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From Cellular Decision Making to Adaptive Handoff in Heterogeneous Wireless Networks

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***Abstract*—Handoff decision making is critical for mobile users to reap potential benefits from heterogeneous wireless networks. This letter proposes a biologically inspired handoff decision-making method by mimicking the dynamics which govern the adaptive behavior of an *Escherichia coli* cell in a time-varying environment. With the goal of guaranteeing the Quality of Service (QoS), we formulate a utility function that covers the demands of a user's diverse applications and the time-varying network conditions. With this utility function, we map the dynamic heterogeneous environment to a cellular decision-making space, such that the user is induced by a cellular attractor selection mechanism to make distributed and robust handoff decisions. Furthermore, we also present a multi-attribute decision-making network selection algorithm for any user to determine an access network, which is integrated with the proposed bio-inspired decision-making mechanism. Simulation results are supplemented to show that the proposed method can achieve better QoS and fairness when it is compared with conventional methods.**

***Index Terms*—Heterogeneous wireless networks, quality of service, attractor selection model, multi-attribute decision making.**

I. Introduction

IN heterogeneous wireless networks, it is one of the most important issues to be addressed that how to enable mobile users to make handoffs between networks [1]. There are many challenges, such as increased complexity, lack of centralized control, stochastic and dynamic nature in mobility scenarios, etc [2]. Many studies in wireless communications have paid great attention to the issue of heterogeneous handoff decision-making or network selection. Several approaches have been applied to deal with this issue, including multi-attribute decision-making methods [1], mathematical programming optimization [3], reinforcement learning [4], fuzzification and combinatorial fusion [5], and game-theoretic solutions [6]. A survey of handoff paradigms can be found in [7].

Nonetheless, conventional optimization theory-based handoff algorithms are usually realized based on individual interest, thereby potentially negatively affecting the global benefit, e.g., degrading global QoS performance. Similarly, the fuzzification and combinatorial fusion is based on user equilibrium without considering the global resources allocation. It is known that the reinforcement learning or game-theoretic solutions is unsteady or even diverge, when an action-value function is unstable or cannot be properly tuned. In particular, the degradation in the performance of previous schemes will be further exacerbated by high mobility scenarios. The design of a high effective, robust and scalable handoff framework will be of great significance in leveraging large-scale deployment of heterogeneous networks.

In this letter, we propose a biologically inspired decision-making method, based on a cellular attractor selection mechanism [8], to enable users to make handoffs between networks with distributed adaptability and robustness. Specifically, we formulate a utility function for each user, combining the demands of user's diverse applications and the time-varying networking conditions provided by heterogeneous networks, which specifies the degree of QoS experienced by users. With this utility, we map the stochastic and dynamic heterogeneous environment to the cellular decision-making space, such that we can apply the cellular attractor selection mechanism to induce each user, like a cell, to make decisions in a fully distributed and adaptive manner. We further develop a multi-attribute decision-making algorithm to choose an access network. Extensive simulations based on an actual traffic network under different traffic conditions have been conducted to confirm that our bio-inspired framework can achieve a performance improvement in terms of better QoS and fairness.

II. System Model

A. Problem Formulation

We consider that there exist M different wireless networks, defined by a set $Net = \{i | i = 1, 2, \ldots, M\}$, in the overlapping region of which N mobile communication nodes (users), denoted by a set $MT = \{j | j = 1, 2, \ldots, N\}$, are presented. At current time instant t, a user j is assumed to access a wireless network $i_j \in Net$ and employs this network to serve an array of diverse applications. At this point, we assume that any user's application type set is $\mathcal{S}$ and its networking applications associated with the type $s \in \mathcal{S}$ are denoted by a set $appS_{j,s}$. Additionally, we denote by a set $cNet_j(t)$ any user j's candidate access networks at time t except for the current access network i_j, i.e., $i_j \notin cNet_j(t)$ and $cNet_j(t) \subsetneq Net$. It should be noted that due to the user's

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mobility, $cNet_j(t)$ may change over time t. The objective of any user j is to gain better communication benefit, i.e., better QoS, by determining when is the right time to make a handoff and which network among $cNet_j(t)$ should be chosen as a new access network.

Without loss of generality, we assume that there are $n_i(t)$ applications that are accessing the network i at time t and can sense an equal dynamic throughput per application $p_i(t)$ offered by i. Given the available channels of i at t is $C_i(t)$ and its per-channel throughput is R_i, we can calculate the instantaneous throughput per application provided by i at t is

$$p_i(t) = \frac{R_i \times C_i(t)}{n_i(t)}. \tag{1}$$

For any user i's application associated with the type $s \in \mathcal{S}$, denoted by $a_{j,s} \in appS_{j,s}$, we let the upper and the lower bounds of its bandwidth demand per application be $p_{s,\max}$ and $p_{s,\min}$, respectively. When $a_{j,s}$ is currently served by the network i at time t, we can define by $satisfaction(i,s)$ the degree of QoS perceived by the user's application $a_{j,s}$:

$$satisfaction(i,s) = \begin{cases} 0, p_i(t) \le p_{s,\min}; \\ \frac{p_i(t) - p_{s,\min}}{p_{s,\max} - p_{s,\min}}, p_{s,\min} < p_i(t) < p_{s,\max}; \\ 1, p_i(t) \ge p_{s,\max}. \end{cases} \tag{2}$$

It is obvious that $satisfaction(i,s)$ is an increasing function of $p_i(t)$ and $satisfaction(i,s) \in [0,1]$, implying that a larger throughput provided by a network will serve the application better.

Furthermore, for any user j, we can propose the following utility function to map the communication condition provided by its current access network and the demands of its diverse applications to an experienced QoS measure, $QoS_j(t)$:

$$QoS_j(t) = \sum_{s \in \mathcal{S}} \sum_{a_{j,s} \in appS_{j,s}} \frac{w_{j,s}}{|appS_{j,s}|} satisfaction\left(i_j, s\right) \tag{3}$$

where $w_{j,s}$ is introduced to weigh the individual preference of the user j for an application type s. Here, we assume $w_{j,s} > 0$ and $\sum_{s \in \mathcal{S}} w_{j,s} = 1$.

B. Mapping from Cellular Decision-Making to Handoff

As revealed in [8], a cell of *Escherichia coli* usually performs a synthetic bistable switch between different genetic programs, i.e., attractors, to adapt itself to environmental changes, in which it is driven by noises to select a more stable attractor to survive under new environmental conditions. Such an adaptive behavior of *Escherichia coli* can be described by a group of nonlinear ordinary differential equations (ODE):

$$\begin{cases} \frac{\mathrm{d}m_1}{\mathrm{d}t} = \frac{S(A)}{1+m_2^2} - D(A) \times m_1 + \eta_1 \\ \frac{\mathrm{d}m_2}{\mathrm{d}t} = \frac{S(A)}{1+m_1^2} - D(A) \times m_2 + \eta_2 \\ S(A) = \frac{6A}{(2+A)} \\ D(A) = A \end{cases} \tag{4}$$

where m_1 and m_2 are two cellular state variables, each of which indicates a mRNA concentration. The parameter A, called *cellular activity*, reflects the growth rate of the cell. η_1 and η_2 are two independent white Gaussian noises resulting from environmental fluctuations and gene expression fluctuations. In (4), the functions $S(A)$ and $D(A)$ represent the rates of nutrient synthesis and degradation, respectively. Particularly, as the result of interaction between the cell and the varying environment, the cellular activity is captured by the following ODE:

$$\frac{\mathrm{d}A}{\mathrm{d}t} = \frac{P}{\prod_{l=1}^{2} \left[\left(\frac{Nthr_l}{m_l + N_l} \right)^{n_l} + 1 \right]} - C \times A \tag{5}$$

where the parameters P and C denote the producing and consuming rates of A, respectively. $Nthr_l$ $(l = 1,2)$ is the threshold with regard to the mRNA concentration m_l to produce A, while n_l $(l = 1,2)$ is the corresponding Hill coefficient. N_1 and N_2 represent the level of two different nutrients supplied by the external environment, which can reflect the dynamics of the environment and $N_1, N_2 \in [0,10]$. According to [8], we adopt the values of $Nthr_l = 2, n_l = 5$ for $l = 1,2$ and $P = C = 0.01$ in the study.

From (4) and (5), there exist two adaptive attractors in the system state space, in one of which the value of the corresponding state variable, m_l, will overtake that of the other, $m_{l'}$, i.e., $m_l >> m_{l'}$ $(l \neq l')$. The cell interacting with the environment, after perception of the time-varying environmental state, represented by the pair of (N_1, N_2), will switch from one attractor to another to accommodate the environmental changes when the cell cannot survive under new conditions any longer. Otherwise, it will remain in the current attractor. During such an interaction between the cell and the time-varying environment, (N_1, N_2) plays a key role in driving the cellular adaptive behavior. It is worth pointing out that the detailed analysis on the dynamics of the biological model is out of the scope of this letter. We refer the interested reader to the original paper [8] for a preliminary understanding of this model.

Inspired by the adaptive attractor selection of a cell, we model a handoff decision-making process of any user j as a binary decision process. To be specific, we assume that a user j is associated with a pair of time-varying state variables (m_1, m_2), which are updated by using the attractor selection model (ASM) (4). When a user adapts to the new wireless network environments where the nutrient N_2 is synthesised while N_1 is inhibited, the system converges to one stable state, i.e., selecting a stable attractor, where m_1 overweighs m_2. Contrariwise, the system selects another attractor with $m_1 << m_2$. Accordingly, our bio-inspired handoff decision-making mechanism is as follows: when the attractor with $m_1 >> m_2$ is selected by the ASM, the user j is suggested to make a handoff decision, i.e., triggering a handoff from the current access network to a new one; when the other attractor with $m_1 << m_2$ or $m_1 \simeq m_2$ is selected, the user should keep its current connection and a handoff is not recommended at this moment.

In addition, to facilitate the bio-inspired mechanism aforementioned, we have to map the dynamics of the heterogeneous environment to the time-varying environmental conditions perceived by a cell. First, to smooth out certain short-term

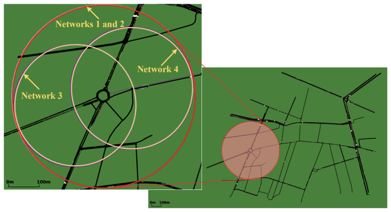

Fig. 1. A heterogeneous access environment simulated in our experiment, where moving vehicles are treated as mobile users and four different wireless networks coexist.

fluctuations in the user j's $QoS_j(t)$, we are based on equation (3) to calculate a moving average of the user's QoS time series, $\{QoS_j(\tau)|\tau \in [t-W_j, t]\}$, within a given time window W_j:

$$h_1 = \sum_{\tau=t-W_j}^{t} \frac{QoS_j(\tau)}{W_j}. \tag{6}$$

Next, to reflect the potential benefit provided by the candidate networks associated with the user j, we further introduce a QoS coefficient, $AvgQoS_j(t)$, to quantify the average QoS level that may be perceived by j from its $cNet_j(t)$

$$\begin{aligned} &AvgQoS_j(t) \\ &= \sum_{k_j \in cNet_j(t)} \sum_{s \in S} \sum_{a_{j,s} \in appS_{j,s}} \frac{\gamma \times w_{j,s}}{|cNet_j(t)|} \frac{satisfaction(k_j, s)}{|appS_{j,s}|}, \end{aligned} \tag{7}$$

where γ is a factor and $\gamma \in (0, 1]$, which is used to discount the average potential benefit due to the fact that a certain uncertainty may exist in the individual perception. For the sake of simplicity, we also denote $h_2 = AvgQoS_j(t)$ hereafter.

Finally, with (6) and (7) given above, we can map h_1 and h_2 into the interval $[0, 10]$ by using a sigmoid function (8) shaped by two parameters a and b, and associate them with the environmental conditions (N_1, N_2)

$$N_i = \frac{10}{1 + exp(-a \times h_i + b)}, \ (i = 1, 2). \tag{8}$$

Based on (8), we can model the interaction between the user and the time-varying heterogeneous environment similar to the interation between a cell and its environment.

III. Access network selection with multi-attribute decision-making

Once a mobile user decides to perform a handoff induced by the cellular decision-making mechanism, it needs to further determine the new access network. To address this issue, we propose a simple and robust network selection algorithm by exploiting advantages in the multi-attribute decision-making theory [9] as follows.

1) We first organize all the potential QoS benefits that each type of the user j's application can potentially perceive from the candidate networks into an information matrix:

$$\boldsymbol{X} = [x(k_j, a_{j,s})] \tag{9}$$

where we set $x(k_j, a_{j,s}) = satisfaction(k_j, s)$ for any $k_j \in cNet_j(t)$, $a_{j,s} \in appS_{j,s}$ and $s \in \mathcal{S}$.

2) In addition, we normalize the matrix $\boldsymbol{X}$ as follows:

$$\begin{cases} x'(k_j, a_{j,s}) = \frac{x(k_j, a_{j,s})}{\sqrt{\sum_{k_j \in cNet_j(t)} x^2(k_j, a_{j,s})}} \\ y(k_j, a_{j,s}) = w_{j,s} \times x'(k_j, a_{j,s}). \end{cases} \tag{10}$$

3) For each application $a_{j,s}$, we evaluate the positive ideal solution, $\boldsymbol{I}^+$, and the negative, $\boldsymbol{I}^-$, by:

$$\begin{cases} \boldsymbol{I}_j^+ = \left\{ \max\limits_{k_j \in cNet_j(t)} y(k_j, a_{j,s}) | a_{j,s} \in appS_{j,s}, s \in S \right\} \\ \boldsymbol{I}_j^- = \left\{ \min\limits_{k_j \in cNet_j(t)} y(k_j, a_{j,s}) | a_{j,s} \in appS_{j,s}, s \in S \right\} \end{cases} \tag{11}$$

4) Furthermore, the differences between any candidate network k_j and the positive ideal network characterized by $\boldsymbol{I}_j^+$, and between k_j and the negative ideal network characterized by $\boldsymbol{I}_j^-$ can be calculated as follows:

$$\begin{cases} Z_j(k_j)^+ = \sqrt{\sum\limits_{s \in S} \sum\limits_{a_{j,s} \in appS_{j,s}} \left(y(k_j, a_{j,s}) - \boldsymbol{I}_j^+(a_{j,s})\right)^2} \\ Z_j(k_j)^- = \sqrt{\sum\limits_{s \in S} \sum\limits_{a_{j,s} \in appS_{j,s}} \left(y(k_j, a_{j,s}) - \boldsymbol{I}_j^-(a_{j,s})\right)^2} \end{cases} \tag{12}$$

5) Each candidate wireless network is ranked with an associated score:

$$Score_j(k_j) = \frac{Z_j(k_j)^-}{Z_j(k_j)^+ + Z_j(k_j)^-} \tag{13}$$

6) Finally, the optimal network is chosen corresponding to the maximum score among $\{Score_j(k_j)\}$, i.e.,

$$k_j^* = \operatorname*{argmax}_{k_j \in cNet_j(t)} \{Score_j(k_j)\}. \tag{14}$$

IV. Performance Evaluation

To evaluate the performance of our proposed method, we carry out comparative simulation experiments. We consider a realistic traffic network scenario in the city of Bologna, where vehicle flows are simulated in a well-known microscopic road traffic simulator, Simulation of Urban MObility (SUMO), and based on field detector datasets provided by the project iTETRIS. We also assume that there exist four different types of wireless networks, $Net = \{i|i = 1, 2, 3, 4\}$, each owning $C_i = 3$ channels. The per-channel throughput of any network is set as $R_1 = 1$, $R_2 = 5$, and $R_3 = R_4 = 3$ (Mbps). We set the coverage radius of the networks 1 and 2 equal to 300m, and that of the networks 3 and 4 to 200m. As shown in Fig. 1, a large roundabout and its nearby traffic region are assumed located in the overlapping area of these heterogeneous wireless networks. In our simulations, we assume that three different types of networking applications are running on any vehicular communication terminal (a user), i.e., $\mathcal{S} = \{\text{voice}, \text{video stream}, \text{data stream}\}$, the demand bounds of which are set in Table I according to [3]. As for any user j, we randomly and uniformly generate a set of applications associated with each type $s \in \mathcal{S}$, $appS_{j,s}$, and the amount of a user's applications with each type s ranges within $[1, 2]$, i.e., $1 \leq |appS_{j,s}| \leq 2$. Additionally, we adopt $\gamma = 0.8$ for (7) and $a = 14, b = 7$ for (8) throughout the simulations.

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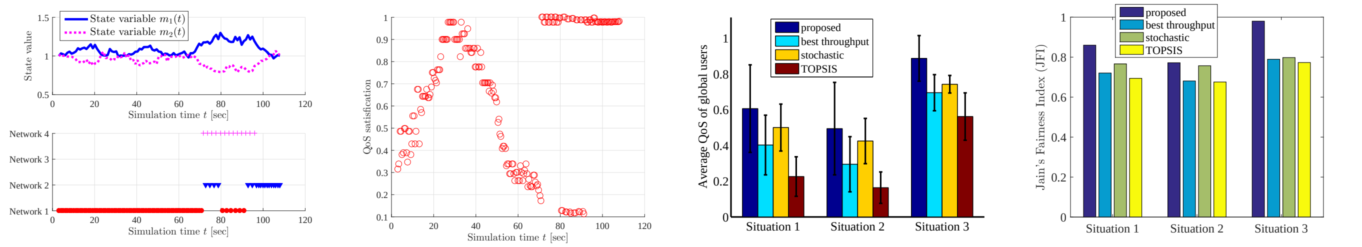

(a) System state evolution (b) Time-varying individual QoS (c) Average QoS of global users (d) JFI of resource allocation

Fig. 2. Simulation results (a) and (b) show the evolution of system state of the ASM associated with an individual user, its handoff decisions as well as the experienced QoS over simulation time. Figures (c) and (d) compare the performance, in terms of global users' mean QoS and fairness in network resource allocation, of different approaches under different traffic situations based on the city of Bologna.

TABLE I
THE BANDWIDTH DEMAND BOUNDS FOR DIFFERENT APPLICATION TYPES.

Application type s	voice	video stream	data stream
$p_{s,\max}$(Mbps)	0.0625	0.1250	0.4883
$p_{s,\min}$(Mbps)	0.0088	0.0293	0.1250

First, we simulate the traffic flows on the Bologna road network with a certain period from 0s to 600s, and then randomly select a mobile user moving in the heterogeneous environment (See Fig. 1) for demonstration of the adaptive attractor selection dynamics. From Figs. 2a and 2b, it can be seen that the user reliably selects an adaptive attractor, in which $m_2(t)$ overtakes $m_1(t)$, during an initial time stage from the initialization to about 70s. After that, it is induced by the environmental dynamics and randomness to switch to the other attractor with $m_1(t)$ overtaking $m_2(t)$. Then it stays in this attractor state from about 70s up to the end. Accordingly, during the first stage, this user can keep wireless connection with Network $i = 1$. It performs successive handoffs between Networks 1, 2 and 4 when the system is in the attractor with $m_1(t)$ overweighing $m_2(t)$. Driven by the attractor selection, this user is enabled to improve its experienced QoS at the beginning of the first stage; then, it robustly and adaptively responses, i.e., by making handoffs, to the QoS degradation it suffers from environmental fluctuations within an intermediate short duration from about 40s to about 70s, such that it can again improve the QoS level finally. The overall figures reveal that the user induced by the bio-inspired mechanism can adapt to environmental changes.

Next, we further compare our method ('proposed') with other conventional schemes, i.e., the best throughput-oriented handoff scheme ('best throughput'), the stochastic handoff scheme ('stochastic') and the other based on Technique for Order Preference by Similarity to an Ideal Solution ('TOPSIS'). For the performance comparison, we simulate the traffic flows on the Bologna road network under different traffic situations, i.e., Situations 1, 2 and 3, which are associated with a normal, a dense and a sparse traffic flow conditions, respectively. In Figs. 2c and 2d, the performance of each compared scheme is evaluated in terms of the average QoS of global users that have accessed the heterogeneous environment and the Jain's Fairness Index [10] of network resource allocation. It is obviously observed that our proposed method can achieve better global QoS and fairness performance in the various traffic situations when compared to the other three conventional handoff paradigms, illustrating potential advantages of the bio-inspired mechanism.

V. CONCLUSION

In this letter, we have studied the handoff decision-making issue that is challenged by a time-varying stochastic heterogeneous environment. This work demonstrates the power of a bio-inspired mechanism, inherent in the dynamics of cellular attractor selection, to design a handoff decision-making framework that is capable of driving users to adapt their heterogeneous accesses with an elegance and efficiency and to handle the dynamic and stochastic nature, heterogeneity and complexity of a heterogeneous environment.

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