

## Adaptive Handover Decision Inspired By Biological Mechanism in Vehicle Ad-hoc Networks

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**Abstract:** In vehicle ad-hoc networks (VANETs), the proliferation of wireless communication will give rise to the heterogeneous access environment where network selection becomes significant. Motivated by the self-adaptive paradigm of cellular attractors, this paper regards an individual communication as a cell, so that we can apply the revised attractor selection model to induce each connected vehicle. Aiming at improving the Quality of Service (QoS), we presented the bio-inspired handover decision-making mechanism. In addition, we employ the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) for any vehicle to choose an access network. This paper proposes a novel framework where the bio-inspired mechanism is combined with TOPSIS. In a dynamic and random mobility environment, our method achieves the coordination of performance of heterogeneous networks by guaranteeing the efficient utilization and fair distribution of network resources in a global sense. The experimental results confirm that the proposed method performs better when compared with conventional schemes.

**Keywords:** Revised attraction selection model, TOPSIS, VANETs, QoS.

### 1 Introduction

VANETs are emerging as a vehicle-to-vehicle communication and network environment for connected vehicles (CV) [Ma, Li, Zhou et al. (2017); Guo, Ma, Xiong et al. (2019)] and connected and automated vehicles (CAVs) [Ma, Hao, Wang et al. (2018)]. Nowadays the development in the wireless communication and networking technologies has brought about the emergence of network selection in VANETs [Chen, Hu, Shi et al. (2017)].

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There are plenty of challenges in highly stochastic and dynamic mobility communication, such as network congestion, performance degradation, etc [Hossain, Chow, Leung et al. (2010); Li, Li, Chen et al. (2018)]. Currently, numerous researchers have focused on handover decision process, and a number of solutions have been proposed in relevant literatures. Existing decision-making methods include the multi attribute decision making (MADM) [Nasser, Hasswa and Hassanein (2006)], reinforcement learning [Du, Wu and Yang (2014)], mathematical programming optimization [Pirmez, Carvalho, Delicato et al. (2010)], game-theoretic solutions [Tseng, Chien, Zhang et al. (2013)], Markov decision processes [Stevens-Navarro, Lin and Wong (2008)] and so forth. Nevertheless, based on individual interests the MADM has the tendency of "ping-pang effect" where the vehicle switches between optimal and suboptimal wireless networks. Accordingly, it is consuming the resource of networking and degrading the global QoS performance. Furthermore, reinforcement learning and game-theoretic are known to be unstable or even to diverge in dynamic scenarios.

As is known to all, the ecosystem has evolved to the perfect system through a long time with some natural characteristics which go far beyond artificial systems. Besides conventional paradigms aforementioned, some other novel solutions have been designed by treating biological systems as a source of inspiration, known as biologically inspired (bio-inspired) solutions. For example, [Tian, Zhou, Wang et al. (2015); Tian, Zhou, Qi et al. (2014)] have presented adaptive network selection algorithms based on an extended attractor selection model. However, these bio-inspired solutions to some extent depend on a centralized infrastructure, such that they cannot be implemented in a fully distributed manner. Hence, the appealing potentials of such adaptive biological mechanism is a source of inspiration of advanced solutions [Balázsi, Van and Collins (2011)].

The critical motivation of our work is that the attractor selection process is simple and robust, and considered as a primordial mechanism for adaptive responses of the cell in environmental changes. In the paper, based on classical attractor selection model [Kashiwagi, Urabe, Kaneko et al. (2006)], we modify the coefficients and proposed the revised attractor selection model. By analogy, we regard an individual communication terminal as a cell, so that we are inspired by the adaptive behavior of the cell in a dynamic environment to develop a novel bio-inspired heterogeneous handover method. To be specific, we formulate a utility function considering the applications running on the vehicle. Because the connected vehicle is driven by the biological mechanism, it is able to make handover decision in an adaptive way. Therefore, our proposed method can achieve good performance in the dynamic and random heterogeneous wireless communication and traffic environments. Furthermore, we introduce the TOPSIS to choose an access network if the handover happens. The method we adopted not only can satisfy the QoS requirements of different vehicle' s applications, but also ensure the efficient utilization and fairness of network resource in a global sense. In summary, this work demonstrates the power of a biologically inspired pattern, inherent in the dynamics of cellular attractor selection, to design a handover decision-making framework that is capable of driving connected vehicles to adapt their accesses with an elegance and efficiency and to handle

the dynamic and stochastic nature, heterogeneity and complexities of communication and traffic environment.

## 2 System model

### 2.1 Revised attractor selection model

In Kashiwagi et al. [Kashiwagi, Urabe, Kaneko et al. (2006)], the cell of *Escherichia coli* switches between different stable genetic programs to accommodate varying environmental conditions. Showed that lack of signal transduction, a cell switches to an appropriate attractor state, implying the cell expressing the genes that afford adaptation to the external condition. We proposed the revised attractor selection model by adding coefficient to the activity producing rate, nutrient synthesis and degradation rate. Considering the internal condition, the behavior of cell can be presented by a group of nonlinear ordinary differential equations:

$$\begin{cases} \frac{dm_1}{dt} = \frac{S(A)}{1+m_2^2} - D(A) \times m_1 + \eta_1 \\ \frac{dm_2}{dt} = \frac{S(A)}{1+m_1^2} - D(A) \times m_2 + \eta_2 \end{cases} \quad (1)$$

Where the two state variables  $m_1$  and  $m_2$  are the concentrations of two mRNA of their protein products, respectively. In Eq. (1),  $\eta_1$  and  $\eta_2$  are two independent white Gaussian noises causing by environmental and gene expression fluctuations. Furthermore,  $A$  is the degree of cellular activity, which is use to quantify the cellular growth and to capture the phenotypic consequence.

$$\begin{cases} S(A) = \frac{6\alpha A}{(2+A)} \\ D(A) = \alpha A \end{cases} \quad (2)$$

The functions  $S(A)$  and  $D(A)$ , respectively represent the coefficients of the nutrient synthesis rate and the degradation rate. In this paper, the key point of the revised attractor selection model is that the addition of the  $\alpha$  which modifies the inherent effect to the cell. Especially, the  $A$  can be calculated by the following equation:

$$\frac{dA}{dt} = \frac{P * \beta}{\prod_{l=1}^2 \left[ \left( \frac{Nthr_l}{m_l + N_l} \right)^{n_l} + 1 \right]} - C \times A \quad (3)$$

where the parameters  $P$  and  $C$  denote the rate of producing and consuming  $A$ , respectively. The other modify of the model is the coefficient  $\beta$  which reflects the preference of diverse conditions.  $Nthr_l$  ( $l = 1, 2$ ) is the threshold corresponding to the nutrient  $i$  to produce  $A$ , while  $n_l$  ( $l = 1, 2$ ) is the relevant sensitivity. The variables  $(N_1, N_2)$  represent the levels of the two nutrients which are supplemented by the external environment. We apply the values of  $Nthr_l = 2, n_l = 5$  for  $l = 1, 2$  and  $P = C = 0.01$  in this paper according to Kashiwagi et al. [Kashiwagi, Urabe, Kaneko et al. (2006)]. In Eqs. (1) and (3), the variables  $m_1$  and  $m_2$  vary along with the environmental conditions where the level of

two different nutrients  $N_1$  and  $N_2$  are supplied by the external environment over time. Accordingly, when the environmental change occurs that the level of the nutrient  $N_1$  is degraded while the nutrient  $N_2$  is synthesized, the system starts to lose the activity, and selects an attractor where  $m_1$  is much larger than  $m_2$ . Similarly, if the environmental conditions are changed to cause the depletion of the nutrient  $N_2$ ,  $m_2$  will rise to increase the cellular activity, which indicates that the attractor with  $m_2$  overweighing  $m_1$  is selected. A cell adapts to the varying environment through switching between attractors, i.e., switching between different gene expression patterns. In this paper, the decision of handover process is determined by the adaptive attractor selection mechanism where there are two options, i.e., remaining current accessing and handover to another network. Inspired by the revised attractor selection model, we assume that a vehicle is related with a pair of dynamic state variables  $(m_1, m_2)$ . Thus, our bio-inspired handover decision-making is as follows: when the attractor with  $m_1 \gg m_2$  is selected, the vehicle is suggested to make a handover decision; when the other attractor  $m_1 \ll m_2$  or  $m_1 \simeq m_2$  is selected, the vehicle is proposed to keep its original access network at that time.

## 2.2 Problem formulation

In our model, the set of all the vehicles is defined as  $MTSet = \{i | i = 1, 2, \dots, N\}$ . Accordingly, the parameter  $N$ , here, denotes the total number of those vehicles. Similarly, the whole available networks are defined by a set  $NetSet = \{j | j = 1, 2, \dots, M\}$ . We assumed that the vehicle  $i$  is connected to  $j_i \in NetSet$  which contains an array of applications at instant time  $t$ . Among the applications, we suppose that the application type set is  $L$  and the applications with type  $l \in \mathcal{L}$  are denoted by a set  $appL_{i,l}$ . Furthermore, the alternative networks at time  $t$  of vehicle  $i$  are denoted by a set  $alterNet_i(t)$  except for the current access network, that is to say,  $j_i \notin alterNet_i(t)$  and  $alterNet_i(t) \subsetneq NetSet$ . In fact, the access network and alternative network of vehicle  $i$  may change over time  $t$  due to the high mobility environment. The goal of each vehicle is to gain better communication benefit, i.e., more QoS, to adapt the time-varying conditions by selecting more suitable network at the right time to make a handover. There are  $n_j(t)$  applications that are accessing the network  $j$  at time  $t$ . At the meanwhile, the available channel of network  $j$  at time  $t$  is  $C_j(t)$  and its per-channel throughput is  $R_j$ . For each application, the vehicle receives the equal throughput  $p_j(t)$  at time  $t$  offered by network  $j$ . Consequently, the instantaneous throughput per application of network  $j$  at time  $t$  can be calculated that is

$$p_j(t) = \frac{R_j \times C_j(t)}{n_j(t)}. \quad (4)$$

We assume the upper and lower bounds of each application's bandwidth demand as  $p_{l,\max}$  and  $p_{l,\min}$ , respectively. In order to measure the degree of QoS, we defined the  $q(j, l)$  when

$a_{i,l}$  is served by the network  $j$  at time  $t$ :

$$q(j, l) = \begin{cases} 0, & p_j(t) \leq p_{l,\min}; \\ \frac{p_j(t) - p_{l,\min}}{p_{l,\max} - p_{l,\min}}, & p_{l,\min} < p_j(t) < p_{l,\max}; \\ 1, & p_j(t) \geq p_{l,\max}. \end{cases} \quad (5)$$

The  $q(j, l)$  is limited in the closed interval  $[0, 1]$  and an increasing function of  $p_j(t)$  which indicates that the more throughput will serve the application better.

In addition, for each vehicle  $i$ , we present the utility function reflecting the communication condition offered by the current access network and the throughput demands for its application, the  $QoS_i(t)$  can be calculated that

$$QoS_i(t) = \sum_{l \in \mathcal{L}} w_{i,l} * q(j_i, l) \quad (6)$$

where  $w_{i,l}$  is presented to evaluate the individual preference of the vehicle  $i$  for the application type  $l$ . Therefore,  $\sum_{l \in \mathcal{L}} w_{i,l} = 1$  and the  $w_{i,l} > 0$  and . Furthermore, in order to quantify the communication conditions reasonably, we map the dynamics of the current environment to the nutrients perceived by a cell. At first, we calculate the  $g_1$  by smoothing the aforementioned  $QoS_i(t)$ . Within a given time window  $W_j$ , the  $g_1$  is obtained by the following equation:

$$g_1 = \sum_{\tau=t-W_j}^t \frac{QoS_i(\tau)}{W_j}. \quad (7)$$

Then, we proposed the  $AvgQoS_i(t)$  embodying the communication circumstance provided by the candidate networks associated with the user  $i$  to quantify the average QoS level that may be perceived by  $i$  from its  $alterNet_i(t)$ :

$$\begin{aligned} & AvgQoS_i(t) \\ &= \sum_{k_i \in alterNet_j(t)} \sum_{l \in \mathcal{L}} \frac{\gamma \times w_{i,l}}{|alterNet_i(t)|} q(k_i, l), \end{aligned} \quad (8)$$

where  $\gamma \in (0, 1]$ , which is a factor from the individual perspective to discount the potential benefit. Simultaneously, we define  $g_2 = AvgQoS_i(t)$  simply.

At last, according to the Kashiwagi et al. [Kashiwagi, Urabe, Kaneko et al. (2006)], we have to map the  $g_1$  and  $g_2$  into the  $[0, 10]$ . Hence, we adopt the sigmoid function (9) shaped by  $a$  and  $b$  to associate them with the environmental conditions  $(N_1, N_2)$

$$N_i = \frac{10}{1 + \exp(-a \times g_i + b)}, \quad (i = 1, 2). \quad (9)$$

### 3 Selecting access network with TOPSIS

Once the vehicle determines to make a handover decision induced by the cellular decision-making mechanism, it is necessary to find the appropriate access network. In

this section, we present the TOPSIS considering the multi-attributes of the communication network to choose the access network [Hwang and Yoon (1981)].

1. At first, we construct the information matrix of the potential QoS benefits of the vehicle  $i$  from the candidate networks:

$$\mathbf{X} = [x(k_i, a_{i,l})] \quad (10)$$

where  $x(k_i, a_{i,l}) = q(k_i, l)$  for any  $k_i \in \text{alterNet}_i(t)$ ,  $a_{i,l} \in \text{appL}_{i,l}$  and  $l \in \mathcal{L}$ .

2. Next, we normalize the matrix as follows:

$$\begin{cases} x'(k_i, a_{i,l}) = \frac{x(k_i, a_{i,l})}{\sqrt{\sum_{k_i \in \text{alterNet}_i(t)} x^2(k_i, a_{i,l})}} \\ y(k_i, a_{i,l}) = w_{i,l} \times x'(k_i, a_{i,l}). \end{cases} \quad (11)$$

3. For each application  $a_{i,l}$ , we calculate the positive ideal solution,  $\mathbf{I}^+$ , and the negative solution,  $\mathbf{I}^-$ , by:

$$\begin{cases} \mathbf{I}_j^+ = \left\{ \max_{k_i \in \text{alterNet}_i(t)} y(k_i, a_{i,l}) \mid a_{i,l} \in \text{appL}_{i,l}, l \in L \right\} \\ \mathbf{I}_j^- = \left\{ \min_{k_i \in \text{alterNet}_i(t)} y(k_i, a_{i,l}) \mid a_{i,l} \in \text{appL}_{i,l}, l \in L \right\} \end{cases} \quad (12)$$

4. In addition, the differences between any alternative network  $k_i$  and the positive ideal network characterized by  $\mathbf{I}_i^+$ , and between  $k_i$  and the negative ideal network characterized by  $\mathbf{I}_i^-$  can be expressed as follows:

$$\begin{cases} Z_i(k_i)^+ = \sqrt{\sum_{l \in L} \sum_{a_{i,l} \in \text{appL}_{i,l}} (y(k_i, a_{i,l}) - \mathbf{I}_i^+(a_{i,l}))^2} \\ Z_i(k_i)^- = \sqrt{\sum_{l \in L} \sum_{a_{i,l} \in \text{appL}_{i,l}} (y(k_i, a_{i,l}) - \mathbf{I}_i^-(a_{i,l}))^2} \end{cases} \quad f \quad (13)$$

5. The scores of each alternative network can be figured as follows:

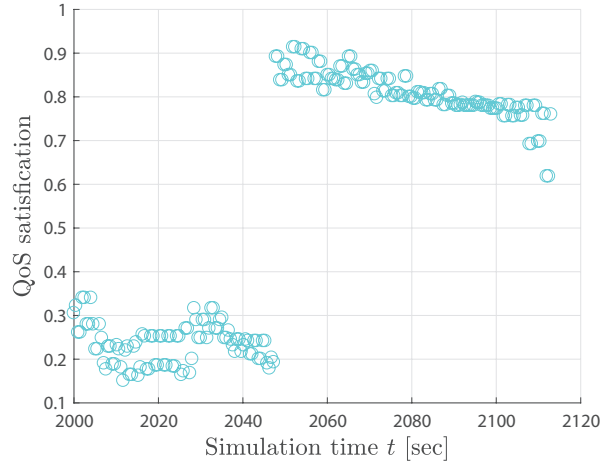
$$\text{Score}_i(k_i) = \frac{Z_i(k_i)^-}{Z_i(k_i)^+ + Z_i(k_i)^-} \quad (14)$$

6. At last, the optimal network is selected corresponding to the maximum score, i.e.,

$$k_i^* = \underset{k_i \in \text{alterNet}_i(t)}{\text{argmax}} \{ \text{Score}_i(k_i) \}. \quad (15)$$

Taken together, we have presented a framework combining the biologically inspired handover mechanism with the optimal network selection algorithm based on the TOPSIS, which can help mobile vehicles, mimicking a cell's adaptive decision making, make handover decisions with an elegance and efficiency in a dynamic heterogeneous environment, and can further help them determine an appropriate access network.





**Figure 3:** The experienced QoS over simulation time associated with a connected vehicle

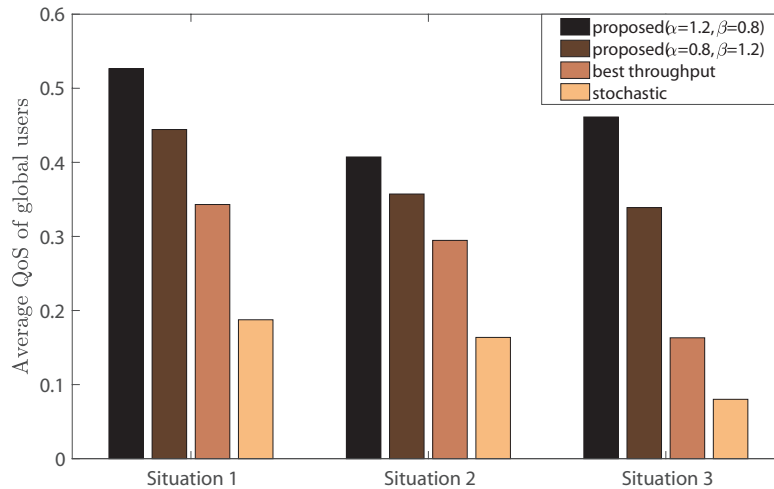
#### 4 Numerical simulation

For the evaluation of the proposed method in this paper, we conduct comparative simulation experiments. So as to have more realistic traffic flow in simulations, we employ the city of Bologna with the a distinguished microscopic road traffic simulator, Simulation of Urban MObility (SUMO) [Krajzewicz, Erdmann, Behrisch et al. (2012)]. Furthermore, the project iTETRIS [Bieker, Krajzewicz, Morra et al. (2015)] provides the field detector datasets. We hold the assumption that there are four different types of wireless networks,  $NetSet = \{j|j = 1, 2, 3, 4\}$ , each owning  $C_j = 3$  channels. We hold the hypothesis that each network process different per-channel throughput where  $R_1 = 1$ ,  $R_2 = 5$ , and  $R_3 = R_4 = 3$  (Mbps). The coverage radius of the wireless network is that networks 1 and 2 are equal to 300 m and networks 3 and 4 are to 200 m. The simulation scenario is where the traffic region in the city are assumed located in the overlapping area of these wireless network. Moreover, there are three different types of networking applications are running on each vehicula, i.e.,  $\mathcal{L} = \{\text{voice, video stream, data stream}\}$ . According to Pirmez et al. [Pirmez, Carvalho, Delicato et al. (2010)], the upper and the lower bounds of voice are 0.0625 and 0.0088 (Mbps). The bandwidth of video stream is from 0.0293 to 0.1250 (Mbps). As for data stream, the restrictions are 0.4993 and 0.1250 (Mbps). In the simulation, we stochastically generate a set of applications associated with each type  $l \in \mathcal{L}$ ,  $appL_{i,l}$ , and the amount of a user's applications within  $[1, 2]$  for the vehicle  $i$ , i.e.,  $1 \leq |appL_{i,l}| \leq 2$ . Furthermore, we assume that  $\alpha = 1.2$ ,  $\beta = 0.8$  for Eq. (1),  $\gamma = 0.8$  for Eq. (8) and  $a = 14$ ,  $b = 7$  for Eq. (9).

First, with a certain period from 2000 to 2600 s, we select a vehicle randomly for illustration of the revised attractor selection dynamics in the traffic flows in the Bologna road network. From Figs. 1, 2 and 3, we can found that the vehicle chooses the attractor in which  $m_2(t)$  overtakes  $m_1(t)$ , during an initial time stage from the initialization to about 50 s. Then,







**Figure 6:** The global vehicles' mean QoS of different approaches under different traffic situations

the vehicle switches to the other attractor induced by the revised attractor selection model with  $m_1(t)$  exceeding  $m_2(t)$ . At last, it remains in this attractor state to the end. At the beginning state of the simulation, the vehicle keeps the network connection with Network  $j = 1$ . After that, it performs successive handover between Network 3 and 4. During the whole period, the vehicle is enabled to improve its QoS. Over the simulation, the activity of the connected vehicle degraded with the external environment changes before the handover when accessing to the Network 1. After about 50 s, The increase of activity with the handover occurring to improve the activity of the vehicles. It is obvious that the promotion of the QoS after the handover decision-making induced by the bio-inspired mechanism. The Figs. 1, 2 and 3 demonstrate that the vehicle adapts to the time-varying environmental changes robustly and adaptively induced by revised attractor selection model.

Moreover, we compare the proposed bio-inspired pattern with other conventional methods, i.e., the best throughput handover scheme ('best throughput') and the stochastic handover scheme ('stochastic'). To evaluate the performance under different traffic situations, we simulate three kinds of traffic flow, i.e., Situation 1, 2 and 3, which are associated with a normal, a dense and a spare traffic flow conditions, respectively. In wireless communication environment, the cost of handover is important issue. In Fig. 4, our proposed method reduce the handover frequency distinctly. In addition, the Jain's Fairness Index [Jain, Chiu and Hawe (1998)] can be calculated to reflect the allocation in global sense. As is shown in Fig. 5, our proposed method achieve fairness performance remarkably. In Fig. 6, in order to evaluate the performance of the proposed method, we modify the  $\alpha$  and  $\beta$  with regard to the global mean QoS. Our algorithm gains better QoS in three different scenarios.



