# Noise-assisted Traffic Distribution over Multi-path Ad Hoc Routing

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## ABSTRACT

Computer networks have become highly complicated and less flexible to handle emerging problems which often occur nowadays. In order to cope with unpredictable problems, the concept of biologically inspired networks has been introduced, which provides a high degree of robustness and adaptability to computer networks. However, the performance of the network often relies heavily on the configurable parameters assigned during the deployment process, where end nodes cannot change these parameters during runtime to achieve the desirable performance. In this paper, we introduce a new method, called *attractor perturbation* (AP) allowing end nodes to influence the average of an observable performance metric at runtime without directly manipulating any optimal parameters of underlying protocols. An example application in this paper is a traffic distribution over multi-path routing protocol in MANETs, where the target variable is end-to-end delay. The approach to solve for the appropriate amount of management influence and simulation results are shown in this paper.

## Categories and Subject Descriptors

C.2.2 [**Computer-Communication Networks**]: Network Protocols

## General Terms

Design, Performance, Algorithms

## 1. INTRODUCTION

Computer network architectures and their protocols have become increasingly sophisticated over time through addition of many features to support new applications, such as multimedia streaming, voice-over-IP (VoIP), or online gaming. These new protocols often require a careful fine-tuning of parameter values to operate at their best performance. However, different traffic conditions may require different settings of protocol parameters that need to be manually readjusted. Since the total number of possible situations occurring in the real world is too large to be handled by preprogrammed sets of definitions, it is necessary that new networking mechanisms are designed in a flexible and adaptive manner to cater for any changes in the environment. Reliability of the communication channel is particularly important for wireless networks due to the limited available wireless spectrum and fluctuating channel characteristics. Additionally, in mobile ad hoc networks (MANETs), a specific type of infrastructure-less wireless network, the nodes can be mobile which leads to sudden changes in connectivity and network topology.

Beside conventional approaches that have been proposed to improve adaptability in ad hoc networks, also concepts based on biological mechanisms have been proposed [3,8] for self-organized control since they are able to provide greater robustness and adaptability to external influences. The underlying idea is to derive a protocol that is based on the model of a natural phenomenon. For example, swarm intelligence is a concept where individual agents mimic the behavior of insect swarms, e.g. ants or bees, during foraging and it has been successfully applied to routing problems [2]. Firefly groups perform a distributed synchronization of their flashing behavior and this was applied to synchronization in sensor networks [11]. Reaction-diffusion describes the chemical dynamics of morphogens in the development of stripes or spots on animal furs. Based on the reaction-diffusion dynamics the coding rate for camera sensor networks can be controlled [12].

Since biological systems are often described as dynamic systems, they rely on a mathematical formulation given as differential equations. In dynamic systems, attractors describe the states to which the system evolves over time. In the past, we studied the concept of attractor selection, which is based on the dynamics found in gene expression [4] and has been previously also applied to tackling problems in communication networks [1, 7]. In this paper, we apply a similar biological mechanism called attractor perturbation (AP), which is derived from the fluctuation-response relationship observed in an experiment on the evolution of functional proteins in a cell [10]. A previous application of AP


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to wireless networks can be found in [6].

To further demonstrate the effectivity of AP, we consider in this paper an application of traffic distribution over multiple paths in MANETs. Our target is to find a method for minimizing the average end-to-end delays of all packets during runtime by smoothly changing the amount of traffic injected into each path. This traffic distribution is performed adaptively following the dynamics of AP and therefore requires no previous parameter tuning like other network routing mechanisms.

The rest of this paper is organized as follows. We first explain the background of the biologically-inspired mechanisms which are used in this study in Section 2. Next, we describe our problem scenario of traffic distribution in multipath routing and the solution steps of the target minimization problem in Section 3. Then, the evaluation results from simulation are presented and discussed in Section 4. Finally, we conclude this paper and describe future work.

# 2. ATTRACTOR BASED CONTROL

In this work, we use the concept of attractors to dynamically control our network. In order to provide the necessary background, we will briefly describe the principles of attractor selection and attractor perturbation in this section.

## 2.1 Attractor Selection

The attractor selection mechanism is modeled after the behavior of *E. coli* cells, which are capable of adapting to dynamically changing nutrient conditions in the environment without any predefined adaptation rules [4]. A mutant *E. coli* cell has a gene regulatory network consisting of two mutually inhibitory sequences of chemical reactions which synthesize two corresponding nutrients. When one of the nutrients becomes scarce, the protein concentration activating a sequence for the missing nutrient increases to return the cell to a stable gene expression. However, there is no explicit rule based mechanism to switch between the sequences of chemical reactions. In [4], a mathematical model describing this bistable behavior of protein concentrations $m_1$ and $m_2$ is proposed as

$$\begin{aligned} \frac{dm_1}{dt} &= \frac{s(\alpha)}{1+m_2^2} - d(\alpha)\, m_1 + \eta_1 \\ \frac{dm_2}{dt} &= \frac{s(\alpha)}{1+m_1^2} - d(\alpha)\, m_2 + \eta_2 \end{aligned} \quad (1)$$

where $s(\alpha)$ and $d(\alpha)$ are the rate coefficients of protein synthesis and decomposition, respectively. Both of them depend on $\alpha$ which represents the cell activity or cell volume growth. The terms $\eta_i$ are independent white noise that exists in gene expression.

The essential point in Eqn. (1) is the interaction between activity $\alpha$ and noise terms $\eta_i$. If the ratio between activity and noise is sufficiently large, the system's behavior remains rather unaffected by noise. On the other hand, if activity approaches zero, the dynamics of the system states $m_1$ and $m_2$ become entirely determined by noise, i.e., they perform a random walk. When the state randomly approaches a new attractor, activity $\alpha$ will increase which results in the state being locked at the new attractor.

## 2.2 Attractor Perturbation

The attractor perturbation model is derived from observations of fluctuation and response in biological systems, in particular, an experiment on the evolution of functional proteins in a clone bacteria cell. In [10], it was found that the fluctuation, which is expressed by the variance of the fluorescence of a bacterial protein, and its response, which is the average change in this fluorescence, have a linear relationship modeled as follows when a force is introduced:

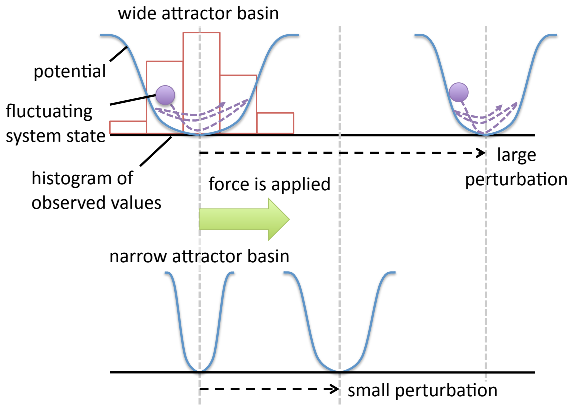



**Figure 1: Dynamics of attractor perturbation**

$$\bar{x}_{a+\Delta a} - \bar{x}_a = b\,\Delta a\,\sigma_a^2 \quad (2)$$

where $b$ is a scalar constant, $x$ is a time dependent measurable variable in the system with mean $\bar{x}$ and variance $\sigma_a^2$, and $a$ is a controllable parameter.

There are two major assumptions underlying the model formulation of AP. First, the variable $x$ must have a Gaussian-like distribution which is often observed in biology. Second, the variable $x$ and the parameter $a$ are closely associated, in other words, a change in the parameter $a$ would strongly affect the distribution of the variable $x$.

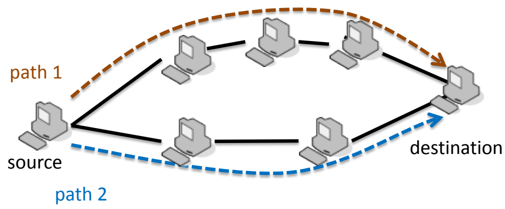
Equation (2) reveals that the difference in the average of the variable $x$ before and after applying a change to the parameter $a$ is linearly proportional to the amount of change in $a$ and the variance of the variable $x$ prior to the change. Since the amount of change in $a$, called *force* can be seen as controllable, it is possible to adjust the difference in average of $x$, called *perturbation*, by taking the current variance of $x$ into consideration. Obviously, using the same amount of force $\Delta a$ to perturb the average of $x$ when the variance $\sigma_a^2$ is large will also lead to a larger perturbation, as shown in Fig. 1. This figure also shows the attractor basins corresponding to each empirical distribution of $x$.

# 3. MULTI-PATH TRAFFIC DISTRIBUTION WITH ATTRACTOR PERTURBATION

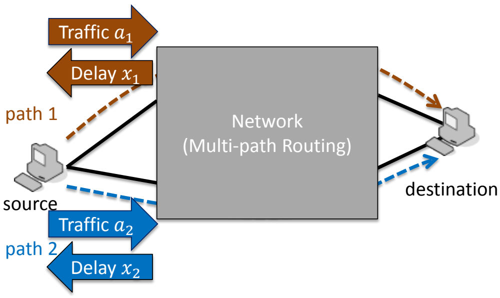
Let us now show the applicability of attractor perturbation as adaptive method for traffic distribution. First, we will briefly describe the multi-path routing scenario and some of the challenges that are involved. Then, we will explain our proposed mechanism for minimizing the packet delays by utilizing the attractor perturbation concept.

## 3.1 Multi-Path Routing Scenario

We consider a situation as depicted in Fig. 2(a). A source node $S$ is connected to the destination node $D$ via multiple paths. The advantage of using multiple paths is that if one path breaks due to failures at intermediate links or nodes,




(a) Traditional approach




(b) AP based approach

**Figure 2: Overview of Traffic Distribution over Multiple Paths**

the other path can still be maintained. Furthermore, using multiple paths permits a better balancing of loads by distributing traffic more evenly in the network. Especially, if nodes in an ad hoc scenario are operated by batteries, this may lead to reduced energy consumption.

First, the source node needs to determine the set of paths to the destination. This can be performed through AODV-like probing for path computation. Once the source node has found its paths for reaching the destination, it can split up its traffic among these paths following an allocation strategy to achieve a certain objective, depending on user-specific criteria. The allocation granularity, which describes the unit of information allocated to each path, is also of great importance [9]. Coarse granularities, such as per-connection or per-flow, tend to reduce the management overhead, but are not as flexible as small granularities, e.g., per-packet, since these permit a better distribution of traffic. However, per-packet granularity may require reordering at the destination, if the latencies differ too much among paths.

## 3.2 Traffic Distribution with Attractor Perturbation

Since AP observes only the average and variance of the variable $x$, it is unnecessary to learn the actual details of the underlying protocols. In short, traffic distribution with AP can be made by looking at the system as a black box with the parameter $a$ as input and variable $x$ as output, which is fed back to the system, see Fig. 2(b). With this simplified view, it is possible to perform various types of network control with ease. As example of network control, this paper's target is to minimize the average end-to-end delay of all packets by only observing the fluctuations of end-to-end delay $x$ and applying traffic rate change $a$ whenever necessary.

### *3.2.1 Definition and Notation*

The targeted multi-path situation consists of $n$ paths. For the sake of simplicity, we consider $n = 2$ in this study, where each path $i$ has the following characteristics:

- Current traffic rate: $a_i$
- Traffic rate change: $\Delta a_i$
- Average end-to-end delay prior applying $\Delta a_i$: $\bar{x}_i$
- Average end-to-end delay after applying $\Delta a_i$: $\bar{x}'_i$

### *3.2.2 Problem Formulation*

In this section, we formulate the minimization problem of the average end-to-end delay of all packets. According to the notation defined in Section 3.2.1 and Eqn. (2), in case of two paths, we have:

$$\bar{x}'_1 = \bar{x}_1 + b_1\, \Delta a_1\, \sigma_1^2 \tag{3}$$

$$\bar{x}'_2 = \bar{x}_2 + b_2\, \Delta a_2\, \sigma_2^2 \tag{4}$$

The average delay of all packets on each path is defined by the product of the traffic rate $a_i$ and the average per-packet delay $\bar{x}_i$. Therefore, the estimation of the average delay after applying traffic rate change $\Delta a_i$ can be made as follows.

$$\begin{aligned} & f(\Delta a_1, \Delta a_2) \\ &= (a_1 + \Delta a_1)\, \bar{x}'_1 + (a_2 + \Delta a_2)\, \bar{x}'_2 \\ &= (a_1\bar{x}_1 + a_2\bar{x}_2) + \left(\bar{x}_1 + a_1 b_1 \sigma_1^2\right) \Delta a_1 \\ &\quad + \left(\bar{x}_2 + a_2 b_2 \sigma_2^2\right) \Delta a_2 + b_1\sigma_1^2 \Delta a_1^2 + b_2 \sigma_2^2 \Delta a_2^2 \end{aligned} \tag{5}$$

Given that $c' = (a_1\bar{x}_1 + a_2\bar{x}_2)$, $c_1 = \left(\bar{x}_1 + a_1 b_1 \sigma_1^2\right)$, $c_2 = \left(\bar{x}_2 + a_2 b_2 \sigma_2^2\right)$, $k_1 = b_1\sigma_1^2$, and $k_2 = b_2\sigma_2^2$, Eqn. (5) can be formulated as a constrained optimization (minimization) problem as follows:

**Minimize**

$$f(\Delta a_1, \Delta a_2) = c' + c_1 \Delta a_1 + c_2 \Delta a_2 + k_1 \Delta a_1^2 + k_2 \Delta a_2^2 \tag{6}$$

$$\textit{subject to} \qquad \Delta a_1 + \Delta a_2 = 0$$

The solution of the minimization problem in Eqn. (6) is the amount of the change in traffic rate to be applied to each path in order to achieve minimal average end-to-end delay of all packets. The *subject to* condition holds since the total amount of traffic prior and after change has to be the same.

### *3.2.3 Lagrangian Optimization*

The minimization problem which has the form as in Eqn. (6) can be solved using *Lagrangian Optimization.*

The Lagrangian has the general form of

$$L(x^*, \lambda^*) = f(x) - \Sigma_i[\lambda_i(g_i(x) - b_i)]$$

where $x^*$ is the optimal solution of $x$ and $\lambda^*$ is the penalizing Lagrangian multiplier.

The associated Lagrangian of Eqn. (6) is:

$$\begin{aligned} L(\Delta a_1^*, \Delta a_2^*, \lambda^*) = c' + c_1 \Delta a_1^* + c_2 \Delta a_2^* + k_1 \Delta a_1^{*2} \\ + k_2 \Delta a_2^{*2} - \lambda^* \left(\Delta a_1^* + \Delta a_2^*\right) \end{aligned} \tag{7}$$

$$\frac{\partial L}{\partial \Delta a_1^*} = c_1 + 2k_1 \Delta a_1^* - \lambda = 0 \tag{8}$$

$$\frac{\partial L}{\partial \Delta a_2^*} = c_2 + 2k_2 \Delta a_2^* - \lambda = 0 \tag{9}$$

$$\frac{\partial L}{\partial \lambda^*} = -\left(\Delta a_1^* + \Delta a_2^*\right) = 0 \tag{10}$$

In the three Eqns. (7)–(9), there are three unknown variables $\Delta a_1^*$, $\Delta a_2^*$, and $\lambda^*$. Therefore, this optimization problem can be solved and we obtain the optimal amount of traffic $\Delta a_i$ for each path $i$ to minimize the sum of average delays. Note that although we only considered $n = 2$, the problem formulation and Lagrangian optimization can be extended to multiple paths case, i.e., $n > 2$, with little effort by using matrix and row elimination.

### 3.2.4 *Optimal Solution*

According to steps taken in Section 3.2.3, the optimal solution in case of two paths is as follows.

$$\begin{aligned}\Delta a_1^* &= \frac{c_2 - c_1}{2(k_1 + k_2)} \\ &= \frac{(\bar{x}_2 + a_2 b_2 \sigma_2^2) - (\bar{x}_1 + a_1 b_1 \sigma_1^2)}{2(b_1\sigma_1^2 + b_2\sigma_2^2)}\end{aligned} \tag{11}$$

$$\Delta a_2^* = -\Delta a_1^* \tag{12}$$

## 4. SIMULATION RESULTS

In this section, we first perform a numerical verification of the AP model by evaluation of stochastic differential equations. Next, we study the behavior of AP based proposal in ad hoc network simulations.

### 4.1 Evaluation of Linearity between Fluctuation and Response

For our numerical evaluation we first show that this attractor perturbation principle actually holds in theory. To do this, we define a simple theoretical attractor model like the one in [5]:

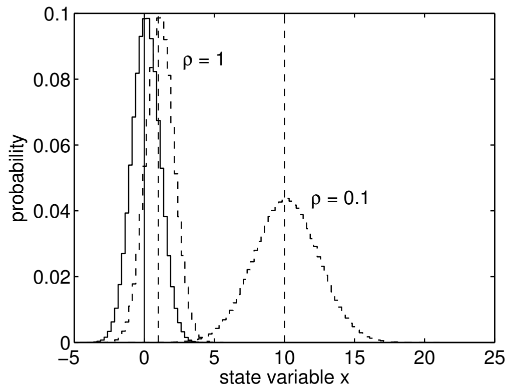
$$\frac{dx}{dt} = -\rho\,(x - x_0) + \eta \tag{13}$$

where $x$ is the state variable, $\rho$ is the speed of adaptation, $x_0$ is the attractor, and $\eta$ is noise. Fig. 3(a) shows how the initial black histogram at $x_0 = 0$ gets perturbed by the same force, but to different offsets for $\rho = 0.1$ and $\rho = 1.0$. The term $\rho$ controls the softness of adaptation in the dynamic system and represent the internal fluctuations. A smaller $\rho$ leads to slower adaptation of $x$ in Eqn. (13) and therefore to a larger variance. Repeating this experiment for different force values (1 and 5) and random $\rho$ shows us the expected linear behavior, when we plot variance of $x$ on the x-axis and average perturbation on the y-axis of Fig. 3(b).

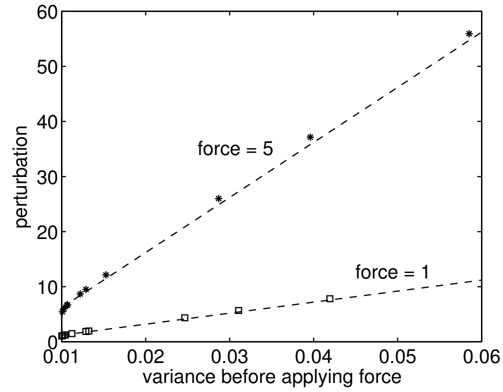
We can see from Fig. 3 that the linear relationship exists and we can exploit this for our traffic distribution method in multi-path networks. Note that the slope of the lines in Fig. 3(b) corresponds to the constant $b$ term in Eqn. (2).

### 4.2 Simulation of Network Traffic

To demonstrate the validity of AP based traffic distribution, we performed simulations of a mobile ad hoc network using the QualNet network simulator. The scenario consists of an area of $1000 \times 1000\,\mathrm{m}^2$, where 25 nodes are uniformly distributed. The simulation duration is 1000 s for each run. There are 5 traffic sessions starting at 1 s: 1 CBR session with packet size of 250 Bytes and 100 ms sending interval, and 4 random traffic sessions with the same packet sizes and exponentially distributed sending intervals with average of 1000 ms serving as background traffic. The underlying routing protocol is MARAS [1].




(a) Normalized histograms



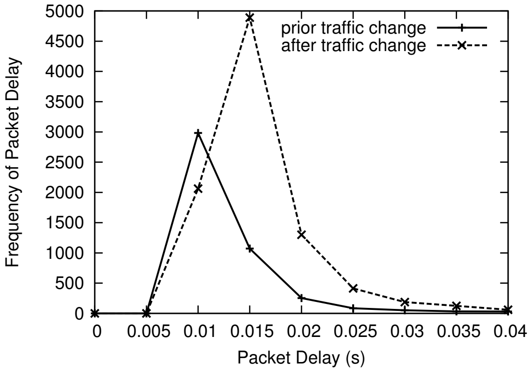

(b) Linear relationship in perturbation

**Figure 3: Numerically simulated fluctuation and response of dynamic system**

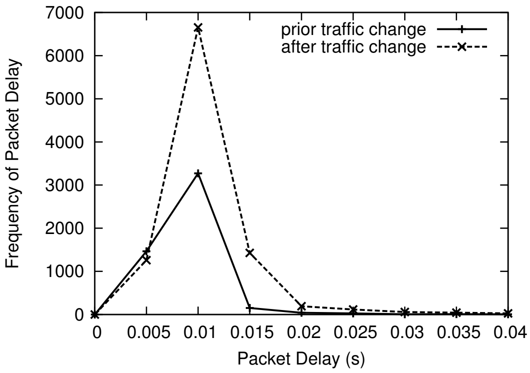
In order to clearly observe the effect of AP, we change the sending interval of CBR packets from 100 ms to 50 ms at half of the simulation time (500 s) and the results are shown in Fig. 4. For several randomly seeded trials, we observe that the variance $\sigma^2$ of end-to-end delays during the first 500 s varied depending on the random initial configuration and we could categorize two cases, one with high variance and one with low variance. In Fig. 4(a) the high variance case is shown and the initial average and variance of end-to-end delay before the traffic rate change were $1.653 \cdot 10^{-2}\,\mathrm{s}$ and $1.176 \cdot 10^{-4}\,\mathrm{s}^2$, respectively. After applying the force to the system through the traffic rate change, the new average delay became $2.009 \cdot 10^{-2}\,\mathrm{s}$. On the other hand, in the case of Fig. 4(b) which has much lower variance of $1.581 \cdot 10^{-5}\,\mathrm{s}^2$ than in the high variance case, the average delay changes from $1.108 \cdot 10^{-2}\,\mathrm{s}$ to $1.391 \cdot 10^{-2}\,\mathrm{s}$. In summary, it can be seen that (i) the average delay can be influenced by the change in traffic rate, and (ii) the perturbation is larger in the case of larger variance.

## 5. CONCLUSION AND FUTURE WORK

In this paper, we introduced *attractor perturbation* (AP), a novel biologically inspired approach which can perform a simplified control of an underlying system. With AP, it is possible to regard the whole underlying system as a black




(a) High variance




(b) Low variance

**Figure 4: Histogram of packet delays when doubling the traffic rate at 500 s**

box and perform control based on observed average and variance of the time series of the considered performance metric. According to our evaluation, it can be seen that the concept of AP is feasible for network control in ad hoc networks. Simulation results showed for a single path as well as numerical evaluations of the theoretical differential equation reveal that the fluctuation-response relationship is visible. As a result, this relationship can be used to estimate the optimal amount of traffic change to achieve minimal average end-to-end delays for all packets in order to distribute traffic over multi-path routing as proposed in this paper.

This paper reported on the first steps of our research on traffic distribution in a multi-path ad hoc network. Even though our simplified network simulations were made over only a single-path routing protocol, we can expect similar results in case of multi-path routing if disjoint paths are used. As our future work, we are planning on extending MARAS to a multi-path routing protocol and re-evaluate the proposed traffic distribution method over it. Since MARAS, as well as AP are driven by noise, we are convinced that this approach will lead to an improved routing protocol that is adaptive and robust without requiring any fine-tuning of parameters.

# 6. ACKNOWLEDGMENTS

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