IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 10, 2022, accepted May 9, 2022, date of publication May 12, 2022, date of current version May 17, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3174578

Computing Effective Vehicular Network Connectivity Using Gaussian Based Attractor Selection Technique (GAST)

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ABSTRACT Decentralized Traffic flow management in its core depends on vehicular wireless communication. Now and beyond 5G communication networks will rely heavily on high-capacity and ultra-reliable vehicle communication. However, when vehicles are roaming on the road attempting to interact with each other, the vehicular communication problem gets more complicated. This work investigates through MATLAB simulation the applicability of E.coli stable gene derivatives that responds to network pattern changes in terms of signal quality and stability in order to reach acceptable level of connectivity under changing environment. In essence, this work incorporates biologically based approach instead of the conventional one, which can be achieved through an attractor selection process known for being adaptive to dynamically changing surroundings. The work combines Gaussian interpolation function with the attractor selection functions to achieve better and more reliable connectivity with controllable coverage and signal spread with soft transition between network connections. To validate and support using Gaussian interpolation, simulation results obtained regarding both the original attractor selection model and the modified model. Simulation is carried out under different network activities and noise levels for two network providers to vehicular communication. Simulation results indicated better performance using attractor selection algorithm with Gaussian interpolation compared to the standard attractor selection algorithm in terms of network state allocation and stable states attainment under both different network activities, dissipation values, and different noise levels. The work proved that Gaussian-based attractor selection algorithm is much more efficient utility function compared to the standard one.

INDEX TERMS Attractor selection, connected vehicles, intelligent transportation system, Gaussian interpolation, network connectivity.

I. INTRODUCTION

The main objective of intelligent transportation systems (ITS) is to enable interaction between vehicles and roads in a safe and reliable manner. In addition, applying the principles of ITS will contribute towards increasing the efficiency of infrastructure and enable a more relaxed and comfortable journeys. Thus, there is a need for all travelling vehicles sharing the same road over a period of time, speed, distance, and location to share and exchange information, together with information from traffic management centers and from traffic control centers [1].

To achieve intelligent transportation systems objectives, vehicular ad-hoc network (VANET) is implanted, in order to enable information exchange among vehicles [2]–[5]. This is achieved using on board units (OBUs), thus forming temporary networks and exchanging at the minimum basic safety messages (BSMs), which provide vehicle trajectories including speed, location and distance, while sharing same road within a transmittable distance [6]. Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication have the common factor of vehicles that needs to have stable, low latency, efficient, and secure communication dealing with different networks and different devices [7]–[10].

Vehicular ad-hoc networks enables a wide range of applications with main objective of reducing accidents and congestion on the roads that result in many cases from unsafe

The associate editor coordinating the review of this manuscript and approving it for publication was Geng-Ming Jiang.

driving, weather conditions, traffic incidents, or simply from traffic mismanagement and drivers' conditions. Cooperative driving principles with intelligent algorithms, plays a pivotal role in traffic monitoring and management. The developed wireless communications standards can be effectively used to efficient enable vehicular communication through Vehicular Ad-Hoc Networking using Dedicated Short Range Communication (DSRC) as a promising technique [11]–[14].

It is critical to be able to effectively assess communication links quality associated with communication channel propagation characteristic used by connected vehicles in order to achieve more efficient communication and enable better traffic management and congestion control with emphasis on safety. Thus it is of prime importance to examine communication route or path length connecting two vehicles with its associated parameter of Network link stability (NLS). Link stability and sustainability is considered a main factor in characterizing network performance for connected vehicles. Communication link properties is closely related to vehicles speed, physical distance, and route hops, energy consumed, communication time, among others [15]–[19].

At the core of traffic management is the control of dynamic traffic flow, which include control of signals and data exchanges between vehicles and other vehicles and between vehicles and infrastructure in an integrated way. Signal stability and control plays a critical role in traffic flow behavior, which is a function of their time duration and signaling sequence and can be very complex due to the large number of vehicles within the traffic network with big data association. Various intelligent, predictive and data mining systems are used to enable adaptive data collection and decision making to enable optimum control. These algorithms include neural networks, fuzzy logic, genetic algorithms, among others, but concentrated in many cases on simplified models or isolated areas [20]–[23].

The dynamic non-linear character of traffic with increasing demand and the requirement for greater road capacity pose numerous obstacles to all proposed approaches to handle traffic flows. Due to network expansion, this adds complexity to traffic management and necessitates both centralized and decentralized adaptive techniques to address basic challenges like randomization, scalability, and big data.

Intelligent transportation systems (ITS) aspire to provide local, regional, and worldwide traffic control management that can intelligently and dynamically adapt to changing traffic conditions while also being able to operate in a distributed environment.

One of the solutions to the vehicular connectivity challenges in terms of reliability and stability, is a biological based system, which is both adaptive and evolutionary. Such system will employ some of the dynamics and characterisitics behavior of biological cells, where gene stability models is considered with its reaction to changing surrounding conditions.

This approach can be used in managing traffic in an adaptive manner, as biological cells have acquired over years of evolution some favorable characteristics. Such characteristics have given them abilities to adapt to surrounding environment, and modify their behavior and state accordingly. This method will help to support self-organizing functions that may successfully work as part of a distributed framework [24].

A particular cell type model that can be used to mitigate connectivity problems, is the Escherichia coli (E. coli), which follows an adaptive behavior called Attractor selection (AS). Modeling of the Escherichia coli biological system constitute adopting the behavior change due to surrounding and environmental factors that affect the system behavior through either adding nutrition to the cell or restricting the cell mechanisms and functions. This adaptive behavior gives the E.coli ability to change from a specific genetic condition to another, thus creating states that adapt better to the new changes. This mechanism enables the modeled biological system to be robust against external variations [25]–[28].

The E.coli model that supports dynamic changes resulting in good performance with state stability, will enable reliable interaction under new environments and dynamically changing conditions. This mechanism can be used in resolving many traffic problems and in particular issues related to vehicular communication and routing of messages between vehicles and between vehicles and infrastructure. Because it is designed after biological cell interaction, which is based on resource sharing between cells, this technique will enable better management of various communicating networks and give improved network connectivity. Attractor selection can thus be used to adapt V2V and V2I communication to changing traffic conditions [29], [30].

A biological cell will change its behavior as a result of environmental effects, which include outside signals that either contributes energy to the cell or negatively affect the cell growth and interaction (noise), and able to shift and flips from a specific genetic condition to another. This behavior results in the creation of phenotypic states that adapt better to the new surroundings and environmental changes. The dynamics fits within an attractor pattern, thus producing attractor states as a result of interactions. The formation of such states enables the modeled cell to be robust against variations in the surrounding environment [31].

The Attractor Selection Model, which reflect the E.coli stable gene presentation in a dynamic cell environment will enable implementation of intelligent, adaptive vehicular communication system that mimics the biological cell behavior. In addition, it has the capacity to avoid being affected by external factors due to varying traffic conditions, and unwanted patterns causing instability and transient levels (noise). This will support application of functions in a smart and distributed manner with ability to operate under limited network resources and fewer inputs in a similar way that the E.coli cell adapts to change in nutrition and lack of resources.

In this work, network connectivity for vehicles and vehicular communication is modeled as an E.coli biological cell that employs attraction selection mechanism to dynamically adapt to a more stable, stronger, and efficient communication network. The objective is to enable V2V and V2I connectivity, as a function of changing environment, which includes signal strength, bandwidth, and stability over distance, attenuation, fading among others. The concept in this work is to guarantee quality of service by making sure that at least one connection to a network is available under all different conditions. This can be applied to centralized communication (V2I) and to decentralized communication (V2V) or a combination of both using node-based communication that enables temporary vehicular clouds to be formed between vehicles or between vehicles and sensors within the infrastructure using radio wave communication such as Dedicated Short Range Communication (DSRC). Modeling is carried out using both standard function and Gaussian interpolation function. The Gaussian interpolation is used to enable better network connectivity selection with higher stability and ability for more reachability and control over the connectivity status and dynamics. This will enable better congestion control, mobility enhancement, and higher efficiency of traffic movement through adaptive resource allocation that provides optimum radio channel connectivity, thus enabling higher QoS.

The rest of this paper is divided as follows: Methodology, Results and Discussion, Conclusions, References

II. METHODOLOGY

The need to access vehicular network services is on the increase, which requires robust wireless communication infrastructure, which will allow different types of networks such as cellular, Wi-Fi, WIMAX, WLAN, LPWAN, and DSRC to coexist and operate efficiently, and to enable V2V and V2I effective communications [32]–[34].

One critical issue in the vehicular wireless networks is to decide which network provides optimum and best connectivity under a dynamic environment. This decision is important in order to enable vehicles to form temporary networks for certain amount of time to exchange messages until they disperse and form other new temporary networks. Also, consideration for a stable connectivity with infrastructure using Road Side Units (RSUs) along the travelled path needs to be considered. Such decision should not only be based on efficiency but also on fair distribution of network resources like bandwidth and network speed.

Research dedicated to analysis of biological systems and their behavior, resulted in the findings that their principles can be utilized to inject intelligence and adaptability to vehicular communication as a distributed systems in a dynamic environment, which reflects the desired decentralized vehicular connectivity that depends on self-organization, and cooperation. This will contribute towards better scalability and design optimization through new biologically based models.

The approach in this work operates on the principle of having stable gene formulations of Escherichia coli that responds dynamically to traffic changes and influence vehicular communication. The behavior of V2V and V2I communication and their adaptability and efficiency under such biologically controlled system is investigated using AS. This will enable balancing of channel loads with dynamical traffic variation, such that the communication channel is adaptable to communication channel load variation, thus providing stable connectivity. The used algorithms shows the effectiveness of bio-intelligence, specifically regarding selection of specific network over other networks.

The following traffic issues can be resolved using Attractor Selection:

1. The nonlinear and dynamic behavior of Traffic accessing roads.
2. The high computational complexity and cost of traffic networks coverage.
3. The advantage of implementing de-centralized traffic wireless communication.
4. Effective, efficient and balanced network resource allocations.
5. Provision of optimum service for vehicular users.
6. Enable self-adaptive and dynamic vehicular network selection.

The presented simulation model in this work is based on the following:

1. Two available network providers
2. Implementation of AS Technique.
3. Implementation of modified Attractor Selection Technique using Gaussian interpolation function with ratio parameters and spread coefficient (β).
4. Different noise levels to characterize the adaptive behavior of the biological model as mapped into vehicular connectivity model.
5. Different values of connectivity generation and dissipation in order to understand the model behavior under various rates of connectivity and lost connectivity.
6. Comparison of AS Technique results and Gaussian based Attractor Selection Technique (GAST)

The simulated environment assumes that each vehicle can only connect to the best network at a time. Such network should be able to allocate sufficient network resources to all communicating vehicles, and provide fair allocation of bandwidth.

The modeled connectivity assumes a steady flow of traffic with and without noise, which is assumed as a white Gaussian noise. The added noise affects connectivity in terms of signal strength, bandwidth variation, fading, attenuation, and path loss, thus affecting stability, which in turn and according to the E.coli model will initiate cell activities in order to reach a new stable state in relation to the new pattern in order to preserve network communication. This in the biological cell sense is survival and adaption to changes in the surroundings. Thus a more selective, sensitive and adaptive function such as Gaussian interpolation is needed to enable better network connectivity optimization with dynamic and smooth stable state transition.

TABLE 1. Nomenclature.

Symbols/ Acronyms	Meaning
γ	Network Activity (Selection Probability)
N_l	Available Vehicular Network provider
V_{thrl}	Vehicular Threshold Connection level
V_l	Vehicular Connection
S_l	Sensitivity to Environmental Change
P	Rate of generating γ
C	Rate of terminating γ
$G(\gamma)$	Connectivity generation rate
$R(\gamma)$	Connectivity dissipation rate
Wgn	White Gaussian Noise
β	Gaussian Width or Coverage
v_{i},j	Vehicular Connectivity to Network Provider
$v_{MAXi,j}$	Maximum Vehicular Connectivity to Network Provider
Dynamic State Selection	Variation in Vehicular connectivity Level to Network Provider which is related to the probability of selecting a stable state.

The proposed methodology is realized by considering a selective vehicular connection to currently formed vehicular networks influenced by attractor selection principles such that each connection is modeled as an individual biological cell with different connections due to different vehicles as cell population.

This approach contributes to enhancing transportation efficiency, by considering connections effect on each other as biological cell interaction that share same environment and resources and dynamically adjust to external changes through achieving new stable levels. The presented method is based on the mapping the E.coli dynamics to represent the network selection mode for a distributed traffic management system using AS as follows with symbols/acronyms and their meaning presented in Table 1.

To model the attractor selection mechanism for the purpose of decision making that supports the selection of the best network connectivity from available networks in a dynamic wireless environment. The concept of fitness is used employing a utility function associated with the E.coli characteristic function. This will provide adaptive solution that mimics the E.coli biological system with bio-inspired selection mechanism.

Assuming that there are V cluster of vehicles on the road trying to connect to N cluster of available networks, then the E.coli cellular activity (vehicular network activities) model is represented by network activity (γ) and can be represented as in equation (1), [12], [20], [25].

$$\left(\frac{d\gamma}{dt}\right) = \left(\frac{P}{\prod_{l=1}^{K}\left(\frac{V_{thr\,l}}{N_l+V_l}\right)^{S_l}+1}\right) - C^{*}\gamma \tag{1}$$

A vehicle v_{i} in cluster V_l can connect to a network node j in cluster N_l providing best connection as in the pair $\{v_{\mathrm{i}}, \mathrm{j}\}$. However, to be able to judge that the connection as the best or optimum connection, a simple utility function can be used to ensure that this selection is an AS. This is shown in equation (2), [20].

$$\left(\frac{d\,(v_i,j)}{dt}\right) = \left(\frac{G\,(\gamma)}{1+(v\,(_{MAXi},j)-(v_i,j))^2}\right) - R\,(\gamma)^{*}\,(v_i,j) + (wgn_i,j) \tag{2}$$

Equation (2) can be further modified to allow better coverage of the network activities using Gaussian hill-like function with interpolation as presented in equation (3).

$$\left(\frac{d\,(v_i,j)}{dt}\right) = \left(\frac{G\,(\gamma)}{1+((v_{MAXi},j)-(v_i,j))*\exp\left(\frac{-((v_{MAXi},j)-(v_i,j))^2}{2\beta}\right)}\right) - R\,(\gamma)^{*}\,(v_i,j) + (wgn_i,j) \tag{3}$$

Vehicular connectivity should occupy a stable state (no variations or fluctuations) with a selected network in the network cluster N_l. Thus:

$$\left(\frac{d\,(v_i,j)}{dt}\right) = 0 \tag{4}$$

It can be safely assumed according to equation (4) that the Gaussian white noise at stable connectivity can also be ignored. Gaussian White Noise with zero mean appearing in equations (2) and (3), reflects E.coli cell activities trying to form stable states in order to reach stability and survival. This model is related to the represented network activities responding to changes in traffic connectivity pattern, before link connectivity reaches stable state with acceptable channel properties. Thus:

$$wgn_i,j = 0 \tag{5}$$

Applying equations (4) and (5) to equation (3), results in equation (6):

$$\left(\frac{G\,(\gamma)}{1+((v_{MAXi},j)-(v_i,j))*\exp\left(\frac{-((v_{MAXi},j)-(v_i,j))^2}{2\beta}\right)}\right) - R\,(\gamma)^{*}\,(v_i,j) = 0 \tag{6}$$

Equation (6) is represented as in equation (7)

$$\left(\frac{G\,(\gamma)}{1+((v_{MAXi},j)-(v_i,j))*\exp\left(\frac{-((v_{MAXi},j)-(v_i,j))^2}{2\beta}\right)}\right) = R\,(\gamma)^{*}\,(v_i,j) \tag{7}$$

Dividing Both Sides by $R(\gamma)$ to obtain a vehicular connectivity expression, yields equation (8).

$$\left(\frac{\left(\frac{G(\gamma)}{R(\gamma)}\right)}{1+((v_{MAXi},j)-(v_i,j))*\exp\left(\frac{-((v_{MAXi},j)-(v_i,j))^2}{2\beta}\right)}\right) = (v_i,j) \tag{8}$$

Assuming that the ratio of connectivity generation to connectivity dissipation rate has values related to stable states and its ratio is deterministic per stable state, then the ratio can be represented as in equation (9).

$$\left(\frac{G(\gamma)}{R(\gamma)}\right) = \varphi \tag{9}$$

Using equation (9), equation (8) becomes equation (10):

$$v_i, j = \left(\frac{\varphi(\gamma)}{1+((v_{MAXi}, j)-(v_i, j)) * \exp\left(\frac{-((v_{MAXi}, j)-(v_i, j))^2}{2\beta}\right)}\right) \tag{10}$$

Considering equation (10) and referring to equation (2) and equation (3), with the inclusion of the Gaussian interpolation function, the following can be stated:

1. Equations (2) and (3) are related to equation (1) through $v_{i,j}$ that connects cluster V_1 to N_1.
2. The difference between equations (2) and (3) is the Gaussian interpolation function, which enables better selectivity, sensitivity and gradual movement from stable state to another one in response to traffic pattern changes.
3. The function in equation (10) is valid and is based on the assumption that steady states are formed under two environments, noiseless and noisy. It is also based on the E.coli biological behavior that aims to survive under all nutrition conditions. Thus, equation (10) can be used to compute effect of nutrition provision, which is modeled as $G(\gamma)$ and its consumption, modeled as $R(\gamma)$, on connectivity and stability regardless of presence of noise, as noise effect is eliminated through the survival mechanism of the E.coli cell.
   This is regarded as an adaptive and intelligent process. The Gaussian interpolation function enables better control and optimization of the modelled E.coli cell behavior through the coverage or spread parameter (β), in addition to symmetry in response. This enables a bidirectional connectivity approach, which makes its selectivity and sensitivity much more than that of a standard function.

The Gaussian interpolation function in equation (10), will converge to distinct solutions:

For $v_i, j \neq v_{MAXi}, j$, then equation (10) can be represented as shown in equation (11):

$$v_{i,j} = \left(\frac{\varphi(\gamma)}{1+\delta}\right) \tag{11}$$

where δ is given by:

$$\delta = \left(((v_{MAXi}, j)-(v_i, j)) * \exp\left(\frac{-((v_{MAXi}, j)-(v_i, j))^2}{2\beta}\right)\right) \tag{12}$$

From equations (10) to (12), equation (13) is obtained:

$$\lim v_i, j = \varphi(\gamma)$$
$$v_i, j \rightarrow v_{MAXi}, j \tag{13}$$

Equation (13) indicates that as v_i, j gets closer to v_{MAXi}, j, then the difference between them is reduced such that there might be a point reached whereby they equate.

Thus for, $v_i, j = v_{MAXi}, j$, then

$$\delta = \left(((v_{MAXi}, j)-(v_i, j)) * \exp\left(\frac{-((v_{MAXi}, j)-(v_i, j))^2}{2\beta}\right)\right) = 0 \tag{14}$$

The result obtained in equations (13) and (14) can also be observed if the difference between v_i, j and v_{MAXi}, j is very large. Thus if $v_{MAXi}, j \gg v_i, j$, then:

$$\delta = \left(((v_{MAXi}, j)-(v_i, j)) * \exp\left(\frac{-((v_{MAXi}, j)-(v_i, j))^2}{2\beta}\right)\right) \rightarrow 0 \tag{15}$$

From the previous discussion and equations (11) to (15), considerations for connectivity generation ($G(\gamma)$) and connectivity dissipation ($R(\gamma)$) in relation to stable states can be obtained as presented in equations (16) and (17).

1. Condition1: $v_i, j = v_{MAXi}, j$ as $\delta = 0$

$$\Delta\varphi(\gamma) = \Delta\left(\frac{G(\gamma)}{R(\gamma)}\right) = Min\ Change \tag{16}$$

2. Condition 2: $v_{MAXi}, j \gg v_i, j$ as $\delta \rightarrow 0$

$$\Delta\varphi(\gamma) = \Delta\left(\frac{G(\gamma)}{R(\gamma)}\right) = Min\ Change \tag{17}$$

Using G(γ) and R(γ) as given in the original E.coli biological model presented by equations (18) and (19) together with equations (16) and (17), and $0 \leq \gamma \leq 1$, results in equations (20) and (21), [26].

$$G(\gamma) = \left(\frac{6\gamma}{2+\gamma}\right) \tag{18}$$
$$R(\gamma) = \gamma \tag{19}$$

1. Condition1: $v_i, j = v_{MAXi}, j$ as $\delta = 0, \gamma \geq 0$

$$\Delta\varphi(\gamma)_{\gamma\geq 0} = \left(\frac{-6\gamma^2+12}{\gamma^2+4\gamma+4}\right) = 3 \tag{20}$$

2. Condition1: $v_i, j = v_{MAXi}, j$ as $\delta = 0, \gamma \leq 1$

$$\Delta\varphi(\gamma)_{\gamma\leq 1} = \left(\frac{-6\gamma^2+12}{\gamma^2+4\gamma+4}\right) = \frac{2}{3} \tag{21}$$

Thus, a convergence exists with effective stable states for connectivity in the interval {0.67, 3}, with γ in the range {0, 1}. The level of connectivity is proved to greatly depend on the generation and dissipation of connections, which is a function of network activity used as selection probability (γ) parameter.

The criteria in equations (20) and (21) applies in the case of negligible level of noise and higher rate of connectivity and signal generation compared to dissipation, hence, reliable formation of stable states.

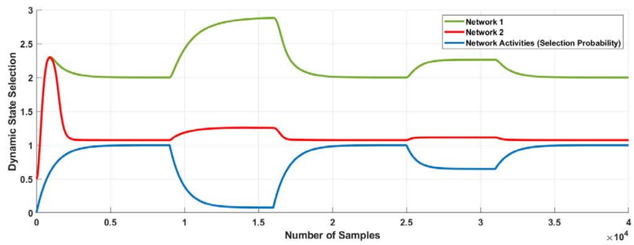

FIGURE 1. **Network dynamic state variation (R(γ) = γ) with Gaussian interpolation.**

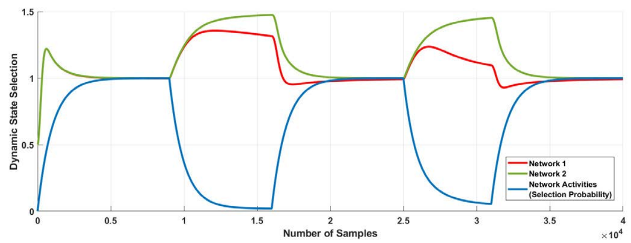

FIGURE 2. **Network dynamic state variation (R(γ) = 2γ) with Gaussian interpolation.**

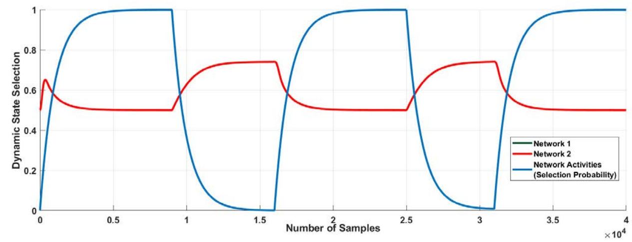

FIGURE 3. **Network dynamic state variation (R(γ) = 4γ) with Gaussian interpolation.**

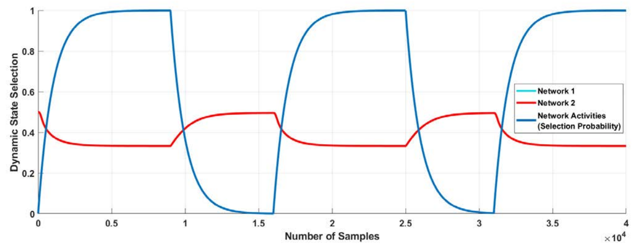

FIGURE 4. **Network dynamic state variation (R(γ) = 6γ) with Gaussian interpolation.**

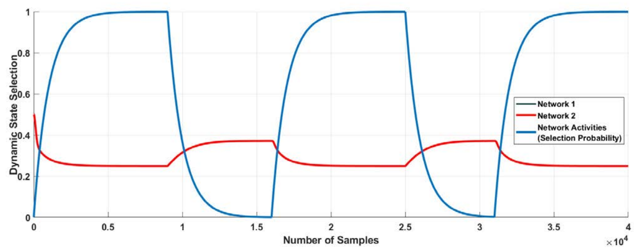

FIGURE 5. **Network dynamic state variation (R(γ) = 8γ) with Gaussian interpolation.**

Testing of the set criteria for stable states under attractor selection technique is carried out using MATLAB simulation. Also, the presented equations indicate that the rate of generation of connections should be sufficient to enable stable state formation through the AS model. This implies that any change in the network activities should be within the computed limits.

III. RESULTS AND DISCUSSION

As a result of cost and connection complexity of implementing real networks, and from flexible design point of view, the proposed work relied on simulation of two networks are used in a MATLAB simulation. The idea is to model real world situation as close as possible in the presence of different networks. A heterogeneous environment is assumed, with vehicles ability to connect to the one with the most stable connection and best channel propagation properties. This adds a feature of competitiveness among networks and network service providers with emphasis on quality of service (QoS). Thus the best connectivity and network with highest stability will prevail.

A. EFFECT OF R(γ) ON NETWORK ACTIVITY AND STABLE STATES USING GAUSSIAN INTERPOLATION

Figures 1 to 5 show effect of increasing the dissipation rate $R(\gamma)$ relative to steady generation rate $G(\gamma)$ for two networks 1 and 2. The simulated results obtained for wgn = −70dBW, effectively 0 Watts. From the plots, convergence phenomenon is noticed between the two network providers, such that the two response curves to network connectivity coincide and overlap starting at $R(\gamma) = 4\gamma$ with continuous reduction in dynamic state selection and connectivity level. This, increasing $R(\gamma)$, will effectively leads to equal selection probabilities for both network 1 and network 2. Thus stable state keeps changing dynamically as a result of generation and dissipation functions $G(\gamma)$ and $R(\gamma)$. Hence, the connectivity stable state level $v_{i,j}$ will be affected and moved between levels as selection probability applies itself. The results are within the calculated values in equations (20) and (21).

B. EFFECT OF WGN ON NETWORK ACTIVITY AND STABLE STATES USING GAUSSIAN INTERPOLATION

Figures 6 to 10 show effect of White Gaussian Noise on the dynamic response and stable state selection for vehicular network connectivity as a function of network activities and selection probability for networks 1 and 2. From the plots, it is observed as the level of noise increases, and as expected signal levels changes and fluctuates causing instability in the dynamic response with assumed conditions in equations (4) and (5) no longer applies, thus signal levels exceeded the upper limit of 3 at high noise level. It is evident that the two networks started to suffer the effect of noise at 1 Watt, but

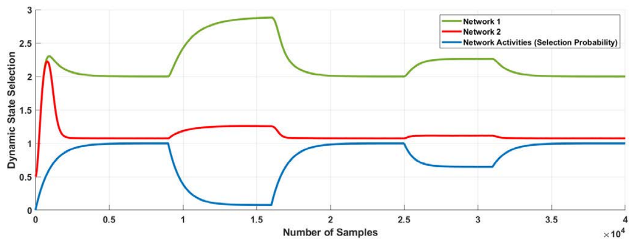

FIGURE 6. Network dynamic state variation Gaussian interpolation (Noise = 0.00001W).

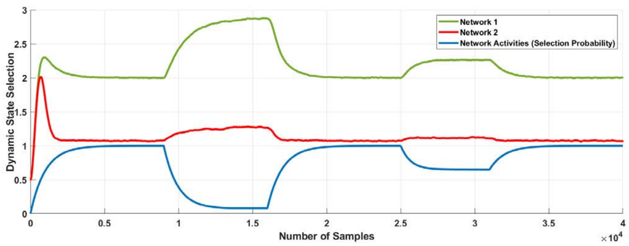

FIGURE 7. Network dynamic state variation with Gaussian interpolation (Noise = 0.001W).

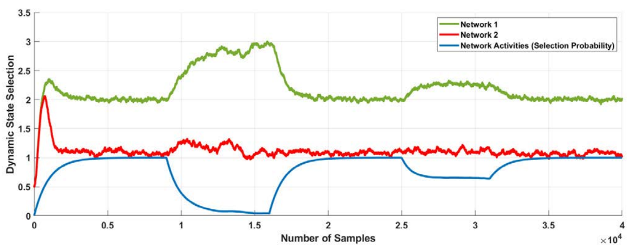

FIGURE 8. Network dynamic state variation (Noise = 0.1W) with Gaussian Interpolation.

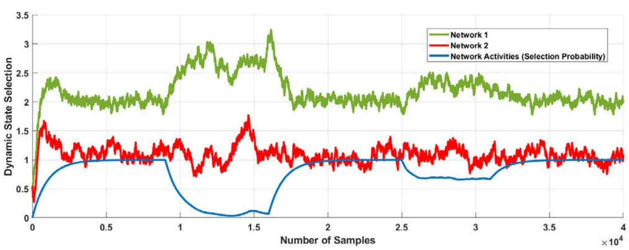

FIGURE 9. Network dynamic state variation (Noise = 1W) with Gaussian interpolation.

still kept their dynamically stable states. However, as noise increases, states in both networks closed on each other, coincided, and overlapped over most of the sampling process, but in part still distinguishable. This effect of separated states for both networks is enhanced using Gaussian interpolation function.

C. EFFECT OF R(γ) ON NETWORK ACTIVITY AND STABLE STATES USING STANDARD FUNCTION

Figures 11 to 15 show effect of increasing the dissipation rate R(γ) of relative to steady generation rate G(γ). The

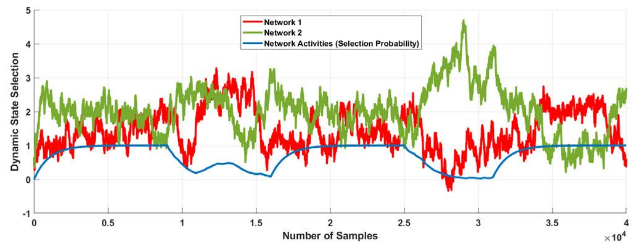

FIGURE 10. Network dynamic state variation Gaussian with interpolation (Noise = 10W).

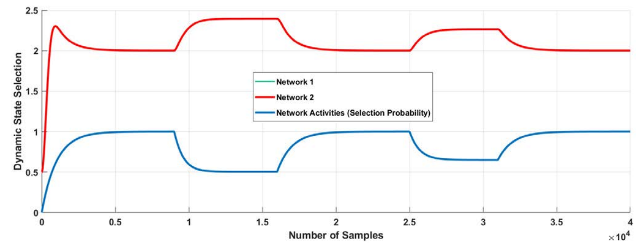

FIGURE 11. Network dynamic state variation (R(γ) = γ).

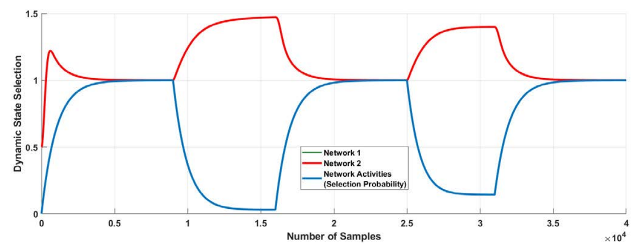

FIGURE 12. Network dynamic state variation (R(γ) = 2γ).

simulated results obtained for wgn = −70dBW, which is effectively 0 Watts. From the plots, convergence phenomenon is noticed between the two network providers, such that the two response curves to network connectivity coincided, and overlapped over the whole range of γ with continuous reduction in signal connectivity level. This leads to the observation that the standard (Non-Gaussian) function does not enable the two networks to have separable stable states at zero noise. Both networks have same selection probability with similar stable states. This effect can partly be explained by considering the two networks behavior (network 1 and network 2) with the provided connectivity, as they both have equal chances and the standard function. However, AS did not detect distinguish and classify one of them as better than the other or more favorable. Thus, standard non-Gaussian function lacks in selectivity.

D. EFFECT OF WGN ON NETWORK ACTIVITY AND STABLE STATES USING STANDARD FUNCTION

Figures 16 to 20 show effect of White Gaussian Noise on the dynamic response of network providers and on the acquired stable states for connecting hosts or nodes. From the plots,

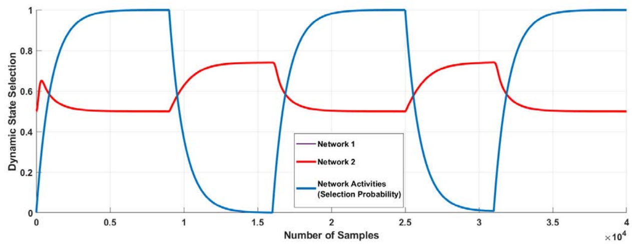

FIGURE 13. Network dynamic state variation $(R(\gamma) = 4\gamma)$.

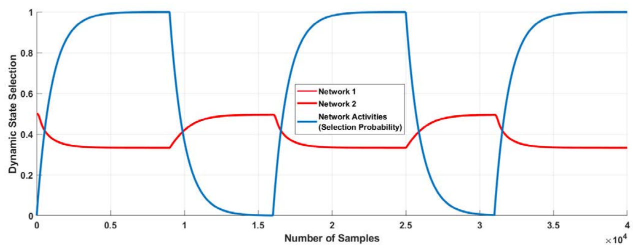

FIGURE 14. Network dynamic state variation $(R(\gamma) = 6\gamma)$.

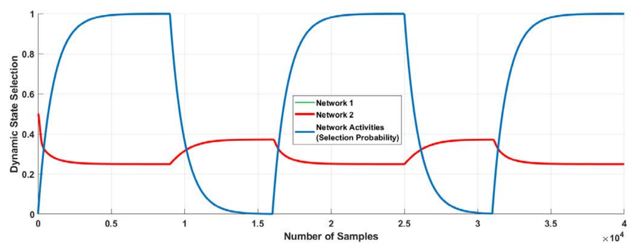

FIGURE 15. Network dynamic state variation $(R(\gamma) = 8\gamma)$.

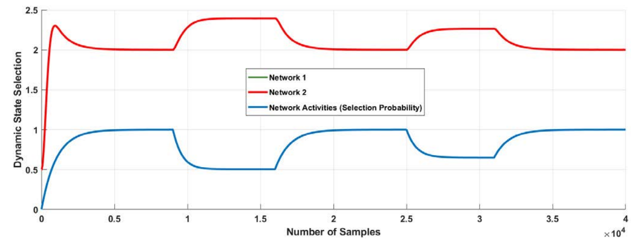

FIGURE 16. Network dynamic state variation Noise = 0.00001W).

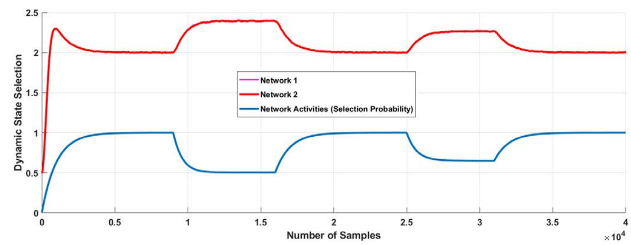

FIGURE 17. Network dynamic state variation (Noise = 0.001W).

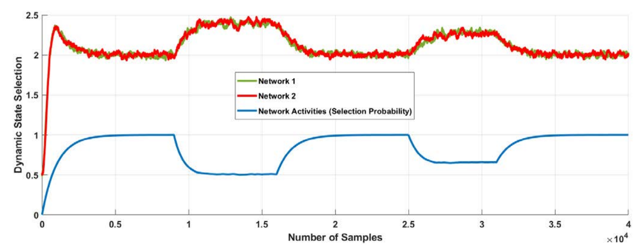

FIGURE 18. Network dynamic state variation (Noise = 0.1W).

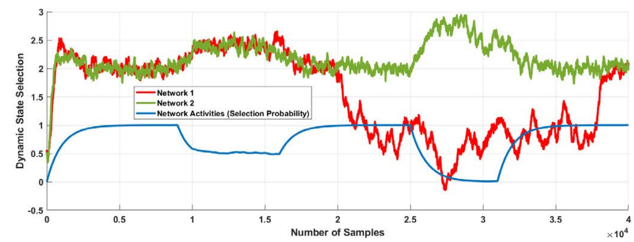

FIGURE 19. Network dynamic state variation (Noise = 1W).

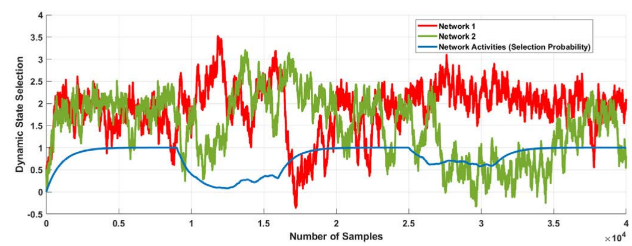

FIGURE 20. Network dynamic state variation (Noise = 10W).

it is observed that as the level of noise increases, connectivity levels changes, as expected. However, the two coinciding and overlapping networks only become distinguishable at high noise level, indicating that the standard (Non-Gaussian) based AS model can only be affective under higher noise levels, thus lacking sensitivity. This is due to its more abrupt performance compared to the Gaussian interpolation, as it effectively behaves as digital system in terms of discriminating between the network states. Also, it functions based on which state gets more affected by noise, otherwise both states will have same selection probability. In addition, the standard function lacks the reachability and spread property using the parameter β that the Gaussian interpolation function provides with the smooth sensitivity transition due to the exponential component of the Gaussian function.

In comparison with other research work, researchers in [12] used standard Attractor selection model for Mesh multi-path QoS routing (MMQR) protocol under variable and dynamic environments [12], with good simulated results but did not combine the model with any other utility functions. Researchers in [20], [24], [25] employed the attractor selection technique in both its standard form and combined with a sigmoid function to enable better pattern selection and stable state allocation in order to provide better QoS. However, despite the fact that sigmoid has an exponential denominator, it does not possess the same adaptive features and reachability that the Gaussian interpolation function provides and used in this work. This work proved to present better adaptive and intelligent network management solution.

The presented solution provides QoS and better connection stability by combining Gaussian interpolation function with the biological AS model. Researchers in [21] used simulation and both standard attractor selection model and exponential solution to enable adaptive Machine-to-Machine communication in a changing environment, and presented QoS measurement curve in response to selectivity under varying surroundings, but did not use Gaussian interpolation, which if used would give better results in terms of stability, reliability, and sensitivity. Researchers in [26] used standard attractor selection model with standard solution to simulate stable states and the adaptive behavior of the model, but did not combine their model with other functions.

This work projects that if Gaussian interpolation is used, better stability would be achieved. Researchers in [28] employed a probability function together with the standard attractor selection model for optimal path selection. The probability matrix for multi-path, together with the adaptive feature of the attractor selection model proved effective. However, the work did not employ Gaussian interpolation, which this work uses. Researchers in [29] used the adaptive feature of the attractor selection biological model. The model applied to waveform modeling of signals (beamforming) in a V2I communication link. Researchers in [31] approached the problem of scarce spectrum resources, interference caused by excessive demands of mobile users, by incorporating attractor selection model in its standard form with quadratic roots solution.

From the previous works and when compared to this work, all works used simulation but none of them used Gaussian interpolation function with ratio in combination with the standard attractor selection model. As shown in the previous figures, Gaussian interpolation contributed significantly to the intelligence and reliability of the proposed biological model. In addition this work deals with all types of communication networks and communication standards such as Dedicated Short Range Communication (DSRC) with its IEEE802.11p standard as a black box. This is due to the focus of this work on preserving connectivity of network with at least one stable channel in order to guarantee service availability and network connectivity under all conditions. Thus, the idea is to enable competition between networks based on signal quality, stability and strength, and to allow for smooth hooping between connections. This is the core of the E.Coli with an added intelligence and higher level of adaptability provided by the Gaussian interpolation. The many works on Distributed congestion control deals with management to avoid channel congestion and in a statistical manner. The presented work deals with preservation of connections with the option to move to another network connection that provides better QoS.

IV. CONCLUSION

The work investigates through MATLAB simulation both the standard attractor selection algorithm and a Gaussian – based modified algorithm. The work intended to establish the importance of attractor selection algorithm and technique as a bio-inspired intelligent selection technique that help to provide QoS to vehicular networks using different network connections. The obtained results successfully supported a Gaussian-based attractor selection algorithm over standard one.

From the plots and comparing the obtained data using both standard attractor selection algorithm and attractor selection algorithm with Gaussian interpolation function, it is clear that Gaussian interpolation enables smoother stable state transition between networks and allows discrimination between network states under small and large noise and covers wider γ variations affecting $R(\gamma)$, which affects selection probability and states values.

The work presented provides a model that can be utilized and optimized for various networks and their communication channels. The main task is to enable smooth, adaptive resource allocation that will provide stable, reliable, and efficient communication channel. This will greatly increase confidence in vehicular communication and in autonomous driving, as good and high integrity connectivity is made available through resource allocation of best sources under available conditions.

Future investigations regarding effect of number of networks and effect of changes in P and C parameters is recommended.

ACKNOWLEDGMENT

The MATLAB simulation in this work initially used the algorithm originated by Daxin Tian.

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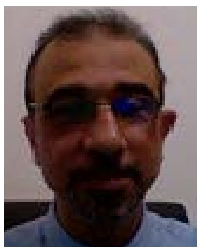

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