Bio-Inspired Neural Network Applied to Urban Traffic Control in a Real Scenario

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***Abstract*— Global economic development has the disadvantage of increasing the population in large urban centers that causes an increase of vehicles traffic in cities and results in traffic jams. Several researches have been developed to provide solutions to the problem of urban traffic. This work aims to apply the Bio-Inspired Neural Network model to control urban traffic semaphores. The proposed model was obtained and developed in previous works in the research group. Therefore, this paper presents the evaluation of the model applied on a real scenario of the big cities through simulations considering characteristics such as: vehicle speed, streets and avenues lengths, traffic semaphore positions and different traffic demands. The chosen scenario is the Paulista Avenue in the central region of city of São Paulo, well known for its high traffic demand. The Bio-Inspired Neural Network algorithm was compared with the fixed-time control, which is currently used for the control of semaphore phases in the city of São Paulo. The behavior of control algorithms were compared for low, average and heavy traffic demands. The performance indicators used were the average travel time of the vehicles and the level of occupation of the roads. The results show that the BiNN model is better in all the simulations made, with the different situations of traffic demands. Tests results show performance up to 44,67% in terms of average travel time, if compared to the fixed time control.**

Keywords—Bio-Inspired Neural Networks; Traffic Lights Control; Semaphore Control; Urban Traffic Control; Travel Average Time; Roads Occupation Levels.

I. INTRODUCTION

The development and growth of large cities today is governed by economy and social development. This explains how the urban population has increased significantly in recent years, according to [1]. In 2007, urban population exceeded the rural population, suggesting that by the year 2050, the urban population will represent 70% of the world population. Hence, the researchers present solutions that seek to improve the solutions to the problem of overcrowding in large urban centers. For this reason the researches are conducted to solve fundamental questions, in subjects such as: energy, sustainable development, security, housing, health and transport [2]–[4].

Transportation is a key issue for the urban development of cities. Solutions to problems related to this area are still a challenge for researchers. When the number of people in a space of similar size increases, vehicle traffic increases as well, being a serious problem faced today in large cities [5], [6]. Increasing the infrastructure of roads and highways, public transportation, and intelligent control at street crossings are some of the actions to be taken to solve transport problems. Semaphores are devices commonly used to control intersections, therefore, an optimum adjust of the time of each phase of traffic can help considerably as it could prevent traffic jams on the roads [7]–[13].

Many studies have been proposed to control the time of each phase at a semaphore. The unpredictable nature of traffic demand makes the task of optimizing the control more difficult. As a consequence, the most varied types of algorithms and methods are found in the literature, although modern urban traffic control can now be divided into two groups: Theory of Optimal Control and Artificial Intelligence. [8].

An adaptive semaphore controller is proposed by Taranjeet Kaur et al. in [13]. The controller uses neural networks and genetic algorithms to adapt the semaphore schedule according to the congestion of each intersection. The neural network receives the signal times as the input and provides the length of the queue as the output. Another example of the use of neural networks is presented in [10]. Authors proposed an optimum adjustment in the signal traffic times, concluding that most of the time, performances of the two proposed algorithms have a similar behavior, but significantly higher than the fixed-time controller. Another observation of that work is that the algorithm is proposed and tested only for a single semaphore crossing.

Finally, in [14], a Biological-inspired Neural Network (BiNN) is proposed and developed, being able to continuously monitor the system status and make decisions. The proposal establishes a multi-agent system concept and allows the coordinate control of several crosses. The vehicle queue size at the intersections of the streets is considered as the system entry variable. Furthermore, it proposes a method for determining parameters according to the desired behavior and provides a method for stability analysis. The algorithm is validated using an urban mobility simulator and compared to a conventional iterative controller. Results show better controlling behavior even in low, moderate and heavy traffic situations. This model extends to a multi-agent model where each agent controls a single intersection of the street and interacts with the neighbor agents to achieve coordinated control of the various crossings. The proposal prevents the saturation of the streets and coordinates the activities of the neighboring agents causing green lights at the semaphores.

Following sections presents the application of BiNN algorithm for semaphore control in a real scenario. Section-II presents some definitions of BiNN algorithm and explains the equations that describe the model. Description of the scenario and the simulation setup is shown in Section-III and Section-IV respectively. Section-V presents and analyzes the results obtained during the simulation. Finally, some concluding remarks are presented in Section-VI.

II. BINN ALGORITHM

BiNN was proposed and evaluated in [14] considering hypothetic traffic scenarios also testing its behavior in controlling dynamic systems. Indeed, authors analyzed its stability and adaptability. The BiNN adopts biological characteristics, such as inhibitory synapses and mechanisms of adaptation of neural networks. Therefore, in this case, BiNN show better performance than artificial neural networks, and has the advantage of not requiring training period. This model, according to [8] and [15], has low computational cost and the mechanism of short-term plasticity and the oscillatory behavior facilitates the change of semaphore phases. Another advantage of the proposed method is the continuous monitoring of traffic status and decision making.

BiNN equations for urban traffic control system of this paper is proposed in [15], and presented in equations (1), (2) and (3):

$$A_i^{t+1} = \sum_{j \in N_i} w_{xy} Q_j^t \quad (1)$$

$$O_i^{t+1} = \frac{1}{1 + e^{-m(A_i^t - s_i^t)}} \quad (2)$$

$$s_i^{t+1} = \frac{vO_i^t + s_i^t}{v+1} \quad (3)$$

Equation (1) determines the activation function A of a neuron i at time $t+1$ based on the weighted sum of its N inputs Q. Equation (2) is a sigmoid function whose slope is determined by m and represents the activation function of neurons. It generates the output O of a neuron, based on its activation A and the displacement s of its activation function, which represents the mechanism of adaptation of the model (intrinsic plasticity). The factor m only represents the slope of the curve. Equation (3) determines the displacement s of the activation function of a neuron i based on its output, v is the adaptation coefficient, which is a small constant value that determines the rate of adaptation of the neurons.

According to [7], this model is split in two parts:

- Control of the phase change of semaphore at an intersection.
- Coordination of intersections that is responsible for green waves.

A. *Control of an intersection*

The structure shown in Fig. 1 is used to control each one of intersection. Each set of neurons (p, h, q) represents a semaphore phase. Considering n intersections, the whore structure will have n neurons sets. The neurons $p_{1,2...n}$ are the excitatory ones, $q_{1,2...n}$ are the sensory neurons, $h_{1,2...n}$ are the interneurons and $q_{a,b,c,d}$ are the sensory receptors, which measure the occupation of the relative pathways, representing the inputs of the system.

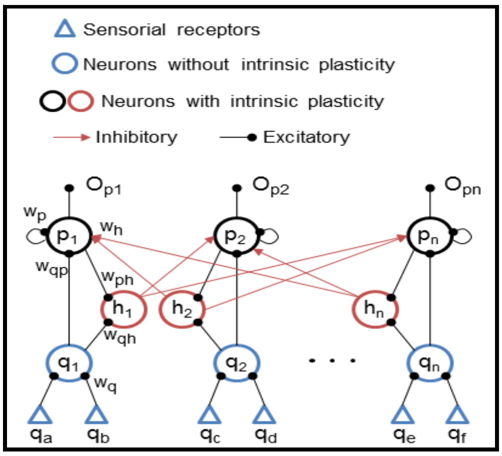

Fig 1. BiNN model structure for semaphore control

B. *Coordination of intersections*

For the coordination of intersections, the structure shown in Fig. 2 is used. The neuron of the semaphore phase 1 of intersection A is represented by $p_{1,A}$, while $p_{1,B}$ represents the same semaphore phase of intersection B. Hence, the traffic phases that control vehicle flows in the same direction are coordinated. Furthermore, $q_{a,A}$ and $q_{a,B}$ are the sensory receptors of intersection *A* and intersection *B*, respectively. All other neurons of the first structure are not considered in the control of intersections [14].

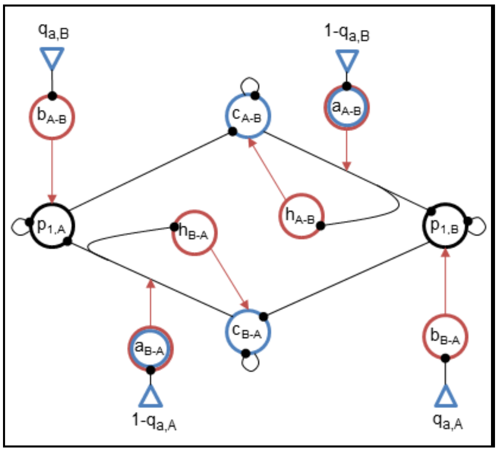

Fig 2. BiNN model structure for a semaphore coordination

The structure in the Fig. 2 has two basic operating principles:

- Storing the information when a semaphore has been activated until the corresponding semaphore of the next intersection is ready to become active.
- Inhibit the next semaphore-phase in cases occupancy of the next intersection is activated, as a way to avoid the overflow effect. This action is performed by the interneurons *b*, which inhibit the *p* neurons in the forward direction according to the occupation of the next intersection.

III. SCENARIO

The city of São Paulo had big problems with the level of traffic bottling. It is one of the largest urban settlements in the world, according to [16], with a population of 12,038,175 only in its metropolitan area, which has an extension of 1521.11 km^2, having a population density of 7,914.07 in habitants per square kilometers in its entire area. The city has a vehicular fleet of approximately 7 million vehicles and a road extension of approximately 17,000 km of streets and avenues [17]. As a result, São Paulo has one of the highest traffic levels, with frequently traffic jams of more than 150 km in the region of the expanded center at rush hour [17]. In such centre region, Avenida Paulista is one of the main avenues of the city, being the headquarters of the largest financial companies in the country, which means high concentration of people, as well as vehicles.

The selected scenario has a total of 4.4 km of streets and avenues, with an area of approximately 0.5 km^2, including 3 parallel streets and 4 cross streets (see Fig. 3), with 10 semaphores distributed in each intersection. This scenario has as border São Carlos do Pinhal street by the north and Alameda Santos street by the south, whereas the Alameda Joaquim Eugênio de Lima street and Teixeira da Silva street are the borders by the west and east, respectively. The distribution of semaphores is as follows: 4 semaphores in the Avenida Paulista, in its 4 intersections of this avenue with each transversal streets, and the other 6 semaphores in the streets that are to the north and south of this main route. There are 6 semaphores that include three phases, the four that are in Avenida Paulista plus two, besides the other four semaphores has two phases.

São Carlos do Pinhal street has only one-way traffic: east-west with two lanes in most of its extension, Avenida Paulista has two-way traffic, each one with three lanes: east-west and west-east, Alameda Santos street has two lanes in the west-east one-way traffic. Alameda Joaquim Eugênio de Lima has just a lane in a north-south way, Avenida Brigadeiro Luís Antônio has two lanes in both each north-south and south-north ways, Manoele da Nobrega street has two lanes in a south-north one-way traffic, Maria Figueiredo street has just a lane from north to south way and lastly, there is Teixeira da Silva street, which also has just a lane, but in a south-north way.

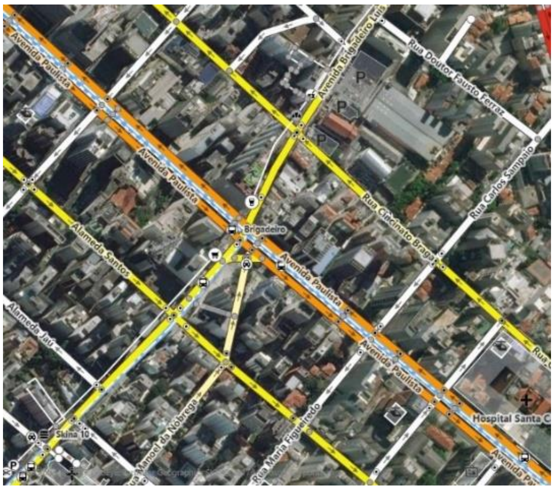

Fig 3. Map of chosen scenario

IV. SIMULATION

The simulations were performed using the MATLAB and SUMO ("Simulation of Urban MObility") tools (see Fig. 4) [18], [19]. The BiNN model was programmed in MATLAB, while the model of the urban transit system was programmed in XML ("eXtensible Markup Language") used in the SUMO environment. To perform the simulations and analysis of results, the protocol TraCI4Matlab [20] was used, which adopts the client-server paradigm and allows the interaction between SUMO (server) and MATLAB (client). All simulations have a duration time of 3600 seconds (one hour).

For analysis of the results, six different types of simulations (see table I), three simulations with different levels of vehicle demand for each type of control algorithm were performed, Fixed-time control and BiNN control.

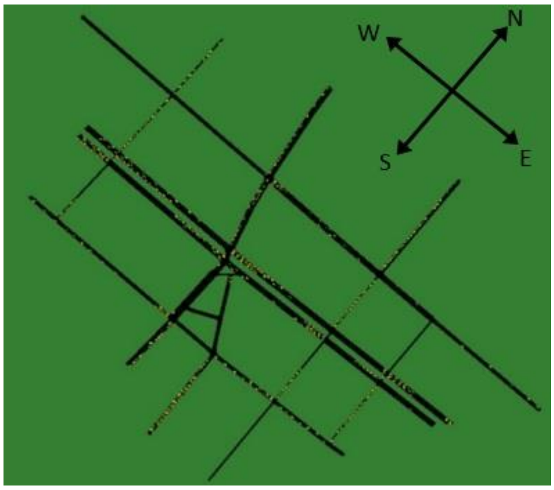

Fig 4. Simulation of scenario in SUMO

TABLE I. SIMULATIONS

Simulation Number	Simulations Descriptions		
	Control Algorithm	***Value (vehicles/ second)***	***Description***
1	Fixed Time Control	1.25	Low traffic
2	Fixed Time Control	2.50	Average traffic
3	Fixed Time Control	3.75	Heavy traffic
4	BiNN Control	1.25	Low traffic
5	BiNN Control	2.50	Average traffic
6	BiNN Control	3.75	Heavy traffic

The demand for 1.25 vehicles per second represents low traffic, while demand of 3.75 vehicles per second represents heavy traffic, so demand 2.50 represents a scenario with average traffic, as used by [8]. All vehicles used have the same characteristics, 5 meters long, with acceleration of 0.8 m/s^2 and maximum speed of 13.89 m/s, which is the speed limit in urban regions according to [17]. In addition, the stochastic steering behavior (SUMO simulator parameter) is equal to 0.5 in all of tests.

The routes of the vehicles were programmed with the same characteristics of the traffic routes described and observed in [17] and [21].

V. RESULTS

The performance indicators adopted are the mean travel time of vehicles, which was used in the analysis made by [14] and [22], and the level of occupation of the lanes in the scenario is the same as that was used by [8] and [9]. For calculating the average travel time of the vehicles was chosen to the east-west route of Avenida Paulista, which is the main avenue of this scenario and the city in general, and the average was obtained by measuring the travel time of 200 vehicles from one border to another of the select scenario. Fig. 5 shows the average travel time values obtained by the six types of simulations.

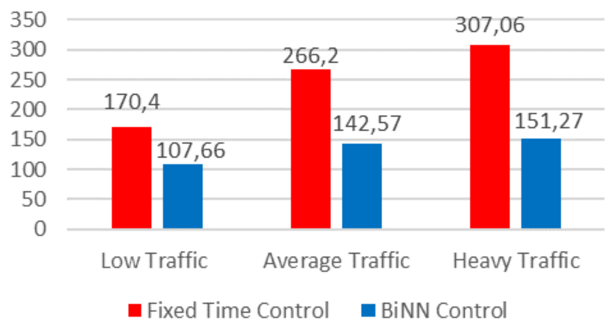

Fig 5. Average Travel Time of vehicles

For the low traffic level, the average travel time of vehicles with the BiNN control decreases by 62.74 seconds, which means more than one minute, which is a significant time for the analysis done on a stretch of avenue with 700 meters. For an average traffic level a difference of 123.63 was obtained, more than two seconds. Finally, for a heavy traffic level, the average travel time difference with the control algorithms applied was 155.79 seconds. We can conclude that the BiNN algorithm has a better response of traffic control than fixed times considering the average travel time. Moreover, its response improves with increasing traffic demand.

Regarding the level of occupancy of lanes, the simulations performed provided the results shown in Fig. 6, Fig. 7 and Fig. 8. The mean differences between the occupancy level of the lanes with the two control algorithms used are shown in table II. The reduction of this value can be justified with the results shown in the Fig. 9 and Fig. 10. While demand for traffic increases if the control designated to regulate traffic is not able to regulate the number of vehicles on the lanes, the scenario does not have enough space for new vehicles to begin their journey, therefore, the number of departed vehicles in the scenario with the average and heavy demand conditions and the fixed time control is lower than those that begin the route with the same demand and with the BiNN control. This situation is observed in Fig. 9, where the number of departed vehicles in the 6 simulations are shown. The difference of the numbers of departed vehicles in two types of control used in the simulation, in the case of the average demand level, is 1236 vehicles, while in the simulation with the heavy demand this difference is even greater, 1636 vehicles. Therefore, if the number of departed vehicles is greater and the control provides a better response to the system, the number of vehicles arriving has been increased using the BiNN control, as shown in Fig. 10.

With the analysis of the average travel time values explained above, we can infer that the BiNN control algorithm has a better response for the three types of simulated traffic demand.

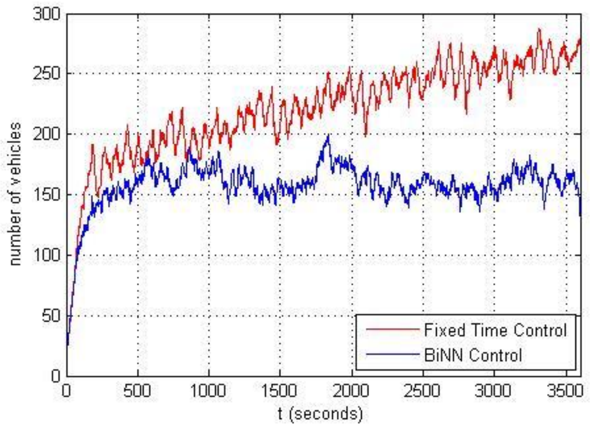

Fig 6. Simulation with low traffic demand

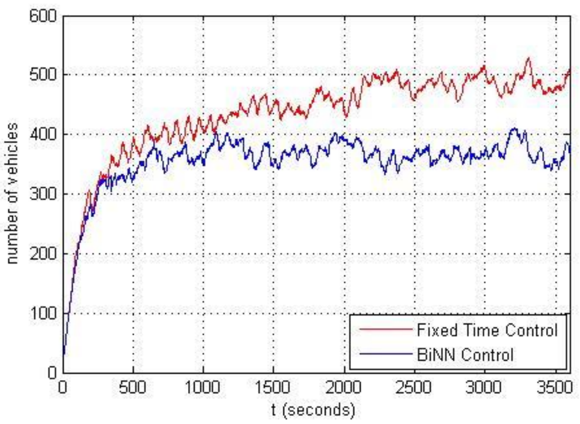

Fig 7. Simulation with average traffic demand

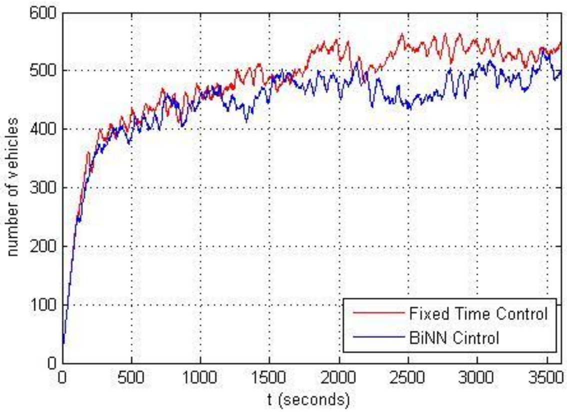

Fig 8. . Simulation with heavy traffic demand

TABLE II. DIFFERENCE AVERAGE IN ROAD OCCUPATION LEVEL

Traffic demand	**Difference Average** (number or vehicles)
Low traffic	62.95
Average traffic	41.11
Heavy traffic	34.55

It is necessary to emphasize that those results are obtained in a small section of the city, therefore they could increase as much as the analyzed scenario is larger. The average time of travel of the vehicles obtained was in an extension of 700 m of length of Avenida Paulista. The total length of this avenue is approximately 4 km. Therefore, if we increase the size of the analyzed scenario we would obtain larger differences between the average travel times with fixed time semaphore control and the proposed BiNN algorithm. The same could happen with the level of occupation of the lanes, which we are analyzing only in an area of 4.4 km of streets and avenues, compared to more than 17,000 km of roads that have the city of São Paulo.

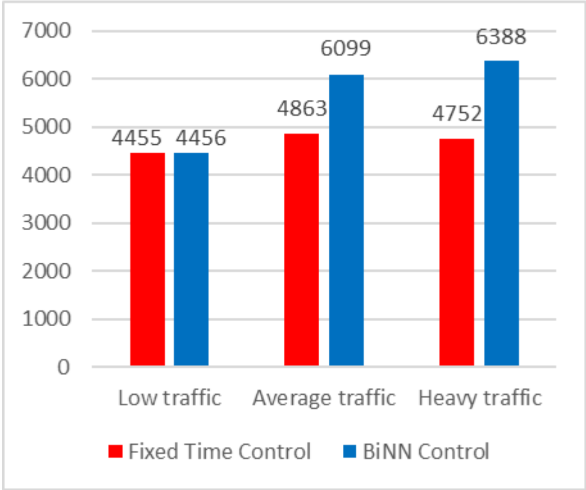

Fig 9. Number of vehicles departed

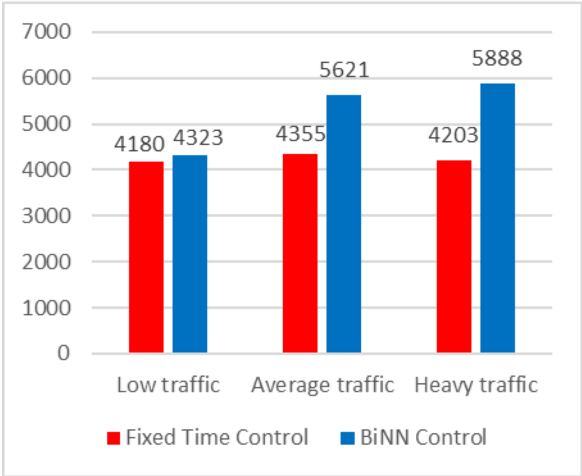

Fig 10. Number of vehicles arrived

VI. CONCLUSIONS

This work describes the application of an algorithm based on Bio-Inspired Neural Networks for the multi-agent control of traffic semaphores, with the purpose of controlling urban traffic and reducing the level of traffic bottling. The algorithm was applied in a real scenario in the city center region of São Paulo obtaining good results, which were compared with results obtained with fixed times control. Test results show up to 22.89% performance under the low traffic conditions, 26.35% under average traffic and 28.86% under the heavy traffic condition compared to the fixed time control, the performance indicators used for this comparison were the average travel time and the level of occupation of lanes. One of the main contributions of this paper is the ability to estimate the real impact on the traffic level that BiNN control could apply in the city of São Paulo. For further research, it is possible to analyze the performance indicators used in this work with increasing of the size of the scenario, the length of the vials and the number of traffic semaphores.

ACKNOWLEDGMENT

This work was supported by CAPES, *Coordenação de Aperfeiçoamento de PEssoal de nível Superior*. Also we would thanks to the *Institute of Transportation Systems* (DLR) for allow the use of SUMO simulation software.

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