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Abstract

Blah, blah, blah...

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1. Introduction

The development of new systems that inform of traffic conditions and the affluence of vehicles on roads, seem to be a key point nowadays. With an increasingly informed population, provided with ubiquitous communication devices, which are commonly used by more than 90% of the population, obtaining information about the traffic in any part of the above 165000 kilometres of Spanish roads would mean an optimal management of a communication network fundamental for a high percentage of users.

In this work, an information system of the traffic status is proposed. This information system is based on data collected by means of bluetooth (BT) device discovery and provides description of the current traffic conditions, as well as a valuable dataset suitable to be used in a time-series forecasting process.

The data-collecting and the time-series forecasting processes [REF] are necessary steps to achieve an ultimate goal: to have information about traffic

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flows that occur or will occur in a certain area, allowing or aiming to optimally manage motion decisions by citizens.

Therefore, from the transport management viewpoint, various needs have been addressed:

- To have a versatile, autonomous data collector, and monitoring device.
- To collect traffic information in real time.
- To process in an adequate way the data being collected,
- And finally, to build a system that allows sharing data and information with those who make decisions about mobility.

In order to fulfil these requirements, the BT device discovery used for this work is able to catch pulses emitted by different technological components. The components can be the ones embedded in vehicles (hands-free or GPS), accessories that the users incorporate to their vehicles, as well as mobile phones, tablets or laptops. The main data being collected is the MAC address of the device BT card. This is an unique identifier for each device, so that passing vehicles can be identified. From the user's personal data protection point of view, the invasion of privacy is minimum since one-way encryption (or codification) algorithms are used to hide the real MAC addresses which are stored. Moreover it is even safer from the point of view of data privacy, since this piece of information can not be attached to any given person.

The work shows how the large amount of data collected, related to detected BT devices (which pass near the device), are considered as the starting point to compute statistics, to study several indicators about the use of vehicles, and to perform time-series forecasting for the monitored area population.

Fot this reason, the paper is organized as follows: ???????In Section **??** current technologies to monitor the traffic that passes through a certain area is summarized. Section **??** details the goals of this paper. In Section **??**, the Intelify device is presented. In Section **??** several analysis and statistics are reported from the data obtained. Finally, we present some conclusions and future work (Section 5).

2. Background and State of the Art

This section introduces the two main components of the work. On the one hand, the methods developed to detect and store data about traffic flows; and on the other hand, the algorithms and techniques considered in the time-series prediction tasks.

2.1. Traffic detection technologies

Traffic detection technologies can be generally classified into two groups: intrusive and non-intrusive.

Intrusive detection technologies imply a physical modification of the roadway, i.e., they are installed on, and frequently, under the pavement. This is the main disadvantage, since it requires the lanes must be closed for the installation process. Moreover it could affect the road life, requiring usually several posterior maintenance tasks. These methods also present some accuracy problems due to the difficulty to detect different types of vehicles. Some examples of intrusive technologies are inductive loop detectors, piezoelectric sensors, or weigh in motion detectors.

On the other hand non-intrusive technologies do not cause traffic interruptions during the installation and maintenance processes, since they are usually placed on the roadway sides, or are installed on traffic or informative signs. Non-intrusive methods are classified in active and passive technologies. Active ones include microwave, ultrasonic and laser radars. Passive methods can be infrared and video image processing or acoustic sensors, among others.

Current technologies most frequently used in traffic monitoring include pneumatic tubes, loop detectors, floating vehicles, and automatic recognition systems, among others. Some of them are explained next:

- *Manual counting* is a traditional method in which human observers, using a counting tool, perform the data gathering task. They can extract information difficult to obtain with other methods, such as vehicle classification or occupancy.

- *Pneumatic road tubes*: are included in the intrusive technologies. They are deployed across the roadway and detect pressure changes when the vehicles pass over them. However, their efficiency depends on the weather conditions and temperature, and are not reliable to recognize low speed traffic flows.

- *Piezoelectric sensors*: are another intrusive components which work in a similar way than the previous tubes, but based in the mechanical deformation of the material, which means an electric signal (potential difference) of different intensity is detected. The deformation depends on the vehicle's weight, so these sensors can differentiate some classes of vehicles and measure speed.

- *Magnetic loops*: the most common intrusive technology in traffic data gathering. They consist in a set of loops placed under the asphalt generating a magnetic field. When a vehicle moves over this field it can be detected and counted. They can differentiate between vehicles (in some range) depending on the detected iron mass size. They have a shorter life (can be damaged by heavy vehicles) and are quite expensive (installation and maintenance), but are not affected by weather conditions.

- *Passive and active infrared sensors*: non-intrusive method which consider the infrared energy which vehicles radiate to detect their presence, speed and even their type. They perform worse in bad weather conditions and have a quite limited covering.

- *Microwave radar*: another non-intrusive technology. It is based in the Doppler effect, and can detect vehicles in movement and their speed. The advantage is that it is not affected by weather conditions.

- *Ultrasonic sensors*: it is also a non-intrusive technology based in sound. There are some devices that emit ultrasonic sound waves which are detected by the sensors when returning once they have rebounded in a vehicle. They measure the returning time for the signal to calculate the vehicle's speed. Weather conditions and temperature affect their performance.

A different technology consists in the use of the so-called *floating vehicles*, i.e. vehicles provided with sensors and anthems to collect information while driving on a predefined route (active) or from an static, and usually strategic, position (passive). This active data gathering is one of the most popular among operators of roads, and is especially used for the calculation of travel times and for loop detectors calibration. Depending on the level of automation in the data collection, the cost can vary.

In some areas, such as electronic toll or transit systems, *automatic vehicle identification systems* (AVI) are also widely used. These sensors are non-exhaustive data sources to identify tags located in vehicles, such as in payment-systems without stopping. The system detects the pass, and the data is sent to the server where it is processed in order to carry out an event (pay toll, opening the fence, etc).

The main disadvantage of all these systems is that they are unable to identify vehicles detected, in order to obtain origin/destination matrixes. Just the number of vehicles and sometimes their type can be computed, but does not allow to obtain moves flow, nor to determine whether a certain vehicle passes repeatedly. In addition, its high cost makes it unprofitable covering secondary roads with them, so they are often located on main roadways.

Thus the *automatic recognition* technology has rapidly grown in recent years due to its ability to detect individual vehicles without relying on in-vehicle systems. *Video image detection* is an example: video cameras record vehicle numbers, type and speed by means of different video techniques, e.g. trip line and tracking. Furthermore, they are used for automatic detection of incidents on the road. That is the main advantage over previous information systems. However, system reliability might not be the best, as the system can be sensitive to meteorological conditions. Moreover, these systems are very costly compared to the previous ones. Finally, from a privacy point of view, the Spanish Data Protection Agency[1] considers the car license plate as a personal data, so their use could require the user consent.

2.1.1. Commercial products

There are different companies working in the traffic information area using approaches similar to the presented in this work.

- **Bit Carrier** (**?**) (**?**): It offers a traffic management system based in BT to count people and commercial routes (pathsolver). Its technology was implanted in highways managed by Abertis for traffic control and monitoring. Actually it has a 150 devices network in Catalonia, so it allows count the traffic times of 200.000 persons each day.

- **Trafficnow** (**?**): Another BT system product. A pilot experience has been implanted in Vigo.

[1] Agencia de Proteccin de Datos

- **Traffax Inc** (?): It is a company that also has used BT for calculating origin-destination and transport time matrixes.
- **Savari Networks** (?): It offers the commercial product StreetWAVE for traffic monitoring to know in real time the traffic status.
- **TrafficCast** (?): They have developed prediction models in different cities based on different technologies, such as cameras, BT and RFID included in the vehicles.

The proposal presented in this work have some common features with the previous approaches, offering similar functionality but with reduced cost.

2.2. Time series forecasting

Briefly described, a time series is a set of chronologically ordered data. Time series forecasting is the task of predicting values of a given series using its own past and present values; the values of any related exogeneous variable can be also used, when available. Time series forecasting is a major field of research, mainly in the areas of statistics (2) and operational research (3), as time series can be found in fields like Engineering, Biology, Economy, or Social Sciences, among many others.

Time series forecasting is usually tackled trying to find out an underlying model that describes the series behaviour. For this reason, there exist a wide variety of methods to perform forecast using both linear and nonlinear models. The group of linear methods comprises the exponential smoothing methods (4; 5), simple exponential smoothing (SES), or State space models (6), among many others. Nevertheless, the most well-known, widely used linear methods are the ARIMA ones (1). ARIMA methods can be summarized as iterative cycles in which: a) the time series is classified as belonging to a pre-established class; b) according to that class, a set of parameters is estimated; and c) the obtained model is verified in other to accept it, or search for another one returning to first step. The models provide by ARIMA integrate in their equations autoregressive (AR) and moving average (MA) components to have into account pass values as well as previous forecasting errors.

Despite their ease of use, linear models have shown no to be accurate for many real applications, being this the main reason why new (but also more complex and difficult to be used) nonlinear methods have been developed. Nonlinear models include regime-switching models, which comprise the wide variety of existing threshold autoregressive (TAR) models (7). Clements (11) exposed main drawbacks of nonlinear methods, mainly the excessively complex models they provide, the lack of robust performance, and, worst of all, the difficulty to use. De Gooijer (2) also concludes that future research on nonlinear models should include, among others, the search for easy to use software.

Forecasting values for time series has been also faced with soft computing approaches; for instance, the ones by Samanta (12) and Zhu (13), who developed methods based on cooperative particle swarm optimization. In (14) and (15) fuzzy time series models are proposed in order to predict new values.Similarly, Yu and Huarng (16) applied ANNs for training and forecasting in their fuzzy time series model. Models such as support vector regression (17) and fuzzy expert system (18) were proposed for the electricity demand forecasting, among others.

As can be seen, ANNs have been applied to time series and they are currently recognized as an important tool for forecasting.

Tang (19) concluded that ANNs could provide better long-term forecasting; moreover, ANNs can perform better than ARIMA models with short series of input data. Furthermore, contrary to the traditional linear and nonlinear time series models, ANNs are nonlinear data-driven approaches with more flexibility and effectiveness in modeling for forecasting (20). Jain and Kumar determined in their work (21) that the ANN models were able to produce more accurate forecasts than traditional models because they do not presuppose any functional form of the model to be developed and they do not depend on the assumptions of linearity.

There exist numerous works of different application areas where ANNs are used to forecast time series. The work by Arizmendi (22) obtained accurate predictions of the airborne pollen concentrations using ANNs. Zhang and Hu (20) employed ANNs, and Rivas et al. (23) RBFNs, for forecasting British pound and US dollar exchange rates. Bezerianos et al. (24) employed RBFNs for the assessment and prediction of the heart rate variability.

Specifically inside the ANNs, the use of RBFs as activation functions for them and its application to time series forecasting were firstly considered by Broomhead and Lowe in 1988 (25). Afterwards, new works by Carse and Fogarty (26), and Whitehead and Choate (27) focused on the prediction of time series.

In later works, Harpham and Dawson (28) studied the effect of different basis functions on an RBFN for time series prediction. Moreover, Du

(29) used time series with an encoding scheme for training RBFNs by GAs. Both the architecture (numbers and selections of nodes and inputs) and the parameters (centers and widths) of the RBFNs were represented in one chromosome and evolved simultaneously by GAs so that the selection of nodes and inputs could be automatically achieved.

Previous works found in literature can also be classified according to the prediction horizon. Thus, forecasting can be divided into short-term, medium-term, and long-term. Generally, forecasting is trended to short-term prediction such as one-step ahead prediction, since longer period prediction (medium-term or long-term) is more difficult, and sometimes may not be reliant because of the error propagation (30). Thus, neural network models have been traditionally applied in short-term forecasting (31; 32). For instance, the work by Perez-Godoy (33) applied a hybrid evolutionary cooperative-competitive algorithm for the design of RBFNs to the short-term and even medium-term forecasting of the extra-virgin olive oil price.

As mentioned, another problem that emerges working with time series is the correct choice of the lags considered for representing the series. The relationship involving time series historical data defines a d-dimensional space where d is the minimum dimension capable of representing such a relationship. Takens' theorem (34) establishes that if d is sufficiently large is possible to build a state space using the correct time lags and if this space is correctly rebuilt also guarantees that the dynamics of this space is topologically identical to the dynamics of the real systems state space.

In order to tackle the lags selection problem, an evolutionary method that performs a search for the minimum number of dimensions, Time-delay Added Evolutionary Forecasting (TAEF), is presented in (35). The methodology is inspired in Takens' theorem [***CITA***] and consists of an iterative hybrid model composed of an ANN combined with a genetic algorithm (GA). In (36) the evolutionary selection of lags is divided into two stages: first, the optimal dimension of the reconstructed phase space is determined by the false nearest neighbors algorithm and then a near-optimal set of time lags is found with a genetic algorithm for a fuzzy inference system.

There are some methods that carry out an automatic search of the relevant lags. QIEHI algorithm (37), for instance, is an evolutionary hybrid intelligent method which is composed of an ANN and a modified evolutionary algorithm to search the minimum dimension to determine the characteristic phase for time series. Another hybrid methodology composed of a modular morphological ANN with an evolutionary algorithm that searches for the best time lags is described in (38). In (39) a study on the selection not only of the lags but also of the exogenous features with classical feature selection algorithms as pre-processing stage is performed. The lag selection is performed as a post-processing stage in (40) with a sensitivity computation of the output to each time lag.

As can be observed, the approaches in the literature consider the lags selection as a pre- or post-processing or as a part of the learning process but, instead of together, in hybrid processes with two or three stages. On the contrary, our goal is to address the selection of the lags which represent the series (with any type of correlation) jointly with the design process.

3. Procedures used for data collection

Identifying the MAC address of BT devices passing by the roads has being achieved using the Intelify device (see Figure 1), a hardware solution with a low power consumption and a high detection range.

intelifychisme1.png

Figure 1: Intelify device with a connected USB 3G dongle.

Intelify is a small autonomous computer that can be installed in any area to be monitored. It is an autonomous unit, provided by several sensors so that it can discover what is happening in its surroundings (like the flow of people and vehicles). At the same time the environment is been scanned, Intelify is able to send the information to a central server for further processing and interpretation. Table 1 shows main features of the device.

This hardware device is based on technology developed by Ciudad 2020 (**?** **?**), and the services it offers are based on a net of Intelify devices. Using such an structure, it has the capacity to discover information about the physical environment and help with decision making to any kind of organization based on people flow and behavior.

Valuable information about tourism, trade and mobility can be gathered through the deployment of autonomous devices around a city. A specific example is the service offered in (**?**). It offers information about foot traffic through Cordoba city center.

Dimensions	113x163x30mm
LEDs	Power 3G activity Ethernet activity
Networking	Ethernet Wireless Bluetooth 3G
USB ports	City Analytics Antenna 3G dongle
Other ports	RS-232 VGA
Power	18v - 1200mA external jack - 5.5mm internal jack - 2.1mm
Network connections	Ethernet RJ45 3G USB Modem
Antennas	City Analytics USB antenna wireless antenna
Microphone	noise sensor
Temperature	main board temperature sensor with extrapolation
Box	1.5mm aluminum box external use possible
Operating System	Debian 6.0 Squeeze

Table 1: Main features of the Intelify device.

The cost of this solution is 1000 euros per device, including maintenance of remote computer, communications using a 3G telephony service and storage and data management.

Data accuracy is very representative, compared against other technologies. In (**?**) it was obtained an a priori error estimation of 8.5% of detections.

??????Descripcin de los datos recopilados For this work, the data collected by 5 nodes during 60 days has been used. First day corresponds to November 24, 2011, while last day corresponds to January 22, 2013. Figure 2 shows the ammount of BT devices detected by each node along this period. Nodes 4 and 5 are shown in a separate graphics since they were located in a highway, so that they registered a higher number of BT devices.

number-of-detected-devices-1-2-3.jpg number-of-detected-devices-4-5.jpg

Figure 2: For each node, the total number of different detected devices per day is shown. Due to the location of nodes 4 and 5, the values they registred are higher than those belonging to nodes 1, 2, and 3; for this reason, they are shown in different graphics.

As figure 3 shows, the number of BT devices detected clearly varies from weekdays to weekends; although the figure shows the sum of the 5 nodes, this charasteristics is also observed when considering every single node.

weekly.jpg

Figure 3: Data summarized with respect to the day of the week. Data collected in Saturday and Sunday is clearly lower than data collected during weekdays.

4. Experiments and results

????? TODO ESTO HAY QUE CAMBIARLO PARA LOS DATOS REALES CON LSO QUE AL FINAL HEMOS TRABAJADO

Node Id.	N. of devices detected
1	31408
2	45032
3	33165
4	358494
5	297874
6	7872

Table 2: Number of BT devices detected by each node.

In this section the analysis of collected data during the monitoring period (November 8 to December 9) to obtain statistics and so study the use of vehicles is carried out.

Specifically, the following subsections report information about the total number of vehicles detected by each node, on weekdays or holidays, information on traffic density by time range on individual movements, and the average speed on a section delimited by two consecutive nodes.

Finally, since November 14 2012 a general strike was held, we will study how the strike affected traffic in the metropolitan area of Granada (Spain), by comparing total number of devices detected that day (November 14), and the following day (November 15).

4.1. Total number of vehicles detected (weekdays and holidays)

The first analysis consisted in calculating the number of devices detected by each node.

In total, 773,845 BT devices have been detected by the six nodes. As shown in Table 2, nodes located in the Sierra Nevada Highway (A44, nodes 4 and 5) have collected a higher number of data, while the node located in a side street (node 6) has detected the smallest number of devices.

4.2. Total vehicles detected on non-working days

To compare the traffic intensity between working and non-working days, the number of pass on holidays and non-working days have been obtained.

Table 3 shows how the number of detected devices lowers by all nodes on non-working days, compared to the number of detections on weekdays. Nodes located in the Sierra Nevada Highway still collected much more data than the remainder, due to the traffic this road supports on holidays.

Node Id.	N. of devices detected
1	2149
2	2804
3	2832
4	32182
5	24166
6	1269

Table 3: Total number of BT devices detected by each node (only on non-working days).

4.3. Traffic density on the road by time range

Traffic density can be calculated taking into account the total number of detected devices by time range.

VehiculosDiferentesPorHoras.jpg

Figure 4: For each node, the total number of different detected devices by time range is shown. Figure is shown in logarithmic scale.

Figure 4 shows higher density on all nodes, at peak times or out of work and school.

4.4. Total detections by time range

Additionally we can calculate for each node, the number of detected devices by time range, without differentiating whether the device is the same or not (repeated passes). Thus, repeated passes of the same vehicle are counted.

VehiculosPorHoras.jpg

Figure 5: For each of the six nodes, the total number of detected devices by time range is shown. Figure is shown in logarithmic scale.

As in the previous case, a greater traffic density can be observed on all nodes, at peak times or out of work and school. (see Figure 5).

No. of nodes	No. of devices	Total number of passes	Mean ± std. dev.
1	72989	165033	2.26 ± 31.16
2	53947	425667	7.89 ± 11.48
3	8125	131570	16.19 ± 24.71
4	1359	39241	28.88 ± 140.82
5	254	8603	33.87 ± 59.51
6	61	3731	61.16 ± 94.78

Table 4: Total number of vehicles that have passed through two nodes, 3 nodes and up to 6 nodes, and average number of times that vehicles have passed through 2, 3, 4, 5 or 6 nodes. In some cases the deviations are high because some devices have a very high number of occurrences for some nodes.

4.5. Number of individual vehicles detections

We can take advantage of the proposed system's ability to identify BT devices. Thus, it can be detected whether vehicles pass by different nodes.

Intervalos.jpg

Figure 6: For each of the six nodes, the total number of detected devices N times (repeated occurrences of the same device) are shown. Figure is shown in logarithmic scale.

Figure 6 shows a large number of vehicles that pass repeated times (up to 10 times) by some of the nodes (mainly those located in the A44). Even it can be seen that nodes 4 and 5 detect about 1,000 vehicles passing more than 25 times repeated. On the other nodes, over 25 repetitions of the same device have been detected only around 120 times.

4.6. Complexity of displacement

To study the complexity of displacements, the number of vehicles that have passed through two nodes, 3 nodes and up to 6 nodes were calculated. Table 4 also shows the average number of times that vehicles have passed through 2, 3, 4, 5 or 6 nodes.

The above information is complemented with Figure 7, that shows how many cars pass by only one node, two nodes, three nodes, etc.

NodosPorDondePasan.jpg

Figure 7: Figure shows how many cars pass by only one node, two nodes, three nodes, etc. Figure is shown in logarithmic scale.

Node	Total number of passes (nov-14)	Total number of passes (nov-15)
2	1841	2722
3	891	1169
4	10807	16942
5	831	4017
6	946	1419

Table 5: Comparison of the number of passes for each node between the general strike day (November 14) and the very next day. Node 1 results are not reported because the hardware device suffered a power supply problem for a couple of days at that time.

As expected, most of the BT devices rarely passed by all nodes, while most of devices pass only by one or two of nodes (their displacements are focused on a small part of the monitored area).

4.7. Effect of Nov-14 strike on zone traffic

Right in the middle of the monitoring period in Spain was held a day of general strike (November 14, 2012), which has been reflected in the number of detected devices (cars) on the nodes.

The effect of the general strike in the traffic of the monitored area has been analyzed and shown in Table 5 as the number of detected devices on November 14 and the very next day.

Table 8 shows a lowest number of detected vehicles the day of the strike that on the following day (working day in which the activity should be normal in the area).

4.8. Analysis of vehicles speed between two consecutive nodes

Finally, taking two consecutive nodes, located on the A44 highway, average speeds in the section bounded by nodes 4 (located at km 119.550) and 5 (located at km 123.250) can be calculated. This highway section where the study takes place is of 3700 meters long. Actually, we can calculate the

Speed range (km/h)	No. of passes
v≤60.0	1495
60.0≤v≤70.0	2585
70.0≤v≤80.0	7421
80.0≤v≤90.0	16339
90.0≤v≤100.0	20144
100.0≤v≤120.0	14384
120.0≤v≤140.0	5434
v≥140.0	1326

Table 6: Average speeds (globally) in the section bounded by nodes 4 and 5.

average speed in the global section, not the speed at which each vehicle has at each instant within the section.

In that section, the speed is limited to 100 km/h. However, although most of the vehicles respect this limit, a lot of cars exceed this limitation.

4.9. Flow traffic prediction by means of time-series forecasting

As far as data is chronologically collected, methods coming from the area of time-series forecasting can be used in order to predict future behaviour of traffic flow.

From the big variety of existing mtethods, 6 different ones have been selected in order to compare the validity of their predictions. The methods being used are: ARIMA, Croston, Theta, Spline,L-Co-R, and as control algorithm, the mean value. Methods ARIMA, Croston, Theta, Spline and Mean have been executed using the R software, by means of the Forecast package (???cita). In the other hand, L-Co-R is a co-evolutionary algorithm of our own, based on radial basis function neural networks. In order to compare the methods, a statistical study is included allowing us to draw some conclusions.

The experimentation has been carried out using the data collected for five nodes over 60 days (from 24/November/2012 to 22/January/2013). The first 53 days have been used to train the methods, and obtain their associated models, and the remaining 7 days have been used to test their generalization capabilities. The prediction of these 7-days test has been made for an horizon of 1, so that known data until day n have been used to forecast day $n + 1$.

For each method and each node, a set of measures have been computed in order to determine the accuracy of the prediction. As most textbooks recommend, one of the chosen measures is the Mean Absolute Percentage Error (MAPE) (53), which was used in the first M-competition (54). Median Absolute Percentage Error (MdAPE) (55; 56) is also used, as a normalized version of the previous one. More recently, the description of many others measures can be found in (2) and (58). Among all of them, in this work we use the followings:

- Mean Absolute Error (MAE):

$$MAE = mean(\mid e_t \mid) \tag{1}$$

- Mean Absolute Percentage Error (MAPE):

$$MAPE = mean(\mid p_t \mid) \tag{2}$$

- Median Absolute Percentage Error (MdAPE):

$$MdAPE = median(\mid p_t \mid) \tag{3}$$

- Mean Absolute Scaled Error (MASE):

$$MASE = mean(\mid q_t \mid) \tag{4}$$

- Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n} {e_t}^2 \tag{5}$$

where Y_t is the observation at time $t = 1, ..., n$; F_t is the forecast of Y_t; e_t is the forecast error (i.e. $e_t = Y_t - F_t$); $p_t = 100e_t/Y_t$ is the percentage error, and $q_t = \dfrac{e_t}{\dfrac{1}{n-1}\sum_{i=2}^{n} \mid Y_i - Y_{i-1} \mid}$

Given the stochastic nature of evolutionary algorithms, and in order to remove biases due to random generator, L-Co-R has been running 30 times per node. Thus, the error attached to this algorithm correspond to the average error values of these 30 executions.

Table 7 show the different error values for every method and node. Boldfaces highlight the lowest (best) values per algorithm, node and measure. As table shows, best algorithms tends to be L-Co-R and ARIMA, since L-Co-R obtains the lowest results for measures MAE, MAPE, MdAPE and MASE (except for node 2), but there is not a clear winner in MSE and SMAPE.

The results yielded by every method have been compared using two non-parametric test: the Friedman test and the Iman-Davenport test. Using this two test, we are able to determine whether there exist significant differences between the methods or not, and we can establish a ranking of methods according to their ability to perform forecast. These test have been carried out using ??? SOFTRWAE DE SALVA. Both, Friedman and Iman-Davenport tests, reveal that results can be considered significantly differents when the computed *P-value* is less than 0.05. Table 8 shows that any of the *P-value* computed by the tests are under 0.05, and this occurs in any of the six error measures being considered.

Futhermore, Friedman test results also provide a mechanism to establish a ranking between the methods, determining which one can be considered the best. Once the method has been found out, it can be compared against the rest methods using the Holm's procedure (???CITA). This method computes the probability that two methods can be considered to have a similar behaviour, being this the null hypothesis. The null hypothesis is rejected when this probabilhttp://www.restaurantelaplatea.com/menu-celebraciones/ity is lower than 0.05, so that methods can be considered to be significantly differents. Holm's procedure has been applied to any of the six error measure being considered. Table 9 summarizes the rankings of methods, as well as the existence or absence of significant differences. Thus, this statistic study shows that L-Co-R is the best algorithm in four of six error measures (MAE, MAPE, MASE, and MdAPE); nevertheless, it can not be said to be better than ARIMA in any case but, for most measures, it overcomes the rest of methods.

Node 1						
	MAE	*MAPE*	*MASE*	*MdAPE*	*MSE*	*SMAPE*
ARIMA	514, 83	40, 42	1, 14	30, 76	424860, 5	36, 83
CROSTON	509, 91	39, 28	1, 13	33, 8	387403, 9	36, 46
THETA	528, 59	41, 16	1, 17	32, 78	443898, 5	37, 87
SPLINE	550, 02	43, 87	1, 21	30, 1	488504, 9	39, 04
MEAN	456, 95	38, 57	1, 01	26, 11	318623, 5	32, 48
L-Co-R	**372,77**	**23,66**	**0,81**	**18,46**	**231731,8**	**28,87**
Node 2						
	MAE	*MAPE*	*MASE*	*MdAPE*	*MSE*	*SMAPE*
ARIMA	433, 52	26, 64	**1,03**	22, 38	**310105,3**	25, 15
CROSTON	532, 87	27, 98	1, 26	27, 89	398979, 9	30, 5
THETA	435, 58	26, 77	1, 03	22, 55	312496, 1	25, 28
SPLINE	535, 86	34, 53	1, 27	24, 7	447557, 4	31, 17
MEAN	489, 57	24, 44	1, 16	28, 64	361070, 5	27, 52
L-Co-R	**429,78**	**11,41**	1, 04	**11,98**	311561, 7	**23,5**
Node 3						
	MAE	*MAPE*	*MASE*	*MdAPE*	*MSE*	*SMAPE*
ARIMA	373, 17	35, 11	1, 32	27, 54	**150293,6**	**33,45**
CROSTON	377, 42	37, 03	1, 34	27, 89	160970, 9	33, 78
THETA	394, 95	38, 11	1, 4	29, 41	175710, 7	35, 34
SPLINE	384, 68	38, 86	1, 36	29, 36	184807, 2	34, 36
MEAN	373, 18	35, 11	1, 32	27, 53	150307, 8	33, 45
L-Co-R	**363,3**	**10,56**	**0,84**	**17,01**	182469, 9	35, 32
Node 4						
	MAE	*MAPE*	*MASE*	*MdAPE*	*MSE*	*SMAPE*
ARIMA	3168, 36	40, 62	1, 04	18, 99	21792093	37, 44
CROSTON	3789, 4	56, 83	1, 25	54, 33	25037291	49, 12
THETA	3085, 3	38, 14	1, 01	25, 42	21510757	37, 48
SPLINE	3758, 06	39, 45	1, 24	43, 53	28745309	48, 79
MEAN	4545, 17	92, 73	1, 5	40, 07	26612429	55, 57
L-Co-R	**540,59**	**6,26**	**0,07**	**4,14**	**1120317,2**	**8,17**
Node 5						
	MAE	*MAPE*	*MASE*	*MdAPE*	*MSE*	*SMAPE*
ARIMA	5012, 95	43, 8	1, 13	20, 19	**29974781**	**33,85**
CROSTON	5583, 14	46, 32	1, 26	26, 12	35082013	37, 51
THETA	5779, 37	45, 78	1, 3	28, 25	35859271	38, 94
SPLINE	5878, 35	46, 26	1, 32	28, 69	37288518	39, 64
MEAN	5013, 48	43, 81	1, 13	20, 19	29980578	33, 85
L-Co-R	**4978,08**	**24,59**	**0,87**	**9,37**	35875329	35, 8

Table 7: Values for the six error measures (MAE, MAPE, MASE, MdAPE, MSE, and SMAPE) yielded for any of the six methods (ARIMA, Croston, Theta, Spline, Mean and L-Co-R) when forecasting time series of nodes 1 to 5. Boldfaces stress best (lowest) values.

Error	*Friedman P-value*	*Iman-Davenport P-value*
MAE	0.0052	0.0003
MAPE	0.0080	0.0008
MASE	0.0141	0.0030
MdAPE	0.0063	0.0005
MSE	0.0213	0.0066
SMAPE	0.0440	0.0233

Table 8: *P-value* yielded by Friedman and Iman-Davenport non-parametrics tests for every error measure. A *P-value* lower than 0.05 (all of them in this case) indicates that there exist significant differences between the errors computed for every method.

5. Conclusions and Future Work

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Error	*Control Method*	*Ranking*	*Method*	*p*	*Null Hypothesis*
MAE	L-Co-R	1	ARIMA	0.176	Accepted
		2	MEAN	0.028	**Rejected**
		3	THETA	0.007	**Rejected**
		4	CROSTON	0.007	**Rejected**
		5	SPLINE	2.003E-4	**Rejected**
MAPE	L-Co-R	1	ARIMA	0.090	Accepted
		2	MEAN	0.0.063	Accepted
		3	THETA	0.011	**Rejected**
		4	CROSTON	0.002	**Rejected**
		5	SPLINE	3.857E-4	**Rejected**
MASE	L-Co-R	1	ARIMA	0.398	Accepted
		2	MEAN	0.063	Accepted
		3	THETA	0.028	**Rejected**
		4	CROSTON	0.018	**Rejected**
		5	SPLINE	7.232E-4	**Rejected**
MdAPE	L-Co-R	1	ARIMA	0.176	Accepted
		2	MEAN	0.042	**Rejected**
		3	THETA	0.004	**Rejected**
		4	SPLINE	0.002	**Rejected**
		5	CROSTON	7.232E-4	**Rejected**
MSE	ARIMA	1	L-Co-R	0.500	Accepted
		2	MEAN	0.398	Accepted
		3	CROSTON	0.176	Accepted
		4	THETA	0.176	Accepted
		5	SPLINE	7.232E-4	**Rejected**
SMAPE	ARIMA	1	L-Co-R	0.866	Accepted
		2	MEAN	0.310	Accepted
		3	CROSTON	0.091	Accepted
		4	THETA	0.043	**Rejected**
		5	SPLINE	0.006	**Rejected**

Table 9: Results of the Holm's procedure for every error. Values of p under or equals to 0.05 lead to reject the null hypothesis, i.e., the errors provided by the control algorithm and the corresponding compared algorithm can be considered significantly differents.

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