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Biologically-inspired Neural Network for Coordinated Urban Traffic Control

Parameter Determination and Stability Analysis

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Abstract— **Traffic congestions are a major concern for big cities around the world due to its multifaceted negative impacts. A cost-effective solution to reduce vehicle travel times and prevent traffic congestions is traffic signal control. In this work, we investigate a biologically-inspired neural network, which, in contrast to other approaches, is able to continuously monitor the system state and make decisions. An extension of a previous model is proposed, establishing a multiagent system and allowing the coordinated control of multiple intersections. Methods for parameter determination and stability analysis are also proposed. Finally, the model performance for different sets of parameters and vehicle demands is evaluated with a simulator of urban mobility and compared to a conventional cycle-based control method.**

Keywords- Computational intelligence; urban traffic control; intelligent transportation systems; complex dynamic systems; biologically-inspired neural networks.

I. INTRODUCTION

Urban traffic is a complex dynamic system with multiple impacts on the economy, the environment and society. Daily traffic congestions affect, for example, human health, due to stress increase; the Gross Domestic Product (GDP), mainly because of the opportunity cost of the additional time citizens spend commuting; and air quality, as a consequence of gas emission. The continuous increase in traffic demand worsens the situation, as it is not accompanied by an equivalent improvement in urban infrastructure.

A cost-effective solution to mitigate these negative impacts is traffic signal control, which optimizes vehicle flows to prevent traffic congestion by determining semaphore green times. Traffic signal control is an important research topic in the intelligent transportation systems field, and hence many approaches were proposed. Among them, the majority is based on optimal control theory and artificial intelligence, as briefly reviewed in the next section. These solutions predominantly adopt a cycle-based control, measuring the system state and determining semaphore green times after each semaphore cycle, which comprises all semaphore phases of an intersection between streets.

However, the resulting large sampling and decision making time restricts the system efficiency, as it prevents a faithful characterization of the system state and does not provide a flexible actuation. This efficiency restriction is also a consequence of the system complexity, which is partially observable and controllable, as driver actions are unpredictable, and has a stochastic nature, nonlinear dynamics, and numerous state and input variables.

Based on the good results of biologically-inspired neural networks (BiNNs) for controlling complex dynamic systems, such as stability and adaptability [1], we further investigate a model for traffic signal control [2]. The main difference between BiNNs and artificial neural networks is that the latter focuses on the learning aspect of biological neural networks, whereas the former focuses on its dynamic behavior, not having – in most cases – a training period. Moreover, BiNNs adopt more characteristics of biological neural networks, such as inhibitory synapses and neural adaptation mechanisms.

The approach investigated has a higher reactivity than other urban traffic control methods, being able to continuously measure the system state and to modify the active semaphore phase at any moment. Previous work [2] presented the neural network model and performed comparative simulations. Nevertheless, only the control of a single intersection was studied and pre-established model parameters were adopted, not allowing the definition of a desired behavior.

Therefore, we extend here the model proposed into a multiagent system, in which each agent controls a single intersection and interacts with its immediate neighbors to achieve coordinated control of multiple intersections. Furthermore, we propose a method to determine the model parameters according to the desired behavior and present a method to analyze the model stability. The model performance for controlling multiple intersections is evaluated in two simulation studies: the first has a constant vehicle demand and different parameter configurations; and the second compares the BiNN to a conventional cycle-based control method for various vehicle demands.

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II. Related Works

Modern urban traffic control can be divided in two groups according to its basis: optimal control theory; and artificial intelligence. Regarding the former group, the predominant control method is the distributed model predictive control, in which each intersection is represented by an agent that interacts with its neighbors in order to determine an optimal solution for the multiagent system. Thereby, agents iteratively predict the system behavior with a linearized model of the urban traffic.

Whilst Tettamanti et al. [3] focused on achieving more robust predictions, other authors focused on the spatial and temporal decomposition of the urban traffic control problem and on the coordination of agents [4, 5]. The main disadvantage of these approaches is the difficulty in predicting the behavior of a stochastic system, such as the urban traffic, with a linearized model [6].

Artificial intelligence is a broadly explored field in urban traffic control, in which works based on fuzzy systems, artificial neural networks, reinforcement learning, and evolutionary algorithms were already surveyed [7]. The majority of them adopt a multiagent basis to decompose the complex problem of urban traffic control, and their main advantage is the exemption of a model of the controlled system.

Among the most recent solutions, Gokulan and Srinivasan [8] proposed a symbiotic evolutionary learning approach to determine the parameters of distributed fuzzy controllers. Tahifa, Boumhidi and Yahyaouy [9] proposed a swarm Q-learning approach, in which agents also learn from neighbor experience. Chu and Wang [10] proposed an approximate Q-learning approach, in order to reduce the computational complexity of the learning algorithm. Nevertheless, learning-based control requires a huge amount of data and training time to adequately represent the behavior of stochastic systems with many variables [3, 7, 8].

Works related to biologically-inspired neural networks (BiNNs) mainly focus on the control of robots, which are also complex dynamic systems. The different BiNNs vary in network structure and neuron model, which comprises membrane potential (activation) and neuron output determination, types of synapses and neural adaptation mechanisms.

According to Nichols, Mcdaid and Siddique [11], the more realistic a neuron model is, the higher its computational cost. The authors adopted the leaky integrate-and-fire neuron model because of its low computational cost, and elaborated a non-recurrent network structure with a neural adaptation mechanism to control the motion of a wheeled robot. Helgadóttir et al. [12] also controlled the motion of a wheeled robot with a non-recurrent neural network, additionally adopting inhibitory synapses and extending the integrate-and-fire model to directly provide neural adaptation to the membrane potential calculation.

Another type of BiNN for robot control is the neural oscillator, which was applied to control walking, crawling, swimming and flying robots, and whose related works were surveyed by Yu et al. [1]. According to Ijspeert [13], the advantages of BiNNs with oscillatory output signals are their intrinsic limit cycle, which indicates stability; few control parameters, which are able to modulate signals with flexibility; and easy feedback integration.

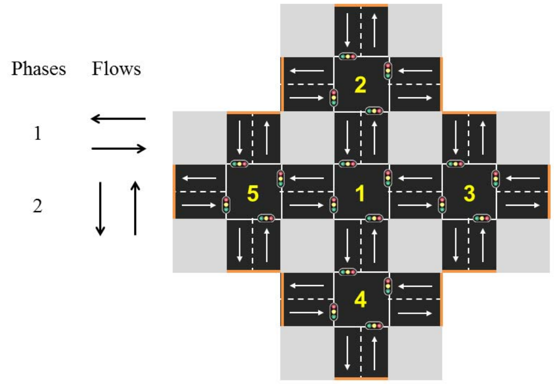

Figure 1. Scenario of the study and semaphore phases.

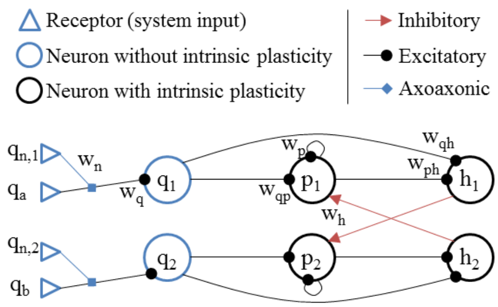

Figure 2. Structure of the biologically-inspired neural network.

The BiNN investigated here has an oscillatory behavior achieved by lateral inhibition dynamics and a neural adaptation mechanism called intrinsic plasticity. Moreover, the neuron model adopted is similar to the model of artificial neural networks, which has the lowest computational cost. As aforementioned, in contrast to the urban traffic control approaches reviewed in this section, the BiNN investigated is not cycle-based, because of its highly dynamic behavior.

III. Biologically-inspired Neural Network

The scenario studied in this work consists of five intersections between streets, which have two semaphore phases each, as illustrated in Fig. 1. Due to the modularity principle of the model, each intersection is represented by an agent, whose behavior is detarmined by a BiNN. In order to consider the interaction between neighboring intersections and to establish a multiagent system dynamics, the model previously proposed [2] is extended with the additional inputs $q_{n,1}$ and $q_{n,2}$, as illustrated in Fig. 2. These sensorial receptors form axoaxonic synapses with receptors q_a and q_b, having a multiplicative effect on them.

Whilst receptor $q_{n,1}$ represents the signals from all immediate neighbors of agent 1 that affect semaphore phase 1, q_a and q_b represent the street occupations related to phases 1 and 2, respectively. Neurons q_1 and q_2 sum all inputs of each phase and do not have intrinsic plasticity, as biological bipolar neurons. Neurons p_1 and p_2 represent the semaphore phases of the controlled intersection, i.e., their output activates their respective semaphore phase. The recurrent connections of neurons p_1 and p_2 represent biological G-Proteins, which maintain an initial activation for longer periods.

Finally, neurons h_1 and h_2 inhibit the activity of their opposite phase with lateral inhibition dynamics, which allows only one phase to become active at a time. These neurons receive inputs from p_i neurons, generating feedback inhibition, as well as from q_i neurons, generating feedforward inhibition. Whilst feedback inhibition reflects the current state of semaphore phases, feedforward inhibition anticipates variations in the system input.

The model dynamics is based on the work of Peláez and Andina [14], and, hence, is represented by (1), (2) and (3). Whilst (1) determines the neuron activation A_i based on its N_i inputs Q_j and their respective synaptic weights w_j, (2) determines the neuron output O_i with a sigmoidal activation function. Equation (3) determines the activation function shift s_i, which represents the intrinsic plasticity of biological neurons and is the adaptation mechanism of the model. In the equation, ξ determines the neuron adaptation speed.

$$A_i^{t+1} = \sum_{j \in N_i} w_j Q_j^t \tag{1}$$

$$O_i^{t+1} = 1 \Big/ \left[1 + e^{-25\left(A_i^t - s_i^t\right)}\right] \tag{2}$$

$$s_i^{t+1} = (\xi O_i^t + s_i^t)/(\xi + 1) \tag{3}$$

The additional input proposed $q_{n,1}$, whose general form is presented in (4), is composed by all interactions of agent 1 with agents 3 and 5. These interactions are: M_k positve signals from neuron outputs of downstream links $O_{p,i}$, wheigthed by a synchronization factor τ to coordinate the agent activities and form green waves; and P_k negative signals from upstream links, which prevent street saturation and are polynomial functions of upstream street occupations q_j.

Street saturation causes the spillover effect, which drastically reduces the urban network mobility [15], whereas green waves reduce vehicle stops at traffic signals, as well as their average travel time [16]. The polynomial term of the equation was empirically defined in order to produce a negligible inhibition for small street occupations and an increasingly stronger inhibitory signal when street occupation overcomes 80%.

$$q_{n,k} = \tau \frac{1}{M_k} \sum_{i \in M_k} O_{p,i}^t - \frac{1}{P_k} \sum_{j \in P_k} \left(0.9 q_j^5 + 0.1 q_j\right) \tag{4}$$

A. Parameter Determination

The extended BiNN, presented in Fig. 2, has 9 parameters: 7 synaptic weights, the adaptation coefficient ξ, and the synchronization factor τ. Due to the huge number of possible parameter combinations, and its broad spectrum of resulting behaviors, we propose in this subsection a simple method for parameter determination according to the desired agent behavior, which ultimately determines the mutiagent system behavior.

Agent behavior can be characterized by three intrinsic proprieties of the BiNN: natural frequency of oscillation Ω, input sensitivity S, and degree of synchrony T. The first intrinsic propriety refers to the oscillation frequency of neuron outputs for constant system inputs, which occurs, for example, in saturated urban networks. Altough the oscillation frequency can vary from Ω, this parameter defines the steady state behavior of the agent.

As each parameter of the BiNN has a different degree of influence on Ω, an experimental sensitivity analysis was conducted to determine the most influent parameters. The analysis consisted in varying each parameter from its lower to its upper bound (0 and 1), whilst the others were maintained at their baseline values, as defined in [2]. The parameter baseline values are: ξ equal to 0.07, w_n and w_q equal to 1, w_p, w_{qp} and w_{qh} equal to 0.4, and w_h and w_{ph} equal to 0.3.

Table I presents the relative influence of each parameter on Ω and shows that w_p and ξ have a combined relative influence of 88.32%. Therefore, Ω can be defined as a function of w_p and ξ, as presented in Fig. 3 by a chart. The chart does not cover all values of w_p and ξ because the values displayed are sufficient to completely represent Ω.

The second intrinsic propriety proposed to characterize agent behavior is input sensitivity S, which regards how variations in the system inputs affect the transition between semaphore phases. Thus, S is a measure of how reactive an agent is, as determined by (5). In the equation, w_{qp} and w_{qh} must have equal values in order to guarantee balanced inhibitory dynamics. A high value of S establishes a high influence of the system inputs on the neuron dynamics, denoting a high reactivity. Meanwhile, low values of S require stronger input variations to cause phase transitions, mantaining the oscillation frequency close to Ω due to a higher inertia.

$$S = \left(w_{qp} + w_{qh}\right)/w_p \tag{5}$$

An agent degree of synchrony T is directly determined by its synchronization factor τ, which defines agent behavior regarding its immediate neighbors. The higher T is, the more synchronized neighboring agents are, activating semaphore

TABLE I. RELATIVE INFLUENCE OF MODEL PARAMETERS ON Ω.

	w_p	ξ	w_{ph}	w_{qp}	w_h	w_{qh}
Influence (%)	56.88	31.44	4.15	3.57	2.44	1.52

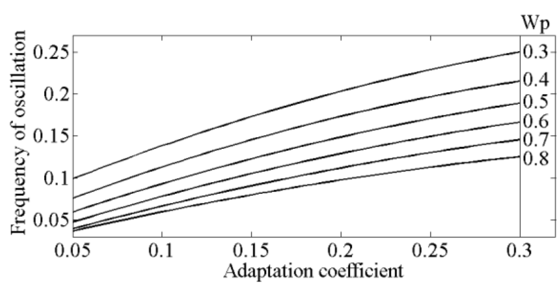

Figure 3. Ω as a function of w_p and ξ.

phases at the same time. In contrast, lower values of T cause a delay between phase activations, optimizing traffic flows according to the street length between neighboring intersections.

B. Stability Analysis

Besides selecting a set of parameters to achieve a desired behavior, the dynamic stability of agents must also be ascertained. We previously [2] proved model stability for the parameter baseline values with simulations, which are insufficient to guarantee stability for different sets of parameters. Instead of conducting numerous simulations for each new set of parameters, we present in this subsection a direct method to analyze model stability.

The idea is to evaluate the stability of a p_i neuron in order to infer the stability of the neural network. As all neurons are interconnected, the behavior of one neuron reflects the behavior of the neural network. Thus, the eigenvalues of a p_i neuron are evaluated at the neural network equilibrium points. According to Fuchs [17], the fixed-points (equilibria) of a discrete dynamic system are obtained by substituting the system state variables in (6).

$$x^{t+1} - x^{t} = 0 \tag{6}$$

The BiNN state varibles are presented in (7), and the resulting system of 8 equations can be either analitically or numerically solved. As the focus of this paper is not the model convergence, this system of equations is numerically solved with MATLAB, presenting an unique equilibrium point for each set of input values.

$$x^{t} = \left[A_{p1}^{t}; A_{p2}^{t}; A_{h1}^{t}; A_{h2}^{t}; s_{p1}^{t}; s_{p2}^{t}; s_{h1}^{t}; s_{h2}^{t}\right] \tag{7}$$

The neuron eigenvalues λ are obtained with the Jacobian J of its state variables, according to (8), in which I refers to an identity matrix and *det()* stands for the determinant of the matrix inside the parenthesis. The Jacobian of neuron p_1, chosen to evaluate the stability of the BiNN, is presented in (9) and is calculated by the partial derivatives of p_1 state variables ($\partial A_{p1}/\partial A_{p1}$, $\partial A_{p1}/\partial s_{p1}$, $\partial s_{p1}/\partial A_{p1}$ and $\partial s_{p1}/\partial s_{p1}$).

$$det(J - \lambda I) = 0 \tag{8}$$

$$J = \begin{bmatrix} \dfrac{25 w_p e^{25(s_{p1}+A_{p1})}}{\left(e^{25 s_{p1}}+e^{25 A_{p1}}\right)^2} & -\dfrac{25 w_p e^{25(s_{p1}+A_{p1})}}{\left(e^{25 s_{p1}}+e^{25 A_{p1}}\right)^2} \\ \dfrac{1}{\xi+1}\left(\dfrac{25\xi e^{25(A_{p1}+s_{p1})}}{\left(e^{25 A_{p1}}+e^{25 s_{p1}}\right)^2}\right) & \dfrac{1}{\xi+1}\left(1-\dfrac{25\xi e^{25\,(A_{p1}+s_{p1})}}{\left(e^{25 A_{p1}}+e^{25 s_{p1}}\right)^2}\right) \end{bmatrix} \tag{9}$$

Solving (8) at each system equilibrium point results in the neuron eigenvalues. As the BiNN equilibrium point varies with its inputs, an additional constraint needs to be imposed in order to couple the BiNN inputs. This constraint, described by (10), adds a normalization effect to neurons q_1 and q_2, whose outputs are O_{q1} and O_{q2}, and establishes a relationship among them, which is presented in (11). Therewith, $q_{n,1}$, $q_{n,2}$, q_a and q_b do not affect the BiNN stability anymore, and, thus, w_n and w_q are set to 1. According to Peláez and Andina [18], neural normalization is a biological characteristic of shunting basket neurons.

$$O_{q1} = O_{q1}/\left(O_{q1} + O_{q2}\right) \tag{10}$$

$$O_{q2} = 1 - O_{q1} \tag{11}$$

As neuron p_1 has two state variables (A_{p1} and s_{p1}), and hence is a second-order system, it has two eigenvalues, which are shown in Fig. 4 as functions of O_{q1}. The real and imaginary parts of the eigenvalues are represented by solid and dashed lines, respectively, indicating the presence of two Hopf bifurcations [19], for O_{q1} values of 0.1 and 0.9. Hopf bifurcations characterize transitions from an equilibrium point to a periodic solution, which, in this case, occur when the purely real eigenvalues become a complex conjugate pair.

In the urban traffic control scenario, a periodic solution represents a sequential transition between semaphore phases, whereas an equilibrium point denotes the maintaince of a single semaphore phase. According to Fig. 4, when O_{q1} equal to less than 0.1 or more than 0.9 equilibria are achieved. Thereby, in the former case phase 1 remains inactive, and in the latter case phase 1 remains active.

Figs. 5 and 6 present the neuron state variables in a two-dimensional plot, showing the behavior discussed and that the Hopf bifurcations are supercritical, i.e., the resulting periodic solution corresponds to a stable limit-cycle. In Fig. 5, O_{q1} has a value higher than 0.9, whereas in Fig. 6 it is equal to 0.5. In the figures, the black dots correspond to the

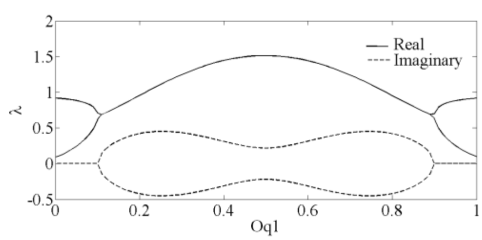

Figure 4. λ as a function of O_{q1}.

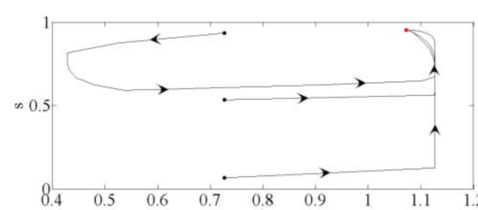

Figure 5. Trajectory of the O_{q1} state variables for $O_{q1} > 0.9$.

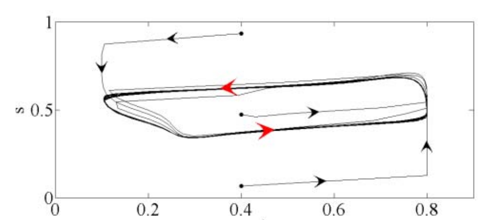

Figure 6. Trajectory of the O_{q1} state variables for $O_{q1} = 0.5$.

intial conditions of the state variables, whereas the red dot represents an equilibrium point and the red arrows represent the stable limit-cycle.

The stability analysis method presented in this subsection can be applied to any set of parameters, revealing the dynamic behavior of an agent in a direct manner. As shown in Fig. 4, the stability chart is symmetrical, which indicates that the convergence of O_{p1} to an inactive equilibrium causes the convergence of O_{p2} to an active equilibrium, and vice versa. When an oscillatory behavior is achieved, both neurons produce oscillatory outputs. Thus, the neural network behavior is extrapolated from the neuron p_1 behavior, defining how the agent controls its semaphore phases.

IV. PERFORMANCE EVALUATION

In this section the BiNN peformance for controlling urban traffic is evaluated in two simulation studies. The first regards how different values of Ω, S and T affect performance, whereas the second compares the BiNN with a conventional cycle-based control method (CBCM), which determines the semaphore green times after each cycle according to street occupations. This control method represents the base concept of all other cycle-based approaches, as reviewed in Section II, and adopts a control cycle of 1 minute and 30 seconds.

The BiNNs, one for each of the five agents, were implemented in MATLAB, whilst the scenario presented in Fig. 1 was modelled in a simulator of urban mobility, SUMO, and the software interface was accomplished by the protocol TraCI4Matlab [20]. All parameter configurations tested were evaluated according to the stability analysis method proposed, showing the desired behavior: a periodic solution.

All simulations last one hour and have an equally distributed vehicle demand. Ten simulation runs were conducted for each scenario configuration, and the performance indicator, mean travel time (MTT) of vehicles, is averaged over all runs. MTT refers to the mean time vehicles need to drive through their whole routes, from origin to destination, in one simulation run. The small resulting coefficients of variation, circa 1% in all cases, indicate that the use of averages to perform the comparisons is an adaquate option.

A. Effects of BiNN intrinsic proprieties on its performance

In the first simulation study, simulations have a constant vehicle demand of 2.75 vehicles per second and the effect of the parameter determination method proposed on MTT of vehicles is analyzed. The first evaluation of this study regards the BiNN performance for different values of Ω. Table II shows the results, indicating that a Ω of 0.2 is the best option for the scenario studied. Natural frequencies of oscillation higher than this value caused short phase durations, increasing vehicle stops at traffic signals. In contrast, the cases with Ω lower than 0.2 presented diminished performances due to the difficulty of coordinating the resulting vehicle platoons, which were larger than the street lenght.

In the second evaluation, Ω is set to 0.2, with ξ equal to 0.195 and w_p equal to 0.3, and the effect of agent input sensitivity S on urban traffic control is analyzed. According to (5) and to the w_p defined, the values of S evaluated correspond to the following values of w_{qp} and w_{qh}: 0.3, 0.4, 0.5, 0.6 and 0.7. Table III shows that a S of 2.67 has the best performance. Higher values of S caused anticipated phase transitions, not allowing the complete vehicle platoons to cross the intersections, whereas lower values presented a low reactivity, forcing vehicles to stop at traffic lights before acknowledging their arrival. Thus, both cases had an increase in the MTT.

The last evaluation regards different values of the agent degree of synchrony T, with Ω equal to 0.2 and S equal to 2.67. As presented in Table IV, a T of -0.3 is optimal, because it imposes a delay between the activation of neighboring agents that synchronize them according to the street length of the scenario studied. Higher values of T present smaller delays, activating the green lights long before vehicle platoons arrive at intersections. For lower values of T, vehicle platoons arive at intersections before the green lights are activated, causing unnecessary vehicle decelerations.

The three-step method proposed reduced a MTT of 134.7 seconds, obtained with baseline parameter values, to 109.9 seconds, which represents a 18.4% gain in performance. Regardless of the BiNN auto-organization capacity, which provides good results in any scenario, the method proposed can further optimize the MTT by considering the scenario specific characteristics, such as street length, number of lanes and vehicle mean speed.

B. BiNN and CBCM performance for various demands

The first vehicle demand evaluated, 2.5 vehicles per second, represents a scenario with low traffic volume, in which the control methods obtain their best results, as shown in Table V. In the second scenario, with moderate traffic, the

TABLE II. MEAN TRAVEL TIME OF VEHICLES FOR DIFFERENT Ω.

Ω	0.05	0.10	0.15	**0.20**	0.25
MTT (s)	136.3	120.7	120.0	**118.7**	121.6

TABLE III. MEAN TRAVEL TIME OF VEHICLES FOR DIFFERENT S.

S	2.00	**2.67**	3.33	4.00	4.67
MTT (s)	117.7	**111.8**	116.7	115.9	118.7

TABLE IV. MEAN TRAVEL TIME OF VEHICLES FOR DIFFERENT T.

T	-0.4	**-0.3**	-0.2	-0.1	0.0	0.1	0.2
MTT (s)	113.3	**109.9**	110.3	111.8	111.8	117.0	118.6

TABLE V. MTT OF CONTROL METHODS FOR VARIOUS DEMANDS.

Demand (vehicles/s)		2.50	2.75	3.00
MTT (s)	BiNN	109.4	109.9	213.0
	CBCM	140.5	146.9	268.6

BiNN maintains its performance due to the well-tuned synchronization between agents, whereas the CBCM has a decrease of 4.9% in performance. The last scenario represents a congested traffic, in which both control methods present a deteriorated performance. Nevertheless, the BiNN obtained a result 20.7% better than the CBCM.

The results show that the BiNN was on average 22.7% better than the CBCM, which is not only due to the dynamic interaction between neighboring agents, but also because of its immediate sensing and responding capability. This simulation study also highlights the relevance of the method proposed for parameter determination, as the BiNN was only 6.9% better than the CBCM with its baseline parameter values.

V. Conclusion

This paper investigated a biologically-inspired neural network (BiNN) for controlling urban traffic, a complex dynamic system with multiple impacts on society. An extension to a previous model was proposed in order to consider the dynamics of neighboring intersections and to establish a multiagent system. The axoaxonic synapse proposed modulates the BiNN sensorial receptors to prevent street saturation and to coordinate the activities of neighboring agents, originating green waves.

Due to the large number of parameter combinations, we proposed a three-step method to determine agent behavior according to three intrinsic characteristics of the BiNN: natural frequency of oscillation, input sensitivity, and degree of synchrony. Simulations showed that tuning these BiNN proprieties can optimize its performance, which was 18.4% better in terms of mean travel time of vehicles in the scenario studied.

Apart from determining agent behavior, we also presented a method to infer the dynamic stability of the BiNN from the stability of a single neuron for any set of parameters. This stability analysis is vital to guarantee an oscillatory behavior, i.e., to prevent a semaphore phase from dominating the other and being indefinitely active.

In comparison to a conventional cycle-based control method, the BiNN was on average 22.7% better in simulations with low, moderate and congested traffic. These results highlight the main contribution of the model proposed: fast-response and coordinated control of a complex dynamic system.

Future research directions include the study of the BiNN computational and behavioral complexity, analyzing the model scalability as well as further investigating the emergent multiagent behavior in larger scenarios with different demand profiles. Moreover, the application of the BiNN proposed for controlling other complex dynamic systems, such as robots, will also be treated.

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