Estimation of highway traffic service level based on Module of Intelligent Transportation System and Artificial Intelligence

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Abstract: International experience shows that several organizations have used traffic data and events occurred on roadways to build quality indicators. This paper explores methods that allow estimating traffic conditions at a given moment or over a given period of time. Traffic data were collected using Module of Intelligent Transport System (MITS), and were processed by means of Artificial Intelligence (AI) techniques based on Highway Capacity Manual (HCM) methodology. Part of these data were used to train the Artificial Neural Network (ANN) and another part were used to compare with that estimated by ANN. Experimental results show that ANN has estimated the level of service (LOS) of traffic with less than 3% error. This method can help the highway users decide the best window time for your displacement.

Keywords: Intelligent Transport Systems, Highway Capacity Manual, Artificial Neural Networks, Artificial Intelligence, ITS, HCM, ANN.

1. Introduction

The State of São Paulo has much of its road network operated by the private sector. Highway Concessionaries are responsible for a large percentage of the Average Daily Traffic (ADT) and are of fundamental importance in the movement of people and cargo in the State [1].

To check the quality of service provided by Highway Concessionaries, the Regulatory Agency needs information to support its decisions. The Concessionaries have, in the segment under its responsibility, Intelligent Transport Systems (ITS) equipment that provides traffic flow and vehicles speed.

The Regulatory Agency has monitored the operations of roadways under concession through a tool called Module of Intelligent Transport System (MITS). It allows the monitoring of equipment and events, through data integration collected in various systems (of ITS) and event maps used by the Concessionaries.

The set of information generated by MITS allows the Regulatory Agency to supervise the Concessionaries, remotely and online, helping them to identify problems and difficulties. This, allows the Regulatory Agency to make decisions based on results and focus on improvements and continuous quality control [5] [6] [13] [18].

The variable relevant to the evaluation of the services provided by Concessionaries should reflect the user's point of view. The choice of these variables directly impacts the way that the

Regulatory Agency monitors the quality of Concessionaries services. Whist there is no consensus in the literature on these variables, the evaluation of traffic conditions is an important variable in several countries.

Countries such as United States, United Kingdom, Australia and Germany have manuals with methods for performance analysis of its highways and transportation systems. It is observed that these manuals, in general, rely on the concepts of capacity and level of service (LOS) proposed by the Highway Capacity Manual (HCM).

From the traffic data generated by the MITS in this paper proposes the joint application of the methodology of the HCM [2] and Artificial Intelligence (AI) techniques [3] on a segment of a highway in the state of São Paulo. This data will be utilized for the LOS calculation, according to the methodology proposed by the HCM, and AI techniques will estimate future values of vehicle speed and traffic volumes and, consequently, the LOS.

2. Module of Intelligent Transport Systems (MITS)

The goal of the MITS is to acquire information originating from ITS systems and events occurring on highways of each concessionaire, centralizing the information in a database in the Information Control Center (ICC) of the Regulatory Agency [4].

It should be noted that the purpose of the MITS system is to integrate information concerning all Highway Concessionaries in São Paulo (in September 2013 there were nineteen). Each Concessionary can have different ITS systems and maps of events. These systems can be from different suppliers and sometimes these suppliers have different versions for their systems. In order to solve this problem of system interoperability, architecture was defined that facilitated the development.

By using this system, the Regulatory Agency can monitor the conditions of the highways in the entire segment granted, as well as oversee the actions taken in relation to the services provided by Concessionaries.

Through the Sub-module of MITS (Equipment Monitoring), through the information presented on the maps for operators it is possible to identify which Concessionaries have warning signs and/or alarms. The warnings are activated when MITS detects an abnormal condition on the highway, for example traffic volume above normal, average speed above that one established for the highway, or equipment failures [15].

As shown in Fig.1, the MITS architecture consists of an ICC, a Processing Agent (or Updater) and an Adapting Agent – independent for each Highway Concessionary. The specifications concerning the concessionary's systems are treated within the framework of the Adapting Agent. This agent accesses the databases of the Concessionary.

Data are converted to standard format and transferred to the Processing Agent. The Processing Agent is responsible for sending this information to the ICC.

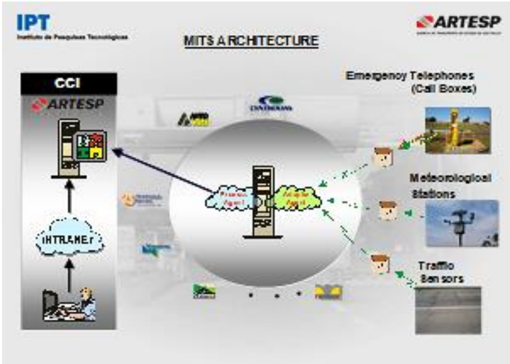

Figure 1: MITS Architecture

The MITS is segregated into two different areas: the public and the private one. Fig. 2 presents the modules of the MITS system.

The purpose of the public area is to provide information about traffic conditions and other information of public interest, for example through Web or Mobile devices.

The purpose of the private area is to supply data that allow the Regulatory Agency to monitor the operation, the maintenance of resources (equipment, vehicles and edifications) and occurrences shown on the events map. This consists of the following modules: User Registration, Location Registration, Management Information (Reports), View Images, Equipment Maintenance, Equipment Monitoring and Map of the OCC.

Among several modules of the private area, as shown in Fig. 2, two of them are described, as follows:

Equipment Monitoring: responsible for the storage, management and provision of information about the Concessionaries. This module allows the Regulatory Agency to monitor and inspect the information about the equipment of the highway Concessionaries. Also generates information about alerts and alarms (telemetry) of Concessionaries equipment.

Map (Operational Control Center - OCC): shows information relating to the event map of Concessionaries.

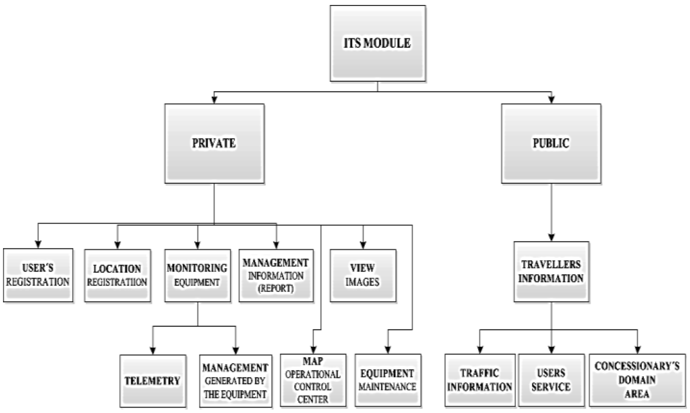

Fig.2: MITS Modules Diagram

More relevant information to the Regulatory Agency is provided by the modules for Equipment Monitoring and Map of the OCC, because they could be considered the best representation of operational conditions of the designated segment.

With the Equipment Monitoring Module, the inspectors from the Regulatory Agency can access information on equipment of all Concessionaries. Thus, as illustrated in Fig. 3, all segments granted to Concessionaires (each one marked by colors), are shown on the map.

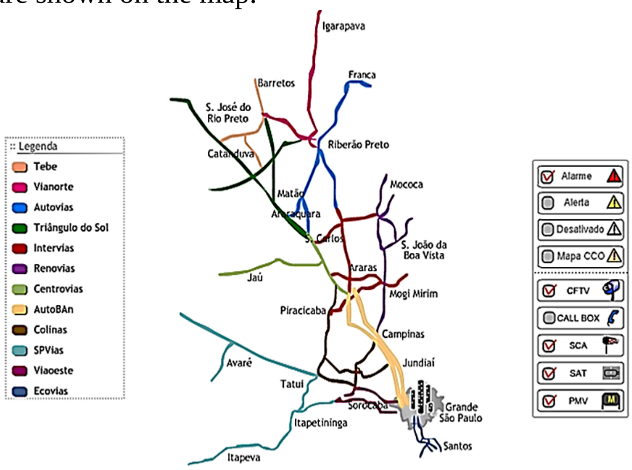

Fig.3: MITS Equipment Monitoring Map

The occurrence of problems is pointed out through effects, for example, flickering on a particular stretch of the highway with a problem. It is possible to obtain more detailed information on equipment such as traffic sensors, weather station, call boxes, Closed-Circuit Television (CCTV) and Variable Message Signs (VMS) panels. For each device are shown alarms / alerts, allowing operator to recognize the problem and perform an action.

3. HCM 2000

The Highway Capacity Manual (HCM) was developed in 2000 by the Transportation Research Board, which is a unit of the United State (US) National Research Council, in order to provide a collection of state-of-the-art techniques for estimating the capacity and determining the level of service for transportation facilities. Previous versions of HCM, however, have been given guidance to Highway Concessionaries and Governmental Agencies for the last 50 years.

3.1 Background

According to the HCM definitions, some concepts used in this project are presented below.

Capacity: is the maximum number of vehicles or people estimated that can pass through a point (section) of a road, during a period of time, under certain operating and traffic conditions (HCM 2000), having as hypotheses:

- Good weather, pavement in good condition and no temporary obstruction of traffic flow;
- Point or Segment of road with traffic characteristics, uniform control and geometry in all the sections considered;
- It is expressed in vehicles (flow per hour or 15 minutes) per lane and determined from the value corresponding to the number of vehicles (volume) ratio that goes through the segment under evaluation over a period of time.

Level of Service **(LOS)**: is a quality indicator that describes the operating conditions of the traffic flow, i.e., speed, travel time, freedom to maneuver, traffic disruptions, comfort and safety.

According to Neto, 2009 [14], the analysis of capacity and LOS allow questions to be answered, such as:

- What is the quality of the operation in peak periods and what is the level of traffic growth that can be supported by the system under current conditions?
- How many traffic lanes are necessary to meet the average daily traffic volumes on a highway?
- What type of highway adequately meets the demand generated by a new real estate development?
- What is the level of the offer necessary for a determined level of vehicular demand which can be satisfactorily serviced?

According to HCM 2000 [2], six LOS levels are defined, from A to F, in which A represents the best operating conditions and F the worst, as is shown in Table 1.

Table 1: Level of service for roads with continuous flow.

Level of Service	Flow Characteristics	Operating Conditions
A	Free Flow	Low Volumes and High Speeds.
B	Reasonable Free Flow	Speed starting to slow down due to traffic conditions.
C	Stable Flow	Restrictions as far as the freedom of the drivers to choose their own speed.
D	Flow Approaching Instability	Drivers have limited freedom of maneuver.
E	Instable Flow	Possible Brief Stops.
F	Forced Flow	Congestion.

Source: HCM 2000 [2] [18].

3.2. HCM 2000 Methodology

For the application of the LOS methodology calculation, the following basic assumptions were adopted: The road is under good weather and visibility; Incidents or accidents are not present; The segment shows a continuous traffic flow (the road does not have devices that disrupt traffic regularly, i.e. traffic lights, intersections, points of entry and on the sides of the road); The minimum lane width is 3.60 m; The roads are separated by some kind of physical device in the middle; The ground is leveled with a ramp of less than 2% slope (because of that, it was considered for the Vehicular Equivalent Factor for Trucks and Buses- E_T - equal to 1.5), as it was adopted, for the Free Flow Speed (FFS) calculation, a volume of no more than 1,000 Equivalent Vehicles (Vp), as shown in Table 2.

Establishing these hypotheses, the following recommended indexes were calculated by the HCM 2000 methodology: Adjustment Factor for Heavy Vehicles (f_{HV}), Peak Hour Factor (PHF), Equivalent Vehicles Flow (Vp), Free Flow Speed (FFS) and Maximum Density (D).

The calculation formulas and the indication of the component factors necessary for determining these indexes are shown in Table 2.

For determining LOS, the Maximum Density index was chosen according to its Free Flow Speed (FFS). This index (Maximum Density) was chosen because the LOS ("A" to "D") remained constant through different FFS. For the Maximum Density calculation the speed was considered at each time period obtained by the harmonic speeds' average provided in the four 15 minute intervals.

When the FFS is an intermediate value (i.e.: 75 km/h) only the calculation of LOS "E" interpolation will be required (in this case: between 70 km/h and 80 km/h).

From the results obtained for the Maximum Density, the LOS was established, according to Table 3 and Fig. 4.

Table 2: Calculation methodology for HCM 2000 indexes for determining the level of service (LOS).

Indexes	Calculation Formula	Definitions
Adjustment Factor for Heavy Vehicles (fHV)	$f_{HV} = \frac{1}{1 + P_T \times (E_T - 1)}$	f_{HV} = Adjustment Factor for Heavy Vehicles. P_T = Percentage of Heavy Vehicles in the composed flow (Heavy Vehicles/TOTAL of Vehicles). E_T = Vehicle Equivalent Factor for Trucks and Buses (obtained from the table below).
Peak Hour Factor (PHF)	$PHF = \frac{V}{4xV_{15}}$	PHF = Peak Hour Factor. V = Hourly Volume (Vehicle / Hour). V_{15} = Maximum flow of vehicles in one of the 15 minutes that compose the one hour (Vehicles / 15 minutes).
Equivalent Vehicles Flow (Vp)	$V_p = \frac{V}{PHF \times N \times f_{HV}}$	V_p = Passenger vehicle flow, equivalents to the peak of 15 minutes (equivalent vehicles / hour / lane). V = Hourly Volume (Vehicles / Hour). PHF = Peak Hour Factor. N = Number of Lanes. f_{HV} = Adjustment Factor for Heavy Vehicles.
Free Flow Speed (FFS)	$FFS = S_{FM} + 0{,}0125 \times \frac{V_f}{f_{HV}}$	FFS = Free Flow Speed (km/h). S_{FM} = Average Speed of Traffic Measured in the Field (km/h). V_f = Flow Rate Observed in the Field, when the data was obtained (vehicles/h). f_{HV} = Adjustment Factor for Heavy Vehicles.
Maximum Density (D)	$D = \frac{V_p}{S_{FM}}$	D = Density (equivalent vehicles / km / lane). V_p = Passenger Vehicle Flow, equivalent to a peak of 15 minutes (equivalent vehicles / hour / lane). S_{FM} = Average Speed of Traffic Measured in the Field (km/h).

Source: HCM 2000 (adapted) [2]

Table 3: Level of service criteria for highways

		Level of Service (LOS)				
Free Flow Speed (FFS)	**Criterion**	**A**	**B**	**C**	**D**	**E**
100 Km/h	Maximum Density (D) (Equivalent Vehicles/km/lane)	7	11	16	22	25
	Average Speed (km/h)	100	100	98,4	91,5	88
90 Km/h	Maximum Density (D) (Equivalent Vehicles/km/lane)	7	11	16	22	26
	Average Speed (km/h)	90	90	89,8	84,7	80,8
80 Km/h	Maximum Density (D) (Equivalent Vehicles/km/lane)	7	11	16	22	27
	Average Speed (km/h)	80	80	80	77,6	74,1
70 Km/h	Maximum Density (D) (Equivalent Vehicles/km/lane)	7	11	16	22	28
	Average Speed (km/h)	70	70	70	69,6	67,9

Source: HCM2000 (adapted) [2]

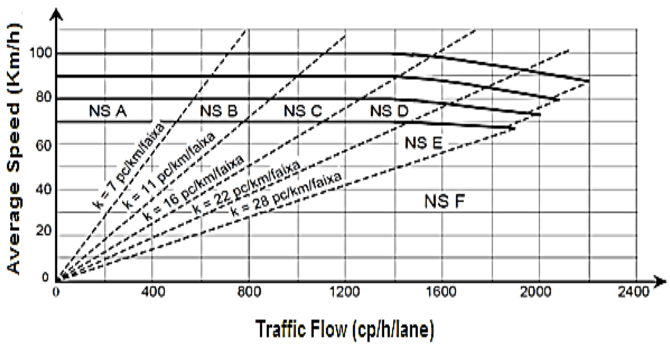

Fig. 4: Flux-speed relation and level of service for highway with convention two-lanes.
Source: HCM2000 (adapted): Figure 21-3, p. 21-4
Obs.: “k” = Maximum Density and “pc” = Equivalent Vehicles

4. Artificial Intelligence (IA) Techniques

Artificial Intelligence (AI) techniques describes how AI can be applied to predict traffic behavior, estimate future values of speed and volume and the LOS, as mentioned in the previous item.

4.1 Artificial Neural Networks (ANNs)

The ANNs are models inspired by the structure of the human brain where, from a sufficient number of artificial neurons, a network is able to achieve an approximation of any continuous function [17].

The ANNs are particularly efficient for the mapping of input/output non-linear systems and performing parallel processing, in addition to simulating complex systems [15]. Another important feature of ANNs is its ability to learn from the incomplete data and subject to noise, generalizing the results obtained from previously unknown data to produce coherent and appropriate responses to standards or samples that have not been utilized in its training [7][16]. The ANNs are also considered a universal approximation of continuous functions [8].

In a conventional computer system, if a part fails, in general, the system deteriorates, while in an ANN, the tolerance to faults is part of the architecture, because the nature of processing is distributed. If a neuron fails, your erroneous output is overwritten by the correct output of its neighboring elements. So, at first, an ANN shows a smooth degradation of its performance instead of presenting a catastrophic failure [7].

A general definition of what is meant to be learning in an ANN can be expressed as follows: "learning is the process by which the parameters of an ANN are adjusted through a continuing form of stimulus by the environment in which the network is operated, being that the specific type of learning held defined by particular manner as the adjustments occur in the parameters" [9].

Various methods for learning have been developed and can be grouped into two main paradigms: supervised learning and non-supervised learning [19].

In supervised learning there is a prior knowledge about the values of the inputs xi and respective outputs yi. This set of ordered pairs (xi, yi), values of which are known before hand, is called the learning database. The algorithm most known is of error back-propagation utilized by ANN of the Multi-Layer Perceptron (MLP) type used in this project [10].

The learning of an ANN, in most cases, happens with a subset of examples (dada vectors) that define the training set, and the ANN test is performed with another subset of examples that define the so-called set of test.

The architecture of an ANN depends on the type of problem in which the network should be used, as it is defined, along with other factors, by the number of layers, number of nodes in each layer, by the type of connection between the nodes (feedforward or feedback) and by its topology (Recurring and Non-recurring) [8].

Table 4 presents some parameters adopted in the learning of ANNs.

Table 4 – Parameters of learning architecture (training) throughout the progress of the training and the ANN performance is monitored.

Parameters	ANNs Architecture	Parameter Functions
Learning Rate	All	Controls the speed of the weights adjustment of Artificial Neural Network.
Momentum	Error Back-Propagation with MLP	Follows the learning rate parameter step by step. Its function is to monitor the possible occurrence of big swings in the values of weight connections.
Error Tolerance	Error Back-Propagation with MLP	Is used to specify the maximum difference between the desired output and that generated by ANN. This parameter specifies how close the ANN output should be to the desired output.
Activation Function	All	Select the activation function, which is used by artificial neural network processing. The sigmoid functions, hyperbolic tangent and Gaussian function, for example, can be used.
Number of Times	SOM Network, MLP	The number of times determines the number of steps for network training through the training data.

Source: Adapted from [3] and [11].

The ANNs can be trained using random initial values for connections with weights. The learning parameters (Table 4) are initialized and the training standards of data vectors are presented for the ANN. The weights of the connections are adjusted

4.2 Multi-Layer Perception (MLP)

An ANN type MLP consists of a set of units (or neurons) which constitute an input layer, of one or more hidden layers and an output layer. The input signal is propagated by ANN layer by layer. Fig. 5 shows the basic structure of an ANN type MLP.

The ANNs possess has the ability to learn by examples and make interpolations and extrapolations of what they have learned. A set of well-defined procedures to adapt the weights of an ANN can be learned, so that a particular function is called training or learning algorithm [3].

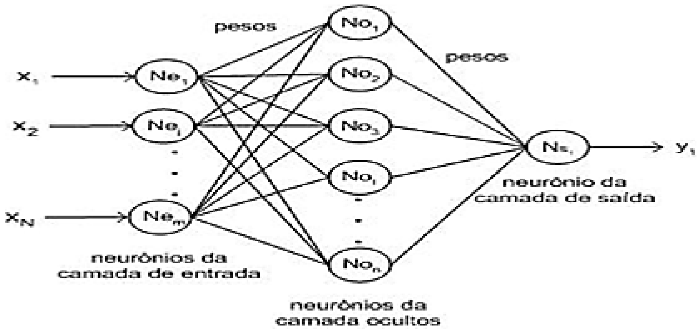

Fig. 5: Basic structure of the ANN type MLP.

The learning of an ANN uses a dataset corresponding to a sample of signals for input and output of the system. For this training, the network uses learning algorithms.

Initially the network remains inert and the learning algorithm modifies individual weights of interconnections in such a way that the behavior of the network reflects the desired action. In other words, the network may change its internal structure incrementally until it reaches the expected performance of data set [12].

The back-propagation algorithm error used in MLP is to determine changes in synaptic weights of ANN, aiming to minimize the error in the output obtained through learning the training vector (input-output).

The back-propagation algorithm error works as follows: If there is a default input layer pattern of the network, this pattern is rendered layer by layer, until the output layer provides the answer, f_{MLP}, function of the MLP, as shown in equation (1):

$$f_{MLP}(x) = \varphi\left(\sum_{1}^{Non} v_l \cdot \varphi\left(\sum w_{lj} x_l + b_{l0}\right) + b_0\right) \quad (1)$$

where vl and wlj are synaptic weights; bl0 and b0 are biases (special unit of the input layer, used to increase the degrees of freedom, allowing better adaptation part on the ANN-MLP of the knowledge provided); and φ the activation function, usually specified as the sigmoid function.

According to Haykin, 2001 [7], the MLP has the following features: non-linear activation function (sigmoidal), one or more layers of hidden neurons and a high degree of connectivity. A trained ANN-MLP with the back-propagation algorithm performs a non-linear mapping of input-output.

5. Experimentation

The experimentation shows an application of the concepts defined by the HCM, implemented by ANN-MLP using data collected by the Module of Intelligent Transport System (MITS), to estimate values of speed and traffic volume and, consequently, the LOS.

5.1 Application to the HCM

The following data were collected by MITS on a highway of São Paulo: volume of vehicles, commercial vehicle volume and average speed of traffic. These data were obtained, at a specific point on the highway, in 15 minute intervals, for Wednesdays in May 2011: 5/4/2011, 5/11/2011, 5/18/2011 and 5/25/2011, 12:00 am to 11:45 pm each day, totaling 96 hours of data collected.

Wednesdays were chosen on the basis of considering these days as typical for the highway. From these data were calculated the indexes listed in HCM 2000: adjustment factor for heavy vehicles (fHV), peak time factor (PHF), equivalent vehicles flow (Vp), free flow speed (FFS), maximum density (D) and level of service (LOS).

Fig. 6 presents the results of the calculation of the LOS at this particular point of the highway. Each LOS corresponds to one of the 12:0 am Wednesday above. There is a pattern that repeats itself in these days.

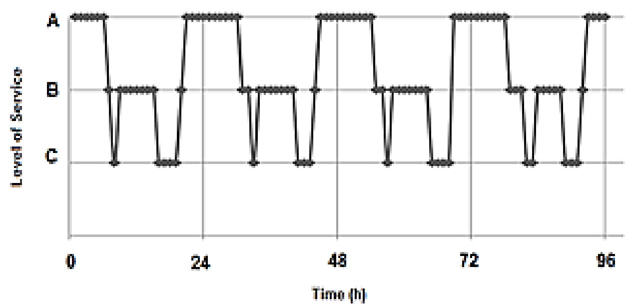

Fig. 6: Service level calculated for typical days at a particular point of highway monitoring.

5.2 Application of an ANN.

The choice was to utilize an ANN type MPL, trained through the error back-propagation algorithm. This choice is because this method is suitable for solving problems that involve sorting and approximation (accuracy and time-series modeling) [7]. With this method it was possible to estimate, with good precision, the stream of equivalent vehicles in the future.

The parameters used for construction of the MLP were: number of input neurons equal to 9, number of layers equal to 3, the number of neurons in the hidden layer equal to 15, learning rate (constant) equal to 0.1, 0.1 equal time factor and maximum number of times equal to 1500.

The following data were used as ANN-MLP entries: Volume of vehicles, commercial vehicle volumes, average traffic speed, percentage of heavy vehicles (P_T),vehicles volume during the peak of 15 minutes during one hour (V_{15}), adjustment factor for heavy vehicles (fHV), peak time factor (PHF), free flow speed (FFS) and maximum density (D). The output data is the equivalent vehicles flow (Vp).

As a result of the training, the ANN produces similar output values to the data set to values equal to the training samples. For intermediate values, the network produced an interpolation.

Fig. 7 presents the result of network training. The data presented in black (dashed) are the measured equivalent vehicles flow (Vp) [calculated by HCM], while data presented in red color (continuous) are the values calculated (based on training) by ANN.

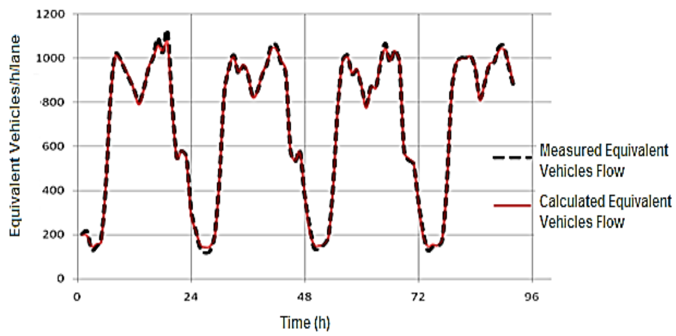

Fig. 7: ANN Training phase on the flow of Equivalent Vehicles Flow (Vp)

A total of 96 hours of data were collected by MITS, 92 hours of data were used for the training of ANN. The 4 hours remaining were estimated by ANN compared with the data collected. The results for this estimated time are presented in Fig. 8.

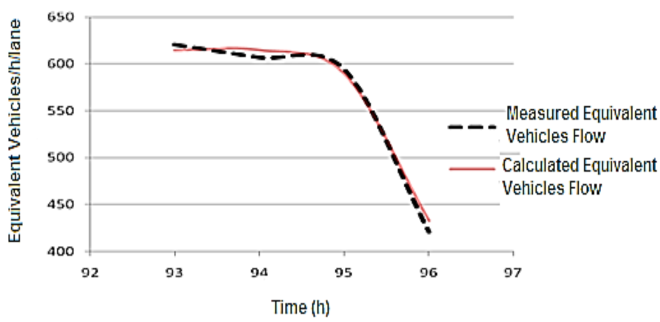

Fig. 8: Comparison of equivalent vehicles flow estimation (Vp) calculated by ANN versus the data

From the values of Equivalent Vehicles Flow (Vp)-calculated by ANN- the calculation of the maximum density and level of service was carried out.

The analysis of Fig. 9 shows that the ANN can simulate reliable density values, compared to those ones calculated by HCM, and allows good approximation results of LOS, considering only the estimated density by ANN, shown in Fig. 9.

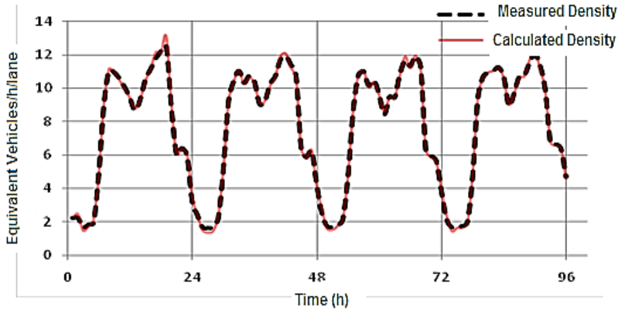

Fig. 9: Simulation by ANN of Maximum Density.

The four estimated times and their errors are shown in Table 5. Note that the ANN has estimated these four hours with a maximum error or less than 3%.

Table 5: Equivalent vehicles flows measured and estimated (by ANN)

Hour	Vp measured	Vp estimated	Error
93	620.3184	615.0079	0.86%
94	606.6521	615.0665	1.39%
95	593.9856	589.9697	0.68%
96	420.7031	432.9998	2.92%

5.3 Discussion

The results obtained were for short-period estimates. This same methodology can be applied to longer estimate periods. This implies necessarily more ANN training period.

If this is applicable, this will allows to more detailed highways' flow dynamics, i.e. predict more accurately the flow of vehicles and the level of service required, which could assist decision-making that precedes the investments that the Government Authorities should make in conjunction with the Concessionaries, avoiding unacceptable LOS.

Thus, estimates will be reached in the future when, for a particular stretch of highway, a low LOS is achieved (i.e.: D). Authorities and Concessionaries, therefore, will be able to anticipate the decision regarding actions that should be taken at this time in order to maintain the LOS on a more acceptable level (i.e. in B or C).

6. Conclusions

The joint application of the methodology HCM and ANN-MLP showed satisfactory results with experimental data and its use producing a result capable to represent the dynamics of flow on highways.

The results obtained pointed out positively for the joint application of the methodologies in the prediction of the flow of vehicles.

For an estimated short term period, the combination of the HCM methodology and the Artificial Neural Network to analyse data from MITS has made possible to predict oscillations in vehicles flow. This may give drivers' information to allow them to decide the best period for their start journey time.

The present research can be continued with studies on the applicability of this methodology proposed (HCM in conjunction with Artificial Neural Network) in order to estimate a longer period of time (for example, in months).

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