Biologically-Inspired Path Selection Scheme for Multipath Overlay Networks

(Invited Paper)

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***Abstract*—In this paper we discuss the application of a biologically-inspired approach for path selection in overlay networks under the constraints of in-order packet delivery. We apply the concept of attractor selection by modeling the path selection process in multipath overlay as a stochastic dynamical system that instantaneously converges to a sufficiently good solution utilizing the system inherent noise to provide a robust and adaptive mechanism. Our method is inspired by a mathematical model for the stochastic dynamics of gene regulatory networks. Simple numerical simulations will show that this proposed method is stable to changes in the environment and adaptable to the objective function, which is in our case the buffer occupancy level of the destination node in an overlay network.**

I. Introduction

Biologically inspired systems are known to exhibit a great robustness and the capability to self-organize and self-adapt to changing environmental conditions [1]. This ability is an essential feature common to most dynamical networks found in nature and in recent years there have been increasing efforts in introducing mechanisms inspired by biology to the field of information and communication networks [2]. While the mechanisms from biology may often seem not directly well suited for application in engineered networks, it is possible to conceive new mechanisms, which resemble the basic behavior of their biological counterparts, especially in highly distributed structures where no centralized control is desired.

Self-adaptation in nature is performed in a more uncontrolled way than in engineered networks. This process is mainly driven by two key factors: *fluctuations* and *feedback*. Fluctuations are essentially ubiquitous in nature, ranging from random interactions on molecular level [3] as the building blocks of life to the random mutations of chromosomes in the DNA as evolutionary process from one generation to the next. However, these fluctuations alone would make the system change uncontrollably, so also a form of feedback is needed to adapt to states that lead to a higher chance of survival. This may consist of *negative feedback* by "learning" from previous bad experiences, or *positive feedback* that helps to generate new structures and finding new solutions.

Both, fluctuations and feedback can be found in the dynamics of gene regulatory networks, which can be described by an attractor selection formulation [4]. The original biological model is based on experimental results on mutually inhibitory operons of E. coli cells and their reaction to the lack of a nutrient in the environment. The adaptation is driven by the inherent noise in gene expression, however, there is a feedback in the form of an activity function which controls the growth rate of the cell.

The attractor selection concept has been previously applied to information networks for selecting appropriate paths in overlay networks [5], [6]. However, in this paper we extend the previous work by taking a key issue in multipath routing into account: the in-order delivery of the packets. In multipath routing, packets are delivered over several different paths and these may differ in latency, bandwidth, and packet loss, which causes unwanted consequences, e.g., out-of-order delivery due to different latencies, so that a reordering at the receiver may become necessary. By appropriately scheduling the packets over stable paths using attractor selection, we show that we can improve the performance over simple conventional schemes. The major benefit of our proposal is that its dynamics is formulated in a mathematical equation system instead of using an explicit algorithmic specification. By this way we avoid the need for defining specific rules for all possibly occurring cases, but can simply describe the dynamics of our approach as a "no-rule" and noise-assisted path selection strategy, making it also especially robust towards small perturbations.

This paper is organized as follows. In Section II we will discuss a considered overlay network scenario and elaborate on the considered problem we are specifically addressing in this paper. Our proposal is based on the biological attractor selection concept, which we will briefly summarize in Section III, before proposing a scheme of how to specifically perform the selection in a multipath overlay network in Section IV. Simple numerical evaluations of our proposal will be provided in Section V and we conclude this paper in Section VI with a brief outlook on future extensions.

II. Packet Scheduling in Multipath Overlay Networks

Before we describe the proposed concept, let us discuss the problem we are dealing from the viewpoint of overlay

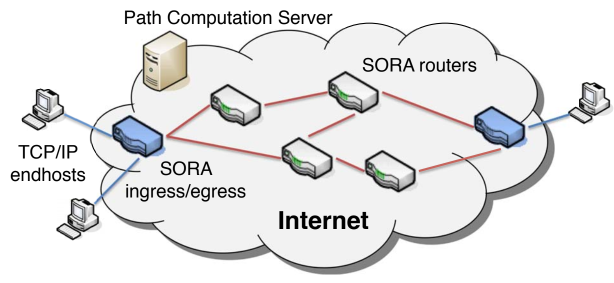


Fig. 1. Simplified SORA overlay architecture

networks. In principle, overlay networks are dynamically-generated networks on application layer, operating over the IP network topology. The advantage of using an application-layer topology is that traffic engineering can be performed in a more application-oriented way, without needing to change the underlying Internet structure and its OSPF routing.

However, it also facilitates the application of directing the traffic not over single paths, but utilizing path diversity over multiple overlay paths constructed from a source node to the destination node. This results in a better ability to distribute the traffic load (*packet dispersion*) over multiple paths and a higher robustness in the case of link failures. Some implementations, such as Resilient Overlay Networks (RON) [7], Scalable One-hop Source Routing (SOSR) [8], or AI-RON-E [9] have demonstrated the advantages of overlay networks utilizing multipath routing.

On the other hand, this benefit comes at the cost of having to deal with the problem of packet reordering at the destination. As more packets are sent over paths with varying latencies, there is a higher risk that these packets will not be received in their proper order at the destination node. Usually, a buffer at the destination node will be able to compensate for some slight variations among the path latencies. However, too large delay variations between packets will have a severe detrimental impact on the behavior of TCP, as when the destination buffer overflows or timeouts occur, the congestion window of TCP will be decreased, leading to a degradation in performance.

The considered scenario is shown in Fig. 1. We assume an overlay network topology that resembles SORA [10], [11], where virtual network instances are implemented as IP routing overlay networks. Beside SORA-enabled routers, the virtual network consists of a dedicated path computation server, which computes virtual network paths between the SORA-enabled routers on-demand. At the end points, unmodified TCP/IP end-systems are connected and their access is via specific SORA ingress/egress routers acting as proxies.

In [11], three possible locations are stated where countermeasures for dealing with out-of-order packets can be taken: at the sender, in the network, at the receiver. While [11] focuses on the control at the receiver, we propose in this work a coordinated mechanism between sender and receiver based on the biologically inspired attractor selection method that we describe in more detail in Section III.

III. The Concept of Attractor Selection

Attractor selection was introduced in [4] by examining in experimental studies the exposure of mutually inhibitory operons of *Escherichia Coli* cells to different media where certain nutrients are available or not. In molecular biology, such experiments are usually carried out by modifying the genetic structure of cells by attaching a fluorescence protein to their operons. The level of fluorescence can be measured to obtain empirical results in the long term dynamics when exposed to a certain environmental condition. In [4], a mathematical model based on their experiments is constructed using a system of stochastic differential equations (SDE) that show the basic reaction and it was observed that convergence to attractors is achieved under certain environmental conditions. However, as biological systems do not adapt instantly to environmental changes, they are driven by the inherent noise in the dynamical system, causing its orbit to approach an attractor through a feedback mechanism.

A. Basic Mathematical Model

The fundamental equation system derived in [4] can be formulated by the following *Langevin*-type of stochastic differential equation system in Eqn. (1). Note that in the following all quantities will be time-dependent functions, so for the sake of readability we will not specifically add the functional dependence on time in our notation.

$$\frac{dx_i}{dt} = f(x_1, \ldots, x_N)\,\alpha + \eta_i \quad i = 1, \ldots, N \qquad (1)$$

The x_i represent the concentrations of the mRNA, f is a function which determines their dynamics, and α is the cell growth rate or activity, which is a function of time indicating the suitability of the current state to the environment. The values η_i are used for modeling the intrinsic noise in gene expression.

From Eqn. (1), we can already observe and discuss the basic dynamics of the system. If the growth rate α is large, the dynamical behavior is determined by the function f. If the steady state solution of Eqn. (1) is a stable attractor, the system will settle in this equilibrium state regardless of the present perturbations until disrupted by a change in the environment. On the other hand, if α approaches or becomes 0, the influence of the first summand on the right-hand side of Eqn. (1) diminishes and the entire dynamics is only influenced by η_i, essentially resulting in a random walk.

B. Formulation of the Attractor Dynamics

In [12], the cell growth rate was investigated and the gene regulatory network was modeled as an on/off-type of expression, which directly feeds back to the growth rate of the cell through its metabolic flow. Cells which have a large growth rate have the ability to perform *mitosis*, i.e., the separation of a cell into two genetically identical cells. The model used there is very similar to the mathematical models for recurrent neural networks and we will use the gene regulatory dynamics of [12] as the basis for our proposed model.

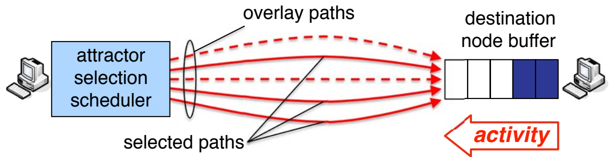


Fig. 2. Attractor selection for multipath scheduling

The dynamics of the considered attractor system is given by the following equation system for $i = 1, \dots, N$.

$$\frac{dx_i}{dt} = \left[s\left(\sum_{j=1}^{N} \alpha\, w_{ij}\, x_j - \theta \right) - x_i \right] \alpha + \eta_i \tag{2}$$

Here, the w_{ij} are weights, which in the original model indicate if one protein i activates or inhibits another protein j. In the context of neural networks, these weights can be adapted over time to store the patterns and perform learning, but as in [12] we assume here only constant weights. The function s is a sigmoid activation function with activation threshold θ.

$$s(x) = \frac{1}{1 + e^{-x}}$$

So far we have not yet discussed about the definition of the activity function α. In [12], the growth rate was controlled by the metabolic flow in the cell regulated by the current gene expression levels x_i. In order to apply the attractor selection concept to multipath packet scheduling we need to define α according to our objective. In the following section, we describe how we propose to apply this method to the in-order packet scheduling problem.

IV. Multipath Packet Scheduling with Attractor Selection

Let us assume that an endhost accesses the SORA overlay network through an ingress router and establishes a session to another endhost. The path computation server delivers on-demand a set of N possible overlay paths between source and destination node. Now the problem we face is how to schedule the packets over each of these paths. It is obvious that due to cross traffic and other contributing factors, each path will have a different time-dependent latency l_i for delivering a packet to the destination node over path i. Small variations in packet delivery latency can be compensated by the receiver node's buffer, however if the buffer's capacity is exceeded or the delivery of the packets to higher layers is overly delayed, it would have severely detrimental effects on TCP traffic.

Our considered scenario is outlined in Fig. 2. Out of the set of N predetermined paths, the attractor selection scheduler chooses several paths which seem best suited. The selection of a path for each packet is done with a probability proportional to x_i. Since we assume no explicit knowledge of the quality of the paths, each path has the same function f in Eqn. (1). This is expressed by a completely mutually inhibitory weight matrix with self-activation, i.e.,

$$w_{ij} = \begin{cases} 1 & i = j \\ -\frac{1}{N-1} & i \neq j \end{cases}. \tag{3}$$

Since the sum of the weights is $\sum_{j=1}^{N} w_{ij} = 0$, there will be a balanced number of active paths as inactive ones expressed by the values x_i and we can set the threshold $\theta = 0$. However, it is also possible to extend or limit the number of active paths by changing this sensitivity parameter.

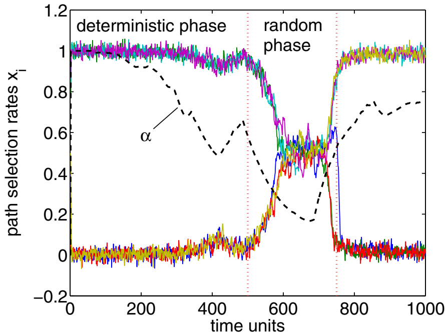
When we now consider that a packet is sent from the source, it will take a path randomly chosen proportional to the distribution of the x_i values. As soon as the packet arrives at the destination node's buffer, the feedback will be generated through the activity value α. Our intended mode of operation is as follows. If the buffer occupancy is small, it is not so important which path is selected. So the selection may be done more randomly (small α value). On the other hand, when the buffer occupancy b at the destination node increases, we want to have a better control over the system and a higher α. We, therefore, select the activity dynamics of α as in Eqn. (4)

$$\frac{d\alpha}{dt} = \rho \left(\frac{b}{B} - \alpha \right) \tag{4}$$

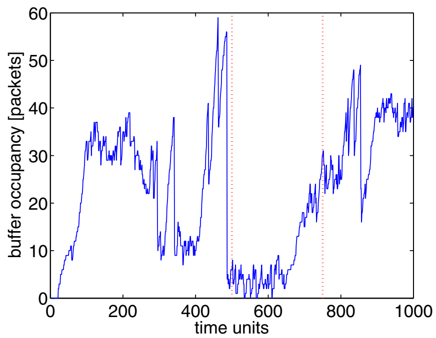
where ρ is the rate of adaptation of α and B is the maximal experienced buffer occupancy. Since the conditions of the environment may change significantly over time, we select B over a limited sliding window and not the entire history over time in order to avoid reacting to outdated peak values.

The dynamics of Eqn. (4) can be explained as follows. Basically, the activity α follows the relative buffer occupancy b/B. So, when the buffer becomes full, we want a tighter and more deterministic control by following the differential equation system. On the other hand, when the buffer occupancy is low, path selection is more random and not as strictly controlled.

An exemplary result of the dynamics for $N = 6$ paths is shown in Fig. 3. In Fig. 3(a) the dynamics of the path selection rates x_i are shown and the activity α is indicated as dashed line, while Fig. 3(b) shows the corresponding dynamics of the buffer occupancy. In all of our experiments, time is discretized in time units (e.g. 100 ms) and every 200 time steps the latencies of all paths are randomly reset. From this experiment we observe the following behavior. In general, there are two phases, a *deterministic phase*, when the buffer occupancy is high and a *random phase*, when the buffer occupancy is low, and the transition between these phases is triggered by α. Furthermore, It can be seen that the selection mechanism is rather stable. This is manifested through the fact that although every 200 time steps the whole environment is changed, the attractor (and hence the associated selected paths) remains the same until about time step 500, when the buffer occupancy drastically drops and the system recovers to enter the random selection phase. However, after about time step 750, the increase in buffer occupancy results in a return to the deterministic phase at a different attractor from the previous one.



(a) Selection rates



(b) Buffer occupancy

Fig. 3. Example of attractor selection based scheduling dynamics

V. Numerical Experiments

In this section we briefly discuss some experimental results obtained from simplified numerical simulations. The purpose of these experiments is to show qualitative results of the dynamics rather than quantitative values.

A. Simulation Settings

In the following experiments we consider that $N = 4$ and $N = 10$ paths are given by a path computation server. At each time step a packet is generated at the source node with a probability p, resulting in a geometrically distributed packet interarrival time with mean $T = (1-p)/p$. The buffer at the destination node is assumed to have infinite capacity and out-of-order packets are buffered first until all packets with smaller id have been received. Each individual simulation experiment is performed for 10000 time units and at an interval of $T_d = 200$ time units the delays of all path transmission durations is uniformly randomly reset between $[0, d_{max}]$. We set the value of d_{max} to 100 time units. The internal noise values η_i in Eqn. (2) are zero-mean Gaussian random variables with a standard deviation of $\sigma = 0.02$. Activity α is computed with an adaptation rate $\rho = 1/T_d$ and the window for considering the maximum buffer size B is also T_d.

We compare the attractor selection mechanism to an entirely random selection and both methods are not aware of the actual latencies that are required for each path and stochastically select the path for transmission on a packet by packet basis. In the following, we will investigate as values of interest, the

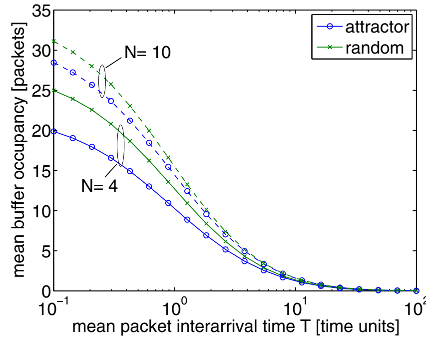


Fig. 4. Mean buffer occupancy over interarrival time

mean buffer occupancy, the mean packet delay, and the mean packet reordering ratio for both methods and all results are obtained from averaging over 10000 experiments.

B. Mean Buffer Occupancy

Fig. 4 shows the mean buffer occupancy in number of packets for attractor selection compared to random selection as a function of the packet interarrival time T. As expected, both curves drop with increasing T since the packet generation time increases over transmission time. It should be noted that especially for small packet interarrival time the buffer occupancy is much smaller for attractor selection compared to random selection. As expected when the inter-packet time T becomes very large, all packets are transmitted smoothly without buffering. The curves for $N = 10$ lie above those for $N = 4$ since the larger number of paths results in a higher variance among the latencies of the actually selected paths.

C. Mean Packet Delay

Since we assume that the buffer at the receiver is of infinite capacity, no packets are actually dropped in these simulations. However, when the packet arrival rate is high, i.e., interarrival time is small, and the latencies over each path differ significantly, there will be a larger queuing time required. Fig. 5 shows the mean packet delay over the packet interarrival time T. In general, these curves correspond to those of the buffer size and attractor selection results in smaller average packet delays. For large T all curves approach 50, which is the mean of the uniformly selected latencies between $[0, d_{max}]$.

D. Mean Reordering Ratio

Our key metric that we want to investigate is the ratio of packet reordering. This value is obtained by counting all packets which remain in the buffer on arrival over all received packets, see Fig. 6. Again we can see that when the packet interarrival time T is relatively large compared to the latencies, both methods achieve nearly equal performance. However, in both cases a peak exists until which the reordering ratio increases with T.

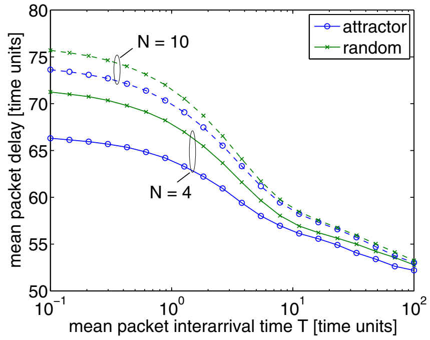


Fig. 5. Mean packet delay over interarrival time

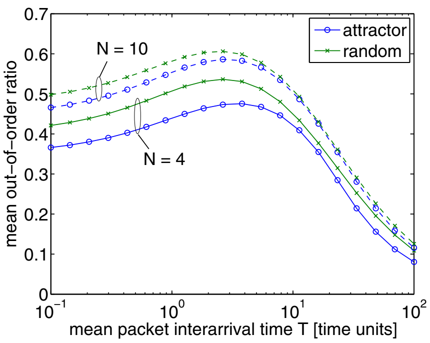


Fig. 6. Mean packet reordering ratio over interarrival time

E. General Remarks

These simple experimental results show that when there is no knowledge of the environmental changes and a probabilistic path selection mechanism is performed, the attractor mechanism can perform better when it comes to in-order packet scheduling than an entirely random selection. By fine-tuning the parameters, as well as adapting the attractors to values derived from the actual path latencies, attractor selection can be even further improved in its stability and performance.

VI. Conclusion and Outlook

In this paper we proposed the application of the biologically inspired attractor selection scheme to the path selection problem in multipath overlay networks. Unlike our previous work, we do not solely consider the problem of selecting only a single best path out a pool of candidate paths [5], [13] on flow level, but stochastically select the path for each individual packet from a set of active paths, which are determined by the attractor selection scheme. The only input that is taken into account is the feedback of the relative buffer occupancy level, which is used to control the stochastic selection process.

In general the current method already shows a highly robust and self-adaptive behavior resulting in less out-of-order packets and less path flapping. However, the mechanism can be further improved in several ways. The first possible improvement is to remove the restriction on the system only being mutually inhibitory, but to also take information of the environment into account. This would result in a better definition of the attractors, which corresponds to a better set of active paths. Furthermore, since the general definition of the equation system resembles that of a stochastic recurrent neural network, the weights may be adapted based on “learning” from a noisy environment [14]. Another issue that we have only briefly covered here is the formulation of an appropriate activity function. In this paper we only take the relative buffer occupancy level into account. However, other metrics of interest, such as packet delay, drop rate, or available bandwidth could be included in the feedback as well. Finally, our goal is to conduct similar experiments as in [10] using the Emulab [15] overlay testbed environment to prove the practical applicability of our approach.

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