \mathbf{1}_{\{Q^t_n>0\}} + Q^t_n)\triangle f}{u + \tau(E^t_n - Y^t_n - \varphi_n)} - \Psi(x^t_{n,m}) & \text{otherwise}. \end{cases} \tag{41}$$

In terms of dynamic network state, the detailed implementation process of iPSO algorithm is shown in **Algorithm 1**, which can obtain the sub-solution of problem **P1**. In **Algorithm 1**, the optimal energy harvesting and dropping rate are obtained based on Eq. (30) and Eq. (32), respectively. Next, the initial position for each particle for time slot t in the swarm is generated. Subsequently, the relevant velocities and positions of the particles are updated until the iteration number reaches $\widetilde{inter}^{\max}$. For the case, in which the position of a particle is out of range, we employ homomorphous mapping to correct the invalid position at each iteration, which is more efficient than the general algorithm that simply drops the invalid positions. Power control variable is achieved using Eq. (41).

$$\begin{aligned}\max_{\mathbf{x}} \quad & \sum_m (V\omega_n + Z_n^t \mathbf{1}_{\{Q_n^t>0\}} + Q_n^t) \sum_n \triangle f \log_2 \Big(\frac{(V\omega_n + Z_n^t \mathbf{1}_{\{Q_n^t>0\}} + Q_n^t)\triangle f}{(u+\tau(E_n^t - Y_n^t - \varphi_n))\Psi(t, \vec{d}_n^{\mathbb{1},t}, x_{n,m}^t)} \Big) \\ & - \sum_n \tau \sum_m (E_n^t - Y_n^t - \varphi_n) \left(\frac{(V\omega_n + Z_n^t \mathbf{1}_{\{Q_n^t>0\}} + Q_n^t)\triangle f}{u+\tau(E_n^t - Y_n^t - \varphi_n)} - \Psi(x_{n,m}^t) \right) x_{n,m}^t \\ \text{s.t.} \quad & \sum_n \sum_m x_{n,m}^t \le 1, x_{n,m}^t \in \{0,1\}. \end{aligned} \tag{36}$$

$$\widetilde{Fitness}(\mathbf{a}_m^{j,i}) = \sum_m \left\{ \begin{array}{c} (V\omega_n + Z_n^t \mathbf{1}_{\{Q_n^t>0\}} + Q_n^t)\triangle f \log_2 \Big(\frac{(V\omega_n + Z_n^t \mathbf{1}_{\{Q_n^t>0\}} + Q_n^t)\triangle f}{(u_n+\tau(E_n^t - Y_n^t - \varphi_n))\Psi(t, \vec{d}_n^{\mathbb{1},t}, a_m^{t\ j,i})} \Big) \\ -\tau(E_n^t - Y_n^t - \varphi_n) \left(\frac{(V\omega_n + Z_n^t \mathbf{1}_{\{Q_n^t>0\}} + Q_n^t)\triangle f}{u+\tau(E_n^t - Y_n^t - \varphi_n)} - \Psi(a_m^{t\ j,i}) \right) \end{array} \right\}. \tag{40}$$

Algorithm 1 : iPSO Algorithm

Input: Network state in time slot t.
Output: Decisions on energy harvesting $\mathbf{H}^t$, dropping rate $\mathbf{D}^t$, frequency selection $\mathbf{x}_t$, and power control $\mathbf{S}^t$.
Compute $\mathbf{H}^t$ and $\mathbf{D}^t$ based on Eqs. (30) and (32);
Select 20% of the particles that have the worst fitness value to restart their positions, and then denote the position of particle O_j as $initial_{position}(\mathbf{a}_t^{j,0})$;
for Each particle O_j **do**
  $p\mathbf{a}_t^{j,0} = initial_{position}(\mathbf{a}_t^{j,0})$;
end for
for $p\mathbf{a}_t^{j,0}$ of each particle O_j **do**
  $g\mathbf{a}_t^0 = \arg\max[\{\widetilde{Fitness}(p\mathbf{a}_t^{j,0})\}_{j\in J}]$;
end for
for $i = 1 : \widetilde{inter}^{\max}$ **do**
  for Each particle O_j **do**
    Update $\tilde{\mathbf{V}}_t^{j,i}$ and $\mathbf{a}_t^{j,i}$ via Eqs. (37) and (39);
    if Position $\mathbf{a}_t^{j,i}$ is feasible **then**
      break;
    else
      Correct $\mathbf{a}_t^{j,i}$ by using homomorphous mapping;
    end if
    Calculate fitness $\widetilde{Fitness}_i$; update $p\mathbf{a}_t^{j,i}$ and $g\mathbf{a}_t^i$;
  end for
end for
Update $\mathbf{S}_{n,m}^t$ based on Eq. (41);

Remark 1. *In the proposed iPSO algorithm, instead of using plenty function, variable substitution is employed to translate Eq. (36) as an unconstrained optimization problem based on the constraint property. Moreover, iPSO reduces the dimensionality of the variables from $(2N) \times M$ for mixed variables to M for integer variables, which greatly decreases the computational complexity of the system and avoids the the issue of dimensionality. Hence, compared with TPA, iPSO can handle the constraints quite well and greatly reduces the length of the convergence time.*

VII. Simulation Results

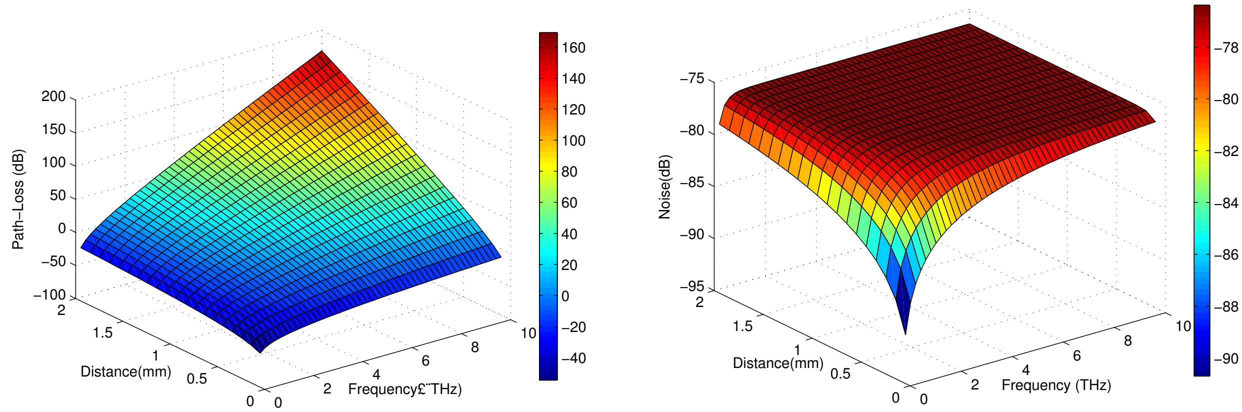
This section presents the extensive simulation results for performance analysis of the proposed iPSO algorithm. The simulations are carried out by using the Matlab. In our simulation study, we first present the channel property of the THz band and then, we discuss the performance of iPSO. Moreover, to verify the effectiveness of iPSO, we compare it with the normal genetic algorithm (GA) and the TPA algorithm. The duration of a time slot t is 6.25s, i.e., $\tau = 6.25s$, and the buffer size for information block of a nano-device is 70MB. In each time slot t, each nano-device undergoes a random walk, and its new position is obtained by sampling the Gaussian random variables with mean $\varrho\tau$ and standard deviation $\sqrt{D_\varrho\tau}$. We also set the following parameters: frequency width $\Delta f = 0.1\ THz$, maximum transmit power $P^{\max} = 80\ pJ$, receive power $R_p^t = 1\ pJ$, and capacity of the power block $\mathcal{E}_n^{max} = 200\ pJ$.

Table I lists the performance analysis of iPSO over different network sizes (nano-devices densities), which demonstrates that the proposed scheme achieves better QoI value in less time as compared to the normal GA and the TPA schemes. Moreover, from Table I, we can see that the convergence time of iPSO increases with the increase in network sizes (nano-devices densities). This is because, that the large network size will lead to the requirements of more radio resources (power and frequency), which further increases the computational complexity and the convergence time of iPSO.

Figure 2 sequentially plots the total path loss and noise of the terahertz channel model versus the communication distance and frequency. From Figure 2(a)-2(b), it can be observed that the Z-axis values increase with the increase in the distance and/or transmission, particularly for the path loss.

Figures 3(a)-3(b) exhibit the dynamic communication block processes and power block processes for the nano-devices, respectively. It can be seen that the lengths of the blocks tend to be stable and stay around the positive values.

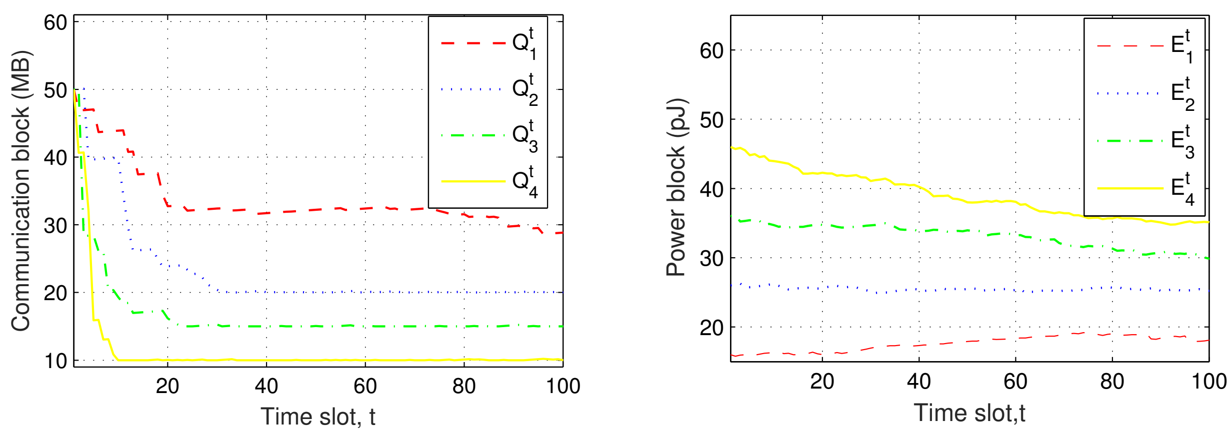
Figure 4(a) presents the updates of the transmission power strategies of the nano-devices for one time slot by using iPSO. It indicates the convergence of iPSO and shows the effects of the network state on the power controls of the nano-devices. Figure 4(b) depicts the average network utilities versus control



(a) Path loss

(b) Noise

Fig. 2: Channel property of the terahertz band.



(a) Communication block process

(b) Power block process

Fig. 3: Dynamic blocks.

parameter V for different initial positions of the nano-devices. It can be found that the average QoI value increases with V, and that smaller initial positions of the nano-devices result in larger utility.

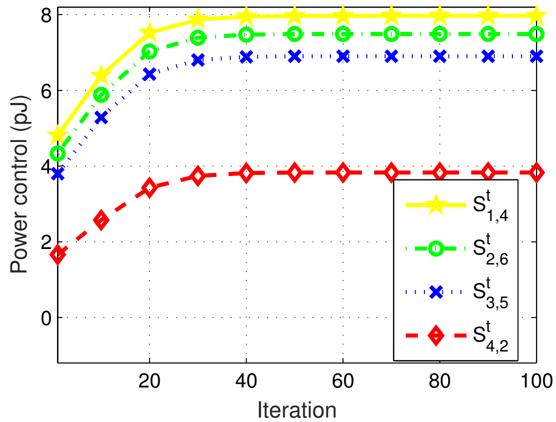
Figure 5(a)-(b) present the average communication blocks and the average power block over control parameter V, respectively. The average communication block length can be used to depict the average transmission delay. Thus, it is clear from Figure 5(a) that the average information transmission delay under iPSO increases as the value of system parameter V increases. Meanwhile, in Figure 5(b), it can be observed that the average power block under iPSO decreases with the value of system parameter V, and the larger value of V contribute more in energy balancing. This is because a larger value of parameter V represents that the system pays more attention towards the average QoI value. Consequently, the advantages of adaptive system policies including energy balancing become more obvious.

TABLE I: QoI and convergence time.

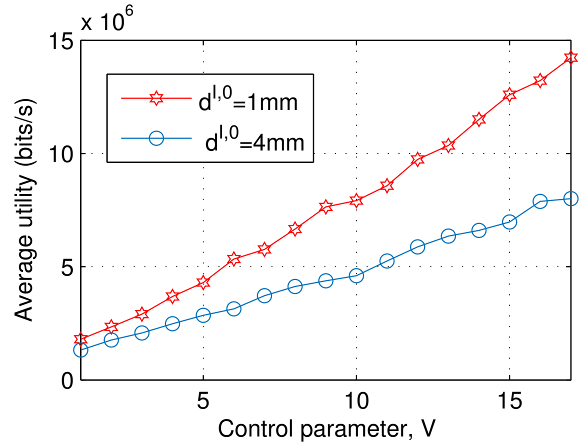
Approach	Network Size	QoI (bits/s)	Con. time (s)
GA		6.441E+6	0.778
TPA	(N=6, M=6)	6.447E+6	2.731
iPSO		**6.452E+6**	**0.585**
GA		6.782E+6	2.213
TPA	(N=12, M=12)	6.796E+6	10.48
iPSO		**6.817E+6**	**1.557**
GA		8.283E+6	4.345
TPA	(N=18, M=18)	8.302E+6	26.23
iPSO		**8.326E+6**	**2.420**
GA		1.132E+7	7.022
TPA	(N=24, M=24)	1.159E+7	51.35
iPSO		**1.175E+7**	**4.178**

VIII. Conclusion

In this paper, we investigated the problem of radio resource allocation for haptic communications in a nanonetwork under the constraints of system stability, energy consumption, and latency. We introduced the Brownian motion to describe the mobility of the nano-devices and developed a time-variant terahertz channel model for the haptic transmission. With the help of the developed channel model, we proposed a stochastic optimization framework to maximize the average network QoI under the constraints of system stability, energy consumption, and latency. The optimization problem was further divided into

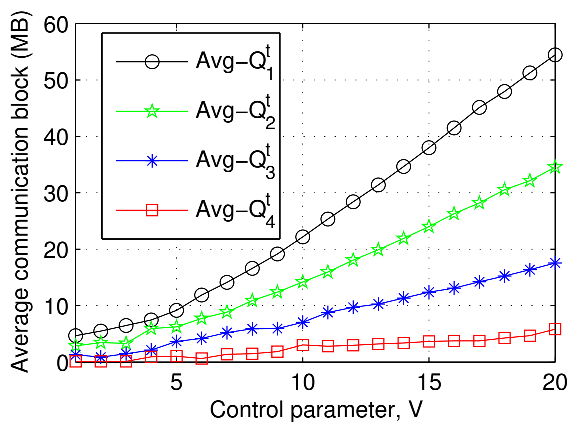


(a) Power control

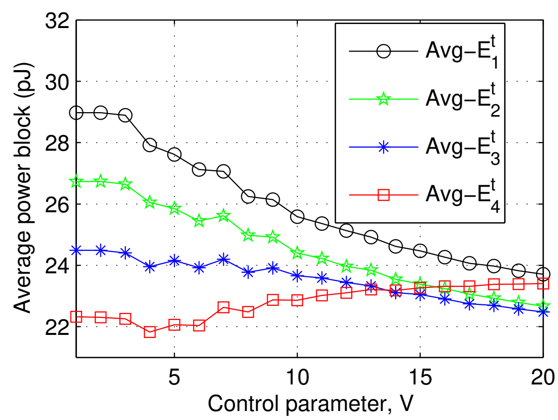


(b) Average utility vs. control parameter V

Fig. 4: Power control and utility vs. control parameter V.



(a) Average communication block



(b) Average power block

Fig. 5: Average communication/power blocks vs. control parameter V.

three sub-problems, such as energy harvesting problem, packet dropping problem, and resource allocation problem over the time slots. Finally, by exploiting the special structure of the reformulated problems, an iPSO algorithm was proposed that outperformed the other compared schemes and dealt with the constraints of the optimization problem while reducing the convergence time significantly. The molecular communication is considered as a key domain of nanonetworks which has significant advantages of energy efficiency and potential bio-compatibility for the communications among cells in the biological environment. Therefore, in future, the proposed work can be extended for the molecular communications for better realization of Tactile-based real-time and e-health applications. Moreover, considering the interference among nano-machines and biological cells, efficient resource allocation schemes can be introduced for molecular-based Tactile Communications.

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