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Internet of Vehicles for E-health Applications: A Potential Game for Optimal Network Capacity

Di Lin[1], Yu Tang[1], Fabrice Labeau[2], Yuanzhe Yao[1], Muhammad Imran[3], Athanasios V.Vasilakos[4]
[1]School of Information and Software Engineering, University of Electronic Science and Technology of China
[2]Department of Electrical and Computer Engineering, McGill University, Canada
[3]Deanship of e-Transactions and Communication, King Saud University, Saudi Arabia.
[4]Department of Computer and Telecommunications Engineering, University of Western Macedonia, Greece

***Abstract*—Wireless technologies are pervasive to support ubiquitous healthcare applications. However, a critical issue of using wireless communications under a healthcare scenario rests at the electromagnetic interference (EMI) caused by RF transmission, and a high level of EMI may lead to a critical malfunction of medical sensors. In view of EMI on medical sensors, we propose a power control algorithm under a non-cooperative game theoretic framework to schedule data transmission. Our objective is to ensure that the non-cooperative game of power control can achieve a network-level objective—the optimal network capacity, though the wireless users are selfish and only interested in optimizing their own channel capacity. To obtain this objective, we show that our proposed non-cooperative game is a potential game, and propose the Best-response-dynamics algorithm which can ensure that the game strategy of each user is induced to the optimal solution to the problem of network-level optimal capacity. Numerical results illustrate that the proposed algorithm can achieve an enhancement of 8% of network performance than the existing algorithm against the variations of mobile hospital environments.**

***Index Terms*—E-health, Mobile hospital, Power control, Game theory, Nash equilibrium**

I. Introduction

Recent developments in cellular networks have enabled the innovative application of E-health anytime and anywhere. However, RF transmission can result in electromagnetic interference (EMI) to all of medical sensors, and a high level of interference can even cause malfunction of medical sensors and potentially injure patients [1], [2]. Thus, the control of EMI (e.g. through power control) is a critical issue to E-health and should be addressed under the environment of mobile hospital, which is defined as Internet of vehicles for E-health applications in this paper. So throughout this paper, we alternatively use the terms of mobile hospital and Internet of vehicles for E-health applications.

There is a large body of works related to the application of wireless networks to support health service [1]–[3]. Phond et al. in [1], [2] present the issue of EMI under the scenario of a wireless local area network (WLAN) for e-health applications within a hospital, but the technology of WLAN is not applicable to our scenario, in which a mobile hospital covers a large-scaled area (e.g., a city or a town). Qinghua et al. in [3] address the possibilities of using wireless technologies in a medical environment, and allocate power and rate according to the channel conditions of users, and do not take the potential EMI impact into account. In such a scenario, a wireless user who stays close to a medical sensor could be allowed to transmit data at a high level of power if only the user's communication channel is in good condition [4]. However, the RF transmission at a high level of power would influence the operation of medical sensors. Such an improper power allocation by these algorithms may lead to the malfunction of EMI-sensitive medical sensors, so the aforementioned algorithms cannot be employed under the scenario of mobile hospital. Also the abovementioned algorithms [1]–[3] are designed to maximize the individual objective of each wireless user, instead of optimizing a network-level objective (e.g., the network capacity). However, usually the maximum of individual objective is inconsistent with the maximum of network-level objective. *The importance of scheduling wireless transmission under a mobile hospital scenario as well as the lack of efficient algorithms for optimizing network-level objective motivate us to investigate how wireless users can adjust their transmit power to achieve certain goals, such as maximizing the network capacity while ensuring the acceptable level of EMI on medical sensors over Internet of vehicles for E-health applications*.

In this paper, we address the problem of dynamically scheduling wireless transmission for wireless users' networks under a mobile hospital environment. The objectives of this paper are to i) maximize certain goals (e.g., network capacity) of network and ii) protect the medical sensors from harmful interference. In this paper, we propose a game of power control in a mobile hospital environment and address a robust power control algorithm, which is shown to converge to the Nash equilibrium of game. *To the best of our knowledge, this is the first work which presents a power control algorithm under a wireless network for E-health applications. The primary contributions of this paper rest at the following issues*: i) addressing the framework of data transmission over Internet of vehicles for E-health applications; ii) establishing a game model of power control to achieve the maximum of network capacity in consideration of EMI on medical sensors; iii) proposing a numerical algorithm which can converge to the

E-mail address: lindi@uestc.edu.cn, yutang@uestc.edu.cn, fabrice.labeau@mcgill.ca, yaoyuanzhe@gmail.com, cimran@ksu.edu.sa, vasilako@ath.forthnet.gr. This work was partially supported by National Natural Science Foundation of China (No. 61370202) and partially supported by a grant from the National High Technology Research and Development Program of China (863 Program, No. 2012AA02A614).

Nash equilibrium of the proposed game.

II. Related work of EMI on medical sensors

The earliest research on EMI in hospital environments mainly focuses on the immunity of medical equipments to mobile phones. Tan et al. in [5] firstly propose that some types of medical equipments, such as ventilators, infusion pumps, and ECG monitors, are quite sensitive to the EMI from cellular phones. Then, an EMI susceptibility test is carried out by the Medicines and Healthcare Products Regulatory Agency (MHRA) of U.K. [6]; this test includes testing the EMI of mobile phones and personal communication networks. The test results show that external pacemakers, anesthesia machines, respirators, defibrillators are also susceptible to EMI. Trigano et al. in [7] and Calcagnini et al. in [8] study the EMI of GSM mobile phones on pacemakers and infusion pumps, respectively. Their results show that infusion pumps and pacemakers are inhibited due to the EMI of GSM mobile phones. With the implementation of 3G mobile phone systems in the United States, Japan, Hong Kong etc., the research of EMI effects on medical equipments in the 3G band has appeared [9], [10]. In 2007, the International Electrotechnical Committee (IEC) publishes the EN60601-1-2 standard, and the immunity levels are recommended as 3V/m and 10V/m for life-supporting equipments (e.g., blood pressure monitors and infusion pumps) and non-life-supporting equipments (e.g., defibrillators), respectively. In view of the advances of electromagnetic compatibility (EMC) technologies, some hospitals in Singapore and the U.K. relax the EMI restriction recommended in the EN60601-1-2 standard, and mobile phones are permitted to use in some areas of hospitals [11]. Chi-Kit et al. in [12] discuss the EMI test in view of the recently developed EMC of medical equipments, and the test takes into account the EMI of GSM900, PCS1800, and 3G mobile communication systems. The testing results show that ECG monitors, radiographic systems, audio evoked potential systems, and ultrasonic fetal heart detectors are sensitive to EMI [12]. Based on the previous literature, it can be concluded that the medical equipments sensitive to cellular phones include fetal monitors, infusion pumps, syringe pumps, ECG monitors, external pacemakers, respirators, anesthesia machines, and defibrillators [13].

Another stream of research focuses on the EMI from devices which access to a wireless local area network (WLAN), which usually works at the frequency band around 2.4GHz. This frequency band is different from the frequency band which mobile phones work at, and the amount of EMI on a medical equipment is related to frequency bands. Given these reasons, the research on EMI in the scenario of wireless healthcare monitoring starts. Krishnamoorthy et al. in [14] measure the EMI on medical equipments from patient and doctor devices, which work around the 2.4 GHZ frequency bands; the measurement is undertaken in two hospitals. The results show that the maximal EMI record is 0.552V/m, which is within the acceptable EMI range recommended by the EN60601-1-2 standard. However, the measurement in [14] has not considered the QoS of data transmitted by patient devices and healthcare staff devices. The policy on mobile phone utilization, such as turning off mobile phone, cannot be applicable for patient devices and healthcare staff devices in a wireless healthcare monitoring system [15]. In wireless healthcare monitoring systems, healthcare staff and patients should employ wireless devices for data transmission and communication, and the restriction on transmit power may reduce the quality of service (QoS) of data transmission, which may increase the risk of medical data loss. Therefore, a contradiction between transmit power restriction and QoS requirements exists in wireless healthcare monitoring systems. In addition, when multiple patient devices and healthcare staff devices transmit data simultaneously, the aggregated signals at medical equipments would cause a higher level of EMI to medical equipments, including life-supporting equipments (e.g., blood pressure monitors and infusion pumps) and non-life-supporting equipments (e.g., defibrillators) [1]. Phond et al. in [1] discuss the EMI in hospital environments, in view of the QoS of patient devices and healthcare staff devices. The conclusion is that EMI on most medical equipments is within the unacceptable range if the transmit power of a WLAN device is larger than 10mW.

All the abovementioned research does not consider the vehicular scenarios for healthcare applications, which are interesting to this paper, and thus the medical sensors in the test may not be vehicle-mounted and wearable medical sensors. In Section III.A., we address a detailed experiment which includes the test of EMI impact on types of vehicle-mounted and wearable medical sensors.

III. Mobile hospital environment

A typical mobile hospital environment is composed of vehicles for e-health applications, and these vehicles are mounted with a few medical devices which can help doctors to monitor the condition of patients. On the vehicle for e-health applications, doctors, healthcare staff, and the relatives of patients may use mobile phones due to these two issues: (1) Doctors and nurses on the same ambulance must report the conditions of patients over phone to the staff in a hospital or in a medical center to arrange the medical actions which will be taken at the arrival of patients. (2) Patients or their relatives need to contact their family members over mobile phone about the change of clinical situations as well as important information. However, the use of mobile phones may lead to EMI impact on nearby medical devices [16]. EMI refers to the disturbance of electrical circuits due to electromagnetic induction or electromagnetic radiation which are emitted from an external source [17]. The disturbance may cause the degradation of circuit's performance, and the degradation can lead to a total loss of data.

In the following, we first present the model of EMI impact in this paper as a constraint of network-capacity optimization problem, which is detailed in Section III.A. Then, we address an experiment to verify the model of EMI on medical devices.

A. Model of EMI impact

A typical vehicle for e-health applications consists of both life-support and non-life-support medical devices (shown in

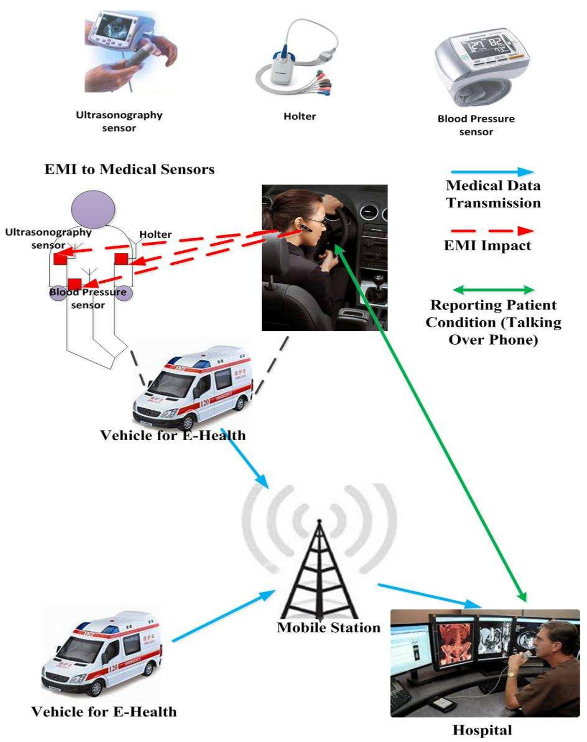

Fig. 1. The Figure illustrates the Internet of vehicles for e-health applications.

Fig. 1). The medical data which are collected by medical devices are required to send to the doctors, who are staying in a hospital to make the plan of taking actions on the patient once the vehicle arrives at the hospital. Also the medical staff on the vehicle need to report the condition of patients over phone to doctors, and the use of mobile phone may lead to EMI on medical devices which are located nearby. The life-support medical devices contain electronic components which are sensitive to EMI, so they are more sensitive to the impact of EMI than non-life-support devices. Life-support medical devices include Ultrasonograph devices, etc., and non-life-support medical devices include holters and blood pressure devices, etc.

Both life-support devices and non-life-support devices may have different requirements on the transmit power of a wireless user to ensure that the user's RF transmission causes an acceptable level of EMI on medical devices. The maximal potential transmit power of each wireless user should satisfy all of these requirements. To the best of our knowledge, Phond et al. in [1] firstly address how to model the EMI effects on medical devices and calculate the maximal potential transmit power of a wireless user subject to the EMI constraints. Mathematically, the constraints on the transmit power of a wireless user can be shown in equation (1) and equation (2), for life-support medical devices and non-life-support medical devices, respectively [1].

$$\sum_{i\in U} \frac{\mu_1\sqrt{P_i}}{D_i(p)} \le E_{NLS}(p),\ \ for\ p \in M_1 \tag{1}$$

$$\sum_{i\in U} \frac{\mu_2\sqrt{P_i}}{D_i(q)} \le E_{LS}(q),\ \ for\ q \in M_2 \tag{2}$$

where $E_{NLS}(p)$ and $E_{LS}(q)$ are the acceptable EMI levels for a non-life-support device p and a life-support device q, respectively; P_i is the transmit power of a wireless user i; $D_i(p)$ is the distance between a transmitter of user i and non-life-support device p or life-support device p; μ_1 and μ_2 are constant, and their values suggested by IEC 60601-1-2 are 7 and 23, respectively [1]. U represents the set of wireless users over the Internet of vehicles. M_1 represents the set of non-life-support devices, while M_2 represents the set of life-support devices.

Let

$$A = \begin{pmatrix} \frac{\mu_1}{D_1(1)} & \cdots & \frac{\mu_1}{D_n(1)} \\ \cdots & \cdots & \cdots \\ \frac{\mu_1}{D_1(m_1)} & \cdots & \frac{\mu_1}{D_n(m_1)} \\ \frac{\mu_2}{D_1(1)} & \cdots & \frac{\mu_2}{D_n(1)} \\ \cdots & \cdots & \cdots \\ \frac{\mu_2}{D_1(m_2)} & \cdots & \frac{\mu_2}{D_n(m_2)} \end{pmatrix}$$

and $x_i = \sqrt{P_i}$, we can represent (1) and (2) as

$$AX \le B, \tag{3}$$

where $X = [x_1, \cdots, x_{m_1}, x_{m_1+1}, \cdots, x_{m_1+m_2}]^T$, $B = [E_{NLS}(1)\cdots E_{NLS}(m_1), E_{LS}(1)\cdots E_{LS}(m_2)]^T$, m_1 is the cardinality of M_1, m_2 is the cardinality of M_2.

Remark 3.1: When the number of rows of A equals to n, i.e. $m_1 + m_2 = n$, then, we can obtain the unique solution $X = A^{-1}B$.

Remark 3.2: When the number of rows of A is less than n, i.e. $m_1+m_2 < n$, then, the linear equation is underdetermined. We select the optimal one from infinite solutions subject to the maximization of $\sum\limits_{i\in U} P_i$.

Remark 3.3: When the number of rows of A is larger than n, i.e. $m_1 + m_2 > n$, then, the linear equation is overdetermined. We relax the constraints of (1) and (2) with the best approximation, i.e. $\min\limits_{X} |AX - B|$. So $X = (A^TA)^{-1}A^TB$.

Remark 3.4: Given the set of wireless users U, the maximal transmit power of any wireless user i (denoted as $\bar{P}_i$) can ensure that all of medical devices are free from EMI effects when $m_1+m_2 \le n$ (see Remark 2.1 and 2.2), and also ensure that the total amount of EMI on medical devices is minimized when $m_1 + m_2 > n$ (see Remark 2.3), since under the latter scenario, the power allocation can ensure $\min\limits_{X} |AX - B|$.

Definition 1: The maximal potential transmit power of user i (i.e. $\bar{P}_i$) to minimize the total amount of EMI on medical devices, as obtained from Remark 2.4, is defined as the maximal effective transmit power (METP).

The METP (i.e. $\bar{P}_i$ for user i) will be employed to establish the problem of (5) in IV.A.

B. Experiment of testing EMI effects

In this experiment, we test the EMI impact on 50 types of vehicle-mounted medical equipments and wearable medical devices from the cellular phones operated by China Mobile, China Unicom, China Telecom. These cellular phones are with the technologies of GSM-900/1800, CDMA2000, TD-LTE, and their average transmit power is 0.8W.

The test is carried out in an anechoic chamber in order to exclude EMI impact from the other sources of RF emission, such as from telecommunication systems. The test procedures are detailed as follows: a) Tabletop devices are placed on a table 80cm above the floor, and floor-standing devices are placed on the floor; b) One investigator who operates a mobile phone controls the maximal power output (0.8W), while another investigator monitors the working status of medical devices; c) The mobile phone is gradually brought closer to the medical device. If the degradation of performance of devices occurs, the mobile phone is turned off to check if the performance degradation ceases, which shows whether the degradation is reversible or irreversible; d) The EMI impact on medical devices, reversible or irreversible, as well as the distance between medical devices and mobile phones at the degradation of performance are recorded.

Test result shows that EMI from cellular phones causes the performance degradation of 68% of medical equipments or devices within a 2m distance away from the cellular phones. Typical degradation in the test includes: a) Artifact in images of ultrasound, X-ray, CT equipments; b) Noise on biomedical signals, such as ECG and EEG; c) Sensor malfunction in infusion pumps, syringe pumps, ventilators; d) Change of operating mode of external pacemakers, such as from aynchronized to fixed rate. This result is in line with the model proposed in [1].

Most problems of performance degradation are due to the component parasitics, and it represents the stray reactive elements which have been found in every component, whether a passive or active component. Capacitors have series inductance, which can lead to a series resonant circuit. Wound inductors have interwinding capacitance, which can lead to a parallel resonant circuit. These circuits resonate at the frequencies from 5MHz to 1000 MHz. Besides the issue of component parasitics, the other issues which may lead to the performance degradation of medical devices include ground impedance, poor cable shielding, stray internal coupling paths, etc. [18]–[21].

IV. Model of network-capacity game

A. Model of game for optimal individual objective

In this subsection, we consider the model of non-cooperative game with a linear pricing factor, and the utility of each wireless user (i.e. the channel capacity of wireless user) [1] is shown as

$$u_i(P_i) = log(\frac{P_i h_{ii}}{\sum_{j \neq i} P_j h_{ji} + N_0}) - \lambda_i P_i, \tag{4}$$

[1]Our work focuses on 3G wireless technologies, which have dominated the 3G mobile technologies. Actually, the primary 3G standards (CDMA2000, W-CDMA, TDS-CDMA) are all based on the technology of CDMA. In the E-health application, mobile phones must be smart phones, since a few mobile APPs must be installed on the smart phones for medical data analysis. In the smart-phone market, 3G overtakes 2G and 4G sales. Thus, CDMA-based technologies dominate the market of smart phones for E-health applications. The model and results of our work can be widely appropriate in real life.

where P_i denotes the transmit power by user i; h_{ji} denotes the channel condition between user i and j; N_0 denotes the power spectral density of additive white Gaussian noise; λ_i is the pricing factor.

Given the abovementioned utility, the game is denoted as

$$\max_{0 \leq P_i \leq \bar{P}_i} u_i(P_i) \quad i = 1, 2, ..., N \tag{5}$$

where $\bar{P}_i$ is the METP defined in Definition 1.

B. Model of game for optimal network-level objective

In this section, we consider optimizing the network-level objective, i.e. $\max_{\mathbf{P}} U(\mathbf{P}) = \sum_i u_i(P_i)$. In the game of (5), each wireless user is selfish and only interested in maximizing his/her utility (i.e. channel capacity) [22]–[25]. Thus, the summation of utility of self-interested users at the Nash Equilibrium is usually not equal to the optimal network utility, i.e.

$$U(\mathbf{P}^*) = \sum_i u_i(P_i^*). \tag{6}$$

usually does not hold, where $\mathbf{P}^* = \arg\max_{\mathbf{P}} U(\mathbf{P})$ and $P_i^* = \arg\max_{P_i} u_i(P_i)$.

In the following, we show that the game of (5) is a potential game and equation (6) holds under the scenario of game (5), i.e. the self-interested users will be induced to contribute to maximizing the network utility $U(\mathbf{P})$:

$$\max_{\mathbf{P}} U(\mathbf{P}) \tag{7}$$

where $\mathbf{P} = [P_1, ..., P_N]$ given N users over the Internet of vehicles for E-health applications, and $U(\mathbf{P}) = \sum_i u_i(P_i)$.

C. Properties of potential game

In this subsection, we address a few properties of potential game to familiarize readers. Firstly, we present the definition of potential game.

Definition 2: A game $g = \langle N, \{u_i\}_{i \in N}, \{\mathbb{P}_i\}_{i \in N} \rangle$ is defined to be a potential game if there exists a function $f : \mathbb{P} \to \mathbb{R}$ satisfying

$$f(P_i, \mathbf{p}_{-i}) - f(\hat{P}_i, \mathbf{p}_{-i}) = u_i(P_i) - u_i(\hat{P}_i)$$

for every $i = 1, \cdots, N$, P_i, $\hat{P}_i \in \mathbb{P}_i$, $\mathbf{P}_{-i} \in \mathbb{P}_{-i}$.

Lemma 1: Let $g = \langle N, \{u_i\}_{i \in N}, \{\mathbb{P}_i\}_{i \in N} \rangle$ be a game in which the strategy sets are intervals of real numbers. Suppose that the utility function u_i is continuously differentiable. Then $f : \mathbb{P} \to \mathbb{R}$ is a potential function for g if and only if f is continuously differentiable, and satisfies

$$\frac{\partial u_i(P_i)}{\partial P_i} = \frac{\partial f(\mathbf{P})}{\partial P_i}$$

Proof: Refer to Proposition 1 of [26]. ∎

Lemma 2: A potential game has a unique Nash equilibrium if its potential function is strictly concave and continuously differentiable over a convex strategy space. In such a scenario, the Nash equilibrium of potential game coincides with the maximizer of the potential function.

Proof: Refer to Proposition 2 of [26]. ∎

D. Best-response-dynamics algorithm of the game

In this subsection, we show that the game of (5) is a potential game, in such that the Nash equilibrium of (5) can be consistent with an optimal solution to the maximization of network utility of (7), i.e. each of self-interested users can be induced to contribute to maximizing total utility at the network level.

We rewrite the utility function of (5)

$$\max_{0 \leq P_i \leq \bar{P}_i} u_i(P_i) \quad i = 1, 2, ..., N$$

and show that the game with such a utility is a potential game.

Theorem 3: A game $g = \langle N, \{u_i\}_{i \in N}, \{\mathbb{P}_i\}_{i \in N} \rangle$ is a potential game with the potential function of

$$f(\mathbf{P}) = \sum_i (log(P_i) - \lambda_i P_i) \tag{8}$$

Proof: Both $f(\mathbf{P})$ and $u_i(\mathbf{P})$ are continuously differentiable, and $f(\mathbf{P})$ satisfies

$$\frac{\partial u_i(P_i)}{\partial P_i} = \frac{\partial f(\mathbf{P})}{\partial P_i} = \frac{1}{P_i} - \lambda_i.$$

According to Lemma 1, g is a potential game. ■

Theorem 4: The potential game g in Theorem 3 has a unique Nash equilibrium.

Proof: Note that $f(\mathbf{P})$ is strictly concave and continuously differentiable. And $\mathbf{P}$ is a convex space which is a subset of one-dimensional Euclidean space of real numbers. According to Lemma 2, g has a unique Nash equilibrium. ■

Theorem 5: At the Nash equilibrium of potential game g, the pricing factor λ_i satisfies $\lambda_i = \frac{1}{P_i^*}$, given the Nash equilibrium of potential game g as $P_i{}^*$.

Proof: Consider the first partial function of $\frac{\partial u_i(\mathbf{P})}{\partial P_i} = \frac{1}{P_i} - \lambda_i = 0$. The proof follows. ■

Remark 4.1: Denote the Nash equilibrium of potential game g as $P_i{}^*$. We consider the set of pricing factor λ_i as $\lambda_i = \frac{1}{P_i{}^*}$. Each wirelss user is only interested in optimizing individual utility, but in the proposed potential game, the Nash Equilibrium of game in (5) can be induced to the optimal network utility, i.e. each consumer who is interested in maximizing individual utility can contribute to the optimization of overall utility at the network level.

In the following, we address the specific algorithm which can lead the Nash Equilibrium of game (5) to the optimal network-level utility. Best response dynamics represent the strategies which can produce the most favorable results for a player in the next round, given the other players' strategies. We first address the best response dynamics of a wireless user with respect to the game of (5). Also we compare the best response dynamics with the optimal operating point, which is defined in the following.

Definition 3: The optimal operating point $O(\mathbf{P})$ is defined as the optimal solution to the problem of (7), i.e. $O(\mathbf{P}) = \arg\max_{\mathbf{P}} U(\mathbf{P})$.

Remark 4.2: The optimal operating point is the global optimum which can maximize a network-level objective in (7). Note that the optimal solution can only be achieved under the assumption that a centralized scheduler is able to access to complete information of users and can control the strategies of users. This assumption is not implementable in a distributed network, such as Internet of vehicles for E-health applications. Thus, we only use the optimal operating point as a benchmark to measure the performance loss with our proposed potential-game approach.

Definition 4: The best response dynamics of the game with pricing $g = \langle N, \{u_i\}_{i \in N}, \{\mathbb{P}_i\}_{i \in N} \rangle$ of (5) is denoted as

$$\theta_i(\mathbf{P}_{-i}) = \arg\max_{P_i} u_i(P_i) \tag{9}$$

with the update of $P_i \leftarrow P_i + \delta(\theta_i(\mathbf{P}_{-i}) - P_i)$, given the step size of δ.

Theorem 6: With the setting of pricing factor λ_i as Remark 3.1, the best response θ_i of game (5) converges to $O(\mathbf{P})$.

Proof: According to (8), game (5) is a potential. Thus, the best response θ_i of game (5) which converges to the Nash equilibrium also converges to $O(\mathbf{P})$ by Lemma 2. ■

Definition 5: Given the best response θ_i of game (5) as well as the optimal operating point $O(\mathbf{P})$, the relative performance loss is defined as $\eta = \frac{|U(\theta_i(\mathbf{P}_{-i})) - U(O(\mathbf{P}))|}{U(O(\mathbf{P}))}$.

Remark 4.3: According to Theorem 6, the relative performance loss η converges to 0 with the best response θ_i of game (5). The reasons of defining performance loss rest at: (1) investigating the dynamics of η at each round of game; (2) comparing the performance loss of our potential game with the other games in publication.

V. Simulation and Discussion

We gather the data on Internet of vehicles from [27], in which a connection of network represents a transmit-receive pair of wireless users. In the simulation, we randomly select the position of 50 vehicles (terminals) within an area of 1000 meters $\times$ 1000 meters. Each terminal has a probability of 0.1 using the mobile phone and is moving with an arbitrary direction at a speed of 10m/s (36km/h). Please note that in cities, when an ambulance is close to densely populated areas, it is possible that 50 terminals have EMI impact on medical devices at the same time. We clarify the characteristics of channel models in Section V.A. Also we normalize the level of EMI E_{LS} or E_{NLS} (see (1) and (2)) to unity, and perform about 100000 Matlab-based experiments to present the results.

A. Characteristics of channel models

We select the commonly used set of empirical channel models, which is specified in ITU-R recommendation M.1225 [28], for simulation. ITU-R M.1225 model is applicable for the test scenarios in urban and suburban areas outside the high rise core where the buildings are of nearly uniform height [28]:

$$L = 40(1 - 4 \times 10^{-3} \Delta h) logR - 18 log \Delta h + 21 log f + 80 \tag{10}$$

where $R[km]$ represents the distance between base station and mobile station; $f[MHz]$ represents the carrier frequency; $h[m]$ represents the base station antenna height, which is measured from the average rooftop level.

Each terrestrial test environment can be modelled as a channel impulse response model based on a tapped-delay line.

Tap	Relative delay (ns)	Average power (dB)	Doppler spectrum
1	0	0.0	Rayleigh
2	310	-1.0	Rayleigh
3	710	-9.0	Rayleigh
4	1090	-10.0	Rayleigh
5	1730	-15.0	Rayleigh
6	2510	-20.0	Rayleigh

TABLE I
PARAMETERS OF PROPAGATION MODELS IN ITU-R RECOMMENDATION M.1225 [28]

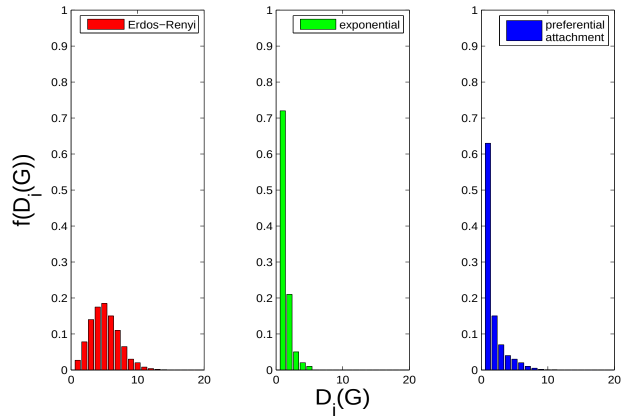

Fig. 2. The Figure illustrates representative vertex degree distributions for Erdös-Rényi (left) with $p = 0.3$, Exponential (center) with $\alpha = 2.5$, and preferential attachment (scale-free) graphs (right) with $\gamma = 15$. All graphs have size 10^5 and edges 10^7 to ensure a single component (with high probability) for the chosen parameterizations of these graphs. $f(D(G))$ is the frequency of the vertex degree $D(G)$.

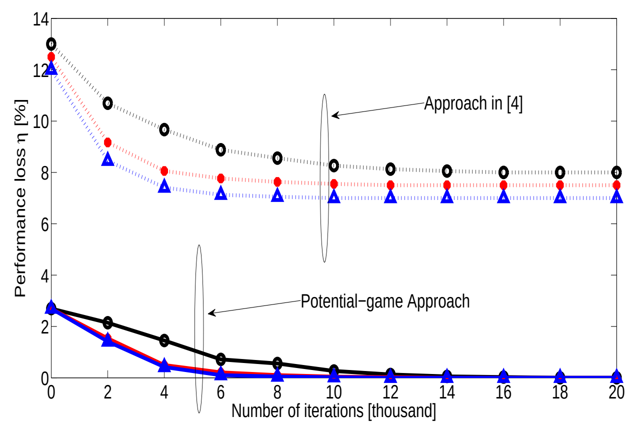

Fig. 3. The Figure illustrates the rate of convergence to the fixed point of our algorithm under different random networks. Blue line with '△' represents Exponential network; Red line with '⋆' represents preferential attachment (scale-free) network; Dark line with 'o' represents Erdös-Rényi network.

The model is characterized by the number of taps, the time delay relative to the first tap, the average power relative to the strongest tap, and the Doppler spectrum of each tap. A majority of time-delay spreads are relatively small, while a few "worst case" multipath characteristics cause much larger delay spreads. Table I identifies the propagation model for each of 6 vehicular test cases. In all of these test cases, we consider the strength and relative time delay of signal components as well as Doppler shift, and assume that each of 6 vehicular test cases occurs with the same probability. Specifically, the primary parameters to characterize each of propagation models include:

– Time delay-spread, its structure, and its statistical variability (e.g. probability distribution of time delay spread);

– Multipath fading characteristics (e.g. Doppler spectrum, Rician vs. Rayleigh) for the envelope of channels.

B. *Performance of proposed algorithm across networks*

In this section, we compare the convergence rate of our algorithm (9) under the scenarios of different random networks (shown in Fig. 2) with the algorithm proposed in [4], in which the EMI on medical devices is not considered. The game in [4] can be modelled as

$$\max_{P_i} \hat{u}_i(P_i) \quad i = 1, 2, ..., N \tag{11}$$

where $\hat{u}_i(P_i) = log(\frac{P_i h_{ii}}{\sum_{j \neq i} P_j h_{ji} + N_0}) - \lambda P_i$, in which λ is constant.

From Fig. 3, we observe that the potential-game approach can achieve a much lower level of performance loss than the approach in [4] does under various scenarios of networks. Indeed, the level of performance loss with potential-game approach keeps zero, while the level with approach in [4] is around 8%. In line with [4], it is observed from Fig. 3 that lower performance loss can be achieved by Exponential network, in which wireless users have only a single or few transmit/receive pairs, than by Erdös-Rényi network in which users have multiple transmit/receive pairs. This is because a user establishes transmit-receive pairs with most of the other users in Erdös-Rényi network, and thus data transmission is easily influenced by the interference from the other transmissions. However, in the Exponential network, the users establish transmit-receive pairs with only a single or few other users, and they suffer little interference from the other transmissions.

Also we observe from Fig. 3 that the algorithm of (9) under the networks with highly concentrated transmit/receive nodes (e.g., Exponential network) quickly converges to the fixed point[2], while the algorithm under the networks without highly concentrated transmit/receive nodes (e.g., Erdös-Rényi network) converges to the fixed point at a low rate. Indeed, the algorithm under the Exponential network reaches the fixed point after 7000 iterations, while its convergence appears after 12000 iterations under the Erdös-Rényi network.

[2]With the Intel Core i7-2760QM processor, the running time of each iteration is around 0.00014s, so the total time of running the algorithm with 6000 iterations is 0.84s. Given that the ambulance is moving at a speed of 10m/s, the algorithm is feasible when the channel conditions are assumed to be invariant within a distance of 8.4m. In a fast-varying mobile environment, we can use a more powerful processor to run the algorithm to ensure its feasibility.

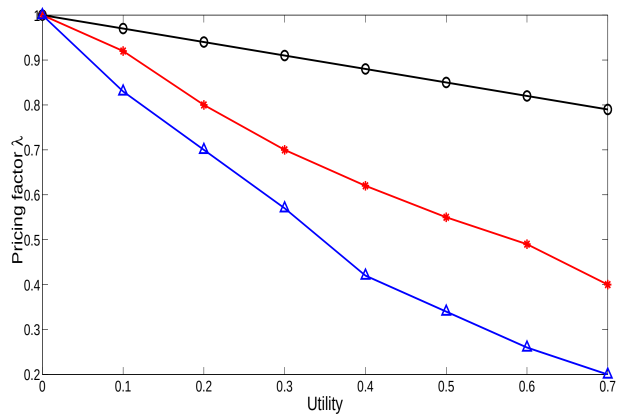

Fig. 4. The Figure illustrates the impact of pricing parameter on the values of utility under different random networks. Blue line with '△' represents Exponential network; Red line with '⋆' represents preferential attachment (scale-free) network; Dark line with 'o' represents Erdös-Rényi network.

C. Impact of pricing factor λ

We first study the impact of pricing on the utility for the various random networks listed above. We normalize the pricing factor λ to ensure that the maximum of λ is 1. Also we normalize the utility function so that the maximum value of utility is 1. Fig. 4 depicts the value of utility across various values of the pricing factor λ.

It is shown in Fig. 4 that higher utility can be captured with a lower value of λ (i.e. a lower price) in the Exponential network, in which a wireless user communicates with few other users. The utility is quite low even at a high value of λ in the Erdös-Rényi network in which a wireless user communicates with multiple other users. This is because the interference is low when one or few users communicate with each other in the network with highly concentrated transmit/receive nodes (e.g., Exponential network), while wireless users suffer large amount of confusion when they communicate with multiple users (e.g., Erdös-Rényi network). These conclusions are in line with the recent publications [29] and [30].

Conclusion

We addressed a potential game to maximize the utility of wireless users by controlling their transmit power under a mobile hospital scenario. We proposed the power control algorithm and showed that the algorithm would globally converge to a unique Nash equilibrium of game, which is the optimal network-level capacity. Some of the key inferences drawn are

• The potential-game approach can lead the Nash equilibrium of game to the optimal network-level strategy of scheduling data transmission within the Internet of vehicles for E-health applications.

• Proposed power control algorithm could dramatically improve the utility of wireless users and reduce the amount of EMI on medical sensors than current algorithm in [4], which is the most widely-used power control algorithm under non-medical settings.

• Under the networks with users who have highly concentrated transmit/receive pairs, the power and rate control algorithm can converge to the fixed point at a higher rate than under the networks in which transmit/receive pairs are evenly distributed among wireless users.

• Networks with users who have highly concentrated transmit/receive pairs can achieve a higher utility than the networks in which transmit/receive pairs are evenly distributed among wireless users .

We are extending our results to the settings in which wireless users can be of different priorities. We would also like to extend our results to a dynamic setting, i.e. the structure of Internet of vehicles is dynamically changing over time.

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