Interoperability Network Model for Traffic Forecast and Full Electric Vehicles power supply management within the Smart City

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ABSTRACT
Information technologies and applied mathematics provide us with a comprehensive framework to search for solutions to problems derived from traffic management. It is relevant for the mobility in our future cities to integrate the Full Electric Vehicle (FEV) in an interoperability network which allows us to track the FEV autonomy and to forecast the traffic and the power supply demand in the city. The target is to optimize the energy consumption and to improve the mobility in the city. To achieve these goals we propose an infrastructure to efficiently manage the power supply availability in the network of charge stations in the city and an adaptive model to predict the traffic based on historic data and on time series obtained mathematically.

Categories and Subject Descriptors
C.1.2 [**Modeling**]: Probabilistic models

C.1.4 [**Modeling**]: Predictive performance models

C.1.5 [**Modeling**]: Mobility modeling

General Terms
Applied computing~Information integration and interoperability, Software and its engineering~Software design engineering.

Keywords
Interoperability for mobility; time series and Markov modeling; power supply and traffic forecast modeling; Smart City ecosystem; prediction algorithm.

1. INTRODUCTION

Nowadays, most people in the world live in cities [1] and the needs of people to be connected are higher and higher. It would be beneficial for all of us, were it not for the rising amount of devices per person connected to the Internet [2]. It implies that more and more systems are getting embedded in a city infrastructure, to the extreme that the number of services and applications integrated in the net may become unsustainable. This is one of the reasons why sustainable development of urban areas is a challenge of highest interest at global level.

A proper management of nearly every field of activity in a city will depend on the capability of properly handling the amount, the nature and the sources of the data to be taken into account. New technologies enable an Internet of Things (IoT) for the city, providing us with a large number of resources to manage the data generated by the city. Hence, data management techniques are needed to ensure interoperability and reusability of the data. They consist mainly of data acquisition, processing and dissemination.

In order to efficiently acquire the necessary data in the city, data standards must be taken into account. Different networks to which we need to be connected, must be in the same type and format to enable data integration along with efficient and useful processing. Data quality imposes the required dimensions of data and leads to the so called data fusion and decision fusion [3]. Data fusion states that the key to improving the final processing is to use all the raw data collected, whereas decision fusion merges raw data in clusters for information processing.

Apart from data acquisition and processing, data analysis tools are needed to monitor and improve performances of applications and services for efficient dissemination of information within the city. All these applications and services should be connected and interact in an urban center. This is what will make the current concept of city evolve towards the intelligent city or Smart City, as it is defined in [3].

A feature of paramount importance is the mobility of the components of the city, as it is what supports the daily routine in the urban model. To provide innovative traffic and transportation services is one of the key goals of Smart Cities [4]. This can be achieved through Smart Traffic Management (STM). STM aims at empowering users with data in order to be better informed, which will allow them to take safer and smarter decisions on using the transportation network. A very relevant element in this context is the Full Electric Vehicle (FEV). The FEV needs to be connected to a smart grid in order to manage its required power supply and to forecast the possible future problems in STM.

Introduction of new technologies such as Smart Grid have changed the operation of the utility companies in the last decade. To tackle challenges imposed by regulatory bodies such as reducing carbon emissions, utility companies are required to create a balance between the restrictions of the regulatory bodies and the target of providing reliable services to the customers at a reasonable price [5]. And this challenge is higher when it comes to FEV. Hence, FEV must be efficiently integrated in the Smart City to contribute to save the environment, to manage the mobility of users in the city and to optimize the costs of power supply.

In this work we present the design of a mobility network model to integrate the FEV in the Smart City. Our aim has been to predict and optimize the energy supply to the FEV. It has required the next tasks:

a. to model the mobility of the FEVs in an area,

b. to analyze the power consumption of the FEVs,

c. to forecast the power demand in the city, and

d. to study and model the power supply availability in the network of charge stations.

The paper is organized as follows: In section 2 we describe the related work. In section 3 we analyze the problems to be addressed to manage the power supply for FEV in an urban smart model and the architecture required to design the FEV mobility model in order to optimize the power supply in the Smart City. In section 4 a solution to the problem of tracking the FEV autonomy from a centralized information system is presented. In section 5 we show how to forecast the global energy demand in the city taking into account the urban roadmap and the FEV fleet available in the city. In Section 6 a model for the estimation of power supply availability in the network of CS as well as the associated results are described.

Not only the power supply in the city has to be managed for the FEV to effectively get integrated into the mobility model for the Smart City but there is another aspect to be taken into account. To ensure mobility is not affected by causes such as traffic problems, it is essential to make decisions in advance. In section 7 we analyze how to design a traffic prediction system to be integrated in the mobility model for the Smart City. Finally, in Section 8 some conclusions and future lines of work are proposed.

2. RELATED WORK

There is a huge amount of literature dealing with different aspects of Smart Cities: the communication resources, the management and analysis of the data, its integration or the use of idle computation, in order to increase safety, efficiency, productivity and quality of life for its citizens.

Different definitions of the Smart City are presented by Fernandez-Anez [3]. We stand out the relationship between IoT and a Smart City (Arasteh et al. [6]). Da Silva et al. [7] survey the architecture for Smart Cities, and El Baz and Bourgeois [8] discuss the architecture of a specific Smart City application (Logistic Mobile Application). Luong et al. [9] analyze the economic and pricing theory and their applications to data collection and communication for IoT. Ijaz et al. [10] study security aspects of a Smart City, and Pellicer et al. [4] present an overview of different ideas to be included under the notion of Smart City around the globe.

Issues like smart mobility and traffic and energy management, its assessment and optimization deserve special attention. Several research activities in the literature focus on these topics. Cardone et al [11] study effective collaborative monitoring in Smart Cities while Krishnan and Balasubramanian [12] tackle the problem of the traffic flow optimization and vehicle safety.

Regarding the need of the Smart City to efficiently manage the power supply and minimize the costs, Ploussard et al. [13] discuss the main challenges to determine which, where, and when new transmission lines should be constructed at the minimum total cost. Their goal is to design a grid that optimizes the energy consumption and allows future expansions using a weighted signed graph model. These results have been relevant for our smart charging infrastructure to be improved.

Papastamatiou et al. [14] give an overview of the different procedures to assess the use of energy in Smart Cities and propose a decision support framework to optimize it, as well as to achieve significant reduction of CO_2 emissions.

Finally, it is remarkable what Abdennahder et al. [15] present in their work. They propose a scheme of distribution of energy in the Smart City in terms of a decision problem taking into account the energy network efficiency and users' comfort. Their work is focused on classifying the energy demands of the users according to certain degrees which are considered critical by different relevant studies and surveys. Their final results aim to increase the satisfaction of the users.

3. PROBLEMS TO BE ADDRESSED AND ARCHITECTURE

Our work was developed under the Smart Vehicle to Grid project [16], funded by the Seventh Framework Program of the European Union.

The design of an interoperability solution in order to integrate the FEV in a city and to optimize the energy supply has required solving the following problems:

- Study of the evolution of the state of charge (SOC) of a FEV. It depends on the battery of the vehicles, the motor and the roadmap.
- Estimation of the global energy demand in the city. We need to know how much energy should be available. It hinges upon the roadmap and the number of FEV available in the city.
- Estimation of the power availability supply. It requires the development of a mobility model. Moreover, to improve the efficiency of the charging infrastructure and to reduce costs it is necessary to include a study of how the smart grid can continue providing power by the time there is a big demand from the users.

The architecture proposed to design the FEV mobility model in order to optimize the power supply in the Smart City is described in the next scheme (see Figure 1).

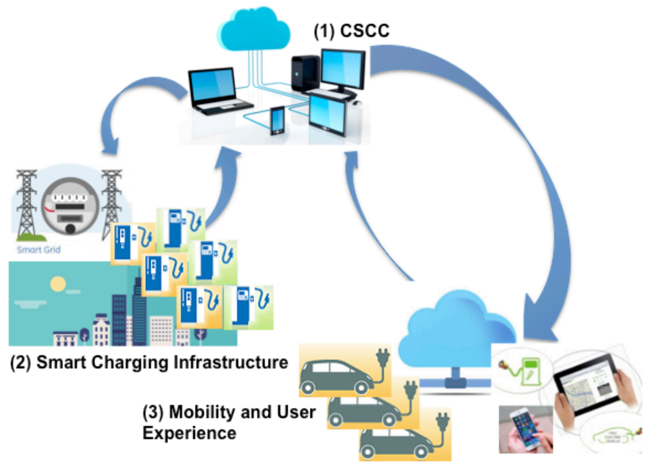

Figure 1. Interoperability System Architecture for FEV integration.

We see that it consists of three parts:

1. Charge Station Control Center (CSCC, [17]). It is the core component of the architecture, the responsible for the management of the network and the different communications among FEVs.

2. Smart Charging Infrastructure. It consists of the Charge Stations (CS) and the smart grid. The CS are connected to the smart grid and are remotely managed according to IEC61851 [18] from the CSCC. The main problem here is how to control these CS from the CSCC. Although the charging infrastructure plays an important role in our architecture, its design will not be covered by our work.

3. User interface. It allows users to access the systems to trace the power consumption of their FEVs, and it provides them with other web services such as the dynamic location of the CS or an intelligent decision maker. The big problem of this third element is to build the relational model needed to implement it. This model has been developed and tested [17].

4. TRACING FEV AUTONOMY IN THE CITY

To find a solution to the first problem described, we have taken into account both the FEV route and the type of FEV battery.

1. After knowing the route, Open Street Map database [19] provides us with APIs which are used to generate a matrix (route matrix) composed by the different steps in XML format to be performed to get our destination.

2. Regarding the FEV battery, we have used the model of Hosseini-Badri-Parvania [20] to simulate a battery which can generate or give power back to the smart grid when it is needed or at least required in order to overcome any difficulty in the CS network. This possible capacity to work together with the smart grid is called vehicle-to-grid (V2G) service and it will be offered by the FEV.

We estimate the consumption of power of FEV by using the data provided by the route matrix and the FEV battery model. We also need to know speed variations, as it is relevant to compare the different results obtained.

The energy (in kWh) used by the FEV is calculated from the principles of theoretical physics, taking into account the recommendations of [20], as follows:

$$\mathrm{W\ (SOC)} = \int_{t=t_0}^{t=t_{current}} \mathrm{C(Wh/km)} \cdot \frac{dv}{dt} \left({}^{m}/_{s^2}\right) \cdot 3600^2 \cdot t \cdot dt \left({}^{s^2}/_{h^2} \cdot h^2\right). \tag{1}$$

This expression allows us to estimate the energy required from the battery to reach the charging station. What we call 'state of charge' (SOC) is the energy which is not used so far. In other words, SOC=E-W, being E the initial estimated energy in the battery.

As far as the scope is concerned, this is calculated taking into account the previous results:

$$\mathrm{Scope} = \frac{\int_{t=t_{current}}^{t=v/d} C \cdot \frac{dv}{dt} \cdot dt}{E - W}, \tag{2}$$

where *v* is the speed average of the FEV and *d* the distance that remains to be travelled, according to the previous analysis of the trip.

Matlab libraries provided by the FEV simulator of Cerero-Tejero [21] and our estimation of the FEV power consumption have let us design an algorithm to obtain the evolution of the SOC in the FEV once the arrival trip point has been reached. To implement this algorithm, whose code details can be seen in [17], we developed the next block diagram. This diagram, shown in the next Figure 2, represents the Matlab implementation of this algorithm.

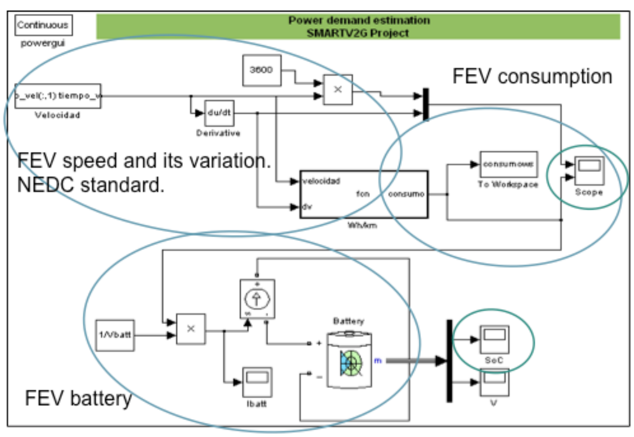

Figure 2. Matlab process to trace the evolution of FEV SOC from CSCC.

It integrates the route map, the speed and variations of speed and the battery features in each one of the blocks outlined in Figure 2. As we can see in this figure, SOC and energy consumption are calculated as a function of the generated route matrix, the loading-unloading process of the FEV battery, the FEV speed and its variation (derivative of the FEV speed). The model follows the New European Driving Cycle (NEDC, [22]), to determine the speed variation of the FEV according to Euro6 norm in Europe and the 98/69/EC directive.

This algorithm enables CSCC and FEV users to know if their FEV can get their destination or they need to go to any CS before getting their destination.

The results obtained in the different tests we conducted show that the relative difference between the real SOC and the calculated SOC at the end of each route is lower than 0,05%. This leads us to assure that evolution of FEV autonomy can be controlled from the CSCC.

5. FORECAST OF THE GLOBAL FEV ENERGY DEMAND IN THE CITY

Forecasting the global energy demand in the city is required to plan how much energy the city needs to have available. It depends on the urban roadmap and the number of FEV in the city.

Taking into account both factors, we have designed an algorithm to foresee the global energy demand in the city. To achieve this goal, we have taken the next steps:

1. Obtaining initial traffic data. Due to the low penetration rate of FEV in European cities, historic traffic data are often not available. In that case, they must be simulated. We used Momoh-Wang artificial neural network ([23]) to simulate initial traffic data, taking into account the roadmap and the number of FEV in the city. This neural network leads to a recurrent process which implements the self-learning of the neural network. The output of this recurrent process is a sequence of data, $\{X_n\}_{n=0}^{\infty}$, where X_n represents the simulated power consumption on each unit of time. We obtain initial traffic data as $\lim_{n\to\infty} X_n = X_s$. These data are an estimation of the urban power demand and we call them 'initial data'. However, we need to have a mathematical function to foresee the power demand in the city in a more efficient way.

2. In order to forecast the power demand on a time unit $X_{(d)}$, we get the initial data obtained the time unit before $X_{(d-1)}$ and the data corresponding to one, two and three weeks before, $X_{(d-7)}, X_{(d-14)}, X_{(d-21)}$. This is done to maintain the possible trend that characterizes each time unit depending on its position on the week. Then, we obtain the function which best approximates these data by the least squares method. The resulting function provides us with what we call the forecasted data.

3. It was relevant for our work to compare both real data (step1) and forecasted data (step2). To do it, we prepared different scenarios defined by the next parameters:

   - Number of FEV in the city.

   - Type of the day when the algorithm is executed: working day (Monday-Friday) or not-working day such as holiday (Saturday-Sunday, local and national holidays). This parameter is defined by the daily driving behaviour of the FEV fleet according to the different travel plans. (i.e. home >work >home, home >work >leisure >home, etc.).

   - Type of charge: fast or slow, depending on the modes allowed by the CS. A load is considered slow when its maximum power is about 3,3kW, as it is stated in [20]. In addition to this, each scenario was characterized by a percentage of fast loads in a day, that is, the proportion of loads of 60-150kW of maximum power.

   We tested these different test scenarios on Matlab to foresee the power demand energy in the city. The results shown in Figure 3 belong to a scenario in which we put in place one thousand FEV moving around the city on a working day in which the percentage of fast loads was about 25%. This scenario was compared with its equivalent one with real data of Ljubljana (Slovenia), where the different tests were executed. In this figure a comparison between forecasted data and real data can be seen.

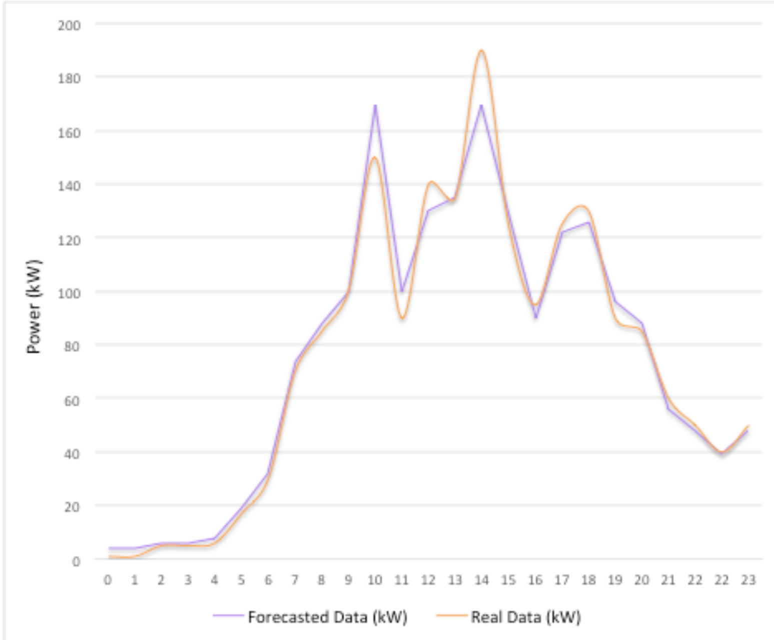

Figure 3. 24-hours charging load forecasting.

In the rest of scenarios prepared to perform the tests, similar results are obtained. The average of the mean square errors of all the scenarios was of $5{,}8252 \cdot 10^{-4}$, using normalized data. This error is small enough to conclude that our algorithm is valid to foresee the global power demand in the city.

6. ESTIMATION OF POWER SUPPLY AVAILABILITY IN THE NETWORK OF CS

Several research activities, such as [24], reveal that the network of CS cannot be endlessly available. Therefore, it is needed to estimate the power supply availability in the city. In order to do that, we need to study from which CS and to which CS FEVs are moving on each time unit considered. It means that we need to model the mobility of FEV fleet in the city. The steps we have taken are the next ones:

1. Let a CS be a state. We consider the CS network as a system with a finite number of states $\mathrm{I} = \{1,2, \dots, \mathrm{m}\}$ that randomly evolves in discrete time. Let $\mathrm{J_n}$ be the random variable representing the state of the system after the n-th transition. The sequence of random variables $\{\mathrm{J_n}\}_{\mathrm{n} \geq 0}$ is a Markov chain. For every $i, j \in I$ we have that the probability of arriving in a state j after having being in a state i only hinges upon this state i, not on the rest of states in which the FEV has been. If we denote this probability as p_{ij}, what we have just explained can be mathematically written as follows:

$$\mathrm{P}(\mathrm{J_n} = \mathrm{j} | \, \mathrm{J_{n-1}} = \mathrm{i}, \dots, \mathrm{J_1}, \, \mathrm{J_0}) = \mathrm{P}(\mathrm{J_n} = \mathrm{j} | \, \mathrm{J_{n-1}} = \mathrm{i}) = \mathrm{p_{ij}} \, . \tag{3}$$

   In other words, the transition probability to a state j depends only on the current state i. Therefore, the distribution of future states depends only on the current state and not on how it has been reached:

$$\mathrm{P}(\mathrm{J_n} = \mathrm{j}) = \sum_{\mathrm{k}=1}^{\mathrm{m}} \mathrm{P}(\mathrm{J_n} = \mathrm{j} | \, \mathrm{J_{n-1}} = \mathrm{k}) \, \mathrm{P}(\mathrm{J_{n-1}} = \mathrm{k}) = \sum_{\mathrm{k}=1}^{\mathrm{m}} \mathrm{p_{kj}} \; \mathrm{P}(\mathrm{J_{n-1}} = \mathrm{k}) \, , \tag{4}$$

   where p_{kk} is the probability of staying in the state k. Then, the transition matrix between states is:

$$P = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{m1} \\ p_{12} & p_{22} & \cdots & p_{m2} \\ \cdots & \cdots & \cdots & \cdots \\ p_{1m} & p_{2m} & \cdots & p_{mm} \end{bmatrix} = [p_{ij}]. \tag{5}$$

We have that $\begin{pmatrix} P(J_n = 1) \\ \cdots \\ P(J_n = m) \end{pmatrix} = P \cdot \begin{pmatrix} P(J_{n-1} = 1) \\ \cdots \\ P(J_{n-1} = m) \end{pmatrix}$, defining hence a Markov chain for each FEV.

2. Let us include the time in the Markov chain. We define a sequence of random variables $\{X_n\}_{n\geq 0}$, where X_n represents the time that FEV stays in the state n, that is, the sojourn time on the state J_{n-1}.

   The conditional distribution function $F_{ij}(x)$ gives the probability of a transition from state i to j in a time x:

$$F_{ij}(n, x) = P(X_n \leq x |\, J_n = j,\ J_{n-1} = i). \tag{6}$$

   According to this expression, the matrix F of distribution functions of conditional probabilities of the sojourn times in a state is defined as $F = [F_{ij}]$.

   Applying the theory of Markov processes ([25]) we can calculate the distribution function of X_n only conditioned to the state *i*. That is to say, the probability that a user is at least for a while *x* in one state before moving on to the next one is given by the following distribution function:

$$H_i(n, x) = P(X_n \leq x |\, J_{n-1} = i) = \sum_{j=1}^{m} p_{ij} \cdot F_{ij}(x). \tag{7}$$

   The combination of these formulae gives the probability of a transition into the state j during the time x assuming that the system is in a state i:

$$Q_{ij}(n, x) = P(J_n = j, X_n \leq x |\, J_{n-1} = i, X_{n-1}) = p_{ij}.F_{ij}(n, x). \tag{8}$$

   The matrix $Q = [Q_{ij}]$ defines a Markov process. Thus, our Markov Process (MP) is characterized by (p, Q) or (p, P, F).

3. In a MP every transition time to a state J_n of the system presents a renewal time T_n given by $X_n = T_n - T_{n-1}$. A two-dimensional process $(J, T) = \{(J_n, T_n)\}_{n>0}$ is called a Markov renewal process. As a consequence, it can be seen that $T_n = \sum_{r=1}^{n} X_r$.

   Renewal processes have a very rich mathematical structure and are used as a basis for building more realistic models. This is the main reason why we use renewal processes theory to model the mobility of FEV fleet in the city.

Let $N_j(t)$ be the random variable representing the number of transitions into the state j in the time interval $(0, t]$. The average number of transitions $N_j(t)$ in t starting from the state i is given by the renewal function:

$$R_{ij} = E\left[N_j(t)|J_0 = i\right] = \sum_{n=0}^{\infty} n \cdot P\left(\frac{N_j(t)=n}{J_0=i}\right). \tag{9}$$

Hence, developing this expression we get the next results:

$$R_{ij} = \sum_{n=0}^{\infty} n \cdot \sum_{k=1}^{n} \int_0^t H_i(k,\tau) \cdot Q_{ij}(k, t-\tau)\, d\tau. \tag{10}$$

$$R_{ij} = \sum_{n=0}^{\infty} n \cdot \sum_{k=1}^{n} H_i(k,t) * Q_{ij}(k,t) = \sum_{n=1}^{\infty} Q_{ij}^{n}(t), \tag{11}$$

where k represents the k-th FEV of the fleet and $Q_{ij}^{n}(t)$ is the n-convolution product defining the probability of the nth transition into state j in a time t starting in the state i.

The renewal Markov matrix is defined according to these probabilities as $R = \left[R_{ij}\right]$.

4. Discretizing the mathematical formulae just obtained, we get the next discrete functions, which represent each probability matrix characterizing the processes we are studying.

   The probability that the k-th FEV of the fleet is in a state j at a time unit u, assuming it is in an initial state i is expressed by the Markov transition function:

$$\phi_{ij}(u,k) = \sum_{l=1}^{m} \sum_{\tau=1}^{k} \phi_{lj}(\tau,k)\, \zeta_{il}(u,\tau), \tag{12}$$

   where

$$\zeta_{ij}(u,k) = \begin{cases} Q_{ij}(u,u) = 0, & \text{if } k = u \\ Q_{ij}(u,k) - Q_{ij}(u,k-1) = 0, & \text{if } k > u \end{cases}. \tag{13}$$

   In the same way, the probability that the k-th FEV of the fleet rests into a state during an interval of time t from an observation in time x is given by:

$$\psi_{ij,(u,k)}(x) = \sum_{\tau=u}^{k} \left(1 - H_j(\tau, x)\right)\left(R_{ik}(u,\tau) - R_{ik}(u,\tau-1)\right). \tag{14}$$

   This function represents the probability of remaining in the state j during the interval $[t, t+x]$.

5. As far as the solution of these equations is concerned, we divide a day in ninety-six time units and we use iterative numerical methods [25] in discrete time. The required input data are the transition probabilities between states (matrix P) and sojourn times between states (matrix F) extracted from the statistical analysis of data from mobility studies.

   Moreover, it is necessary to know the average distance of all the trips between states. Thus, for known P and F matrices and the overall average trip distances among states, the solutions of the linear systems Φ and ψ are given by iterative processes. As we need to operate with huge dimension arrays (96 x 96 x 2) to calculate the probabilities defining the mobility model, we use the Matlab software to implement the functions Φ and ψ.

These functions allow us to estimate the energy which has to be available in the CS to charge the FEV, energy which is called G2V energy [26], and the energy the FEV can generate or give back to the smart grid when it is needed or at least required in order to overcome any difficulty in the CS network, denoting this energy as V2G energy.

It is stated that G2V energy is proportional to transition probabilities and inversely proportional to the SOC of the FEV by the moment it gets the CS:

$$E_{G2V} \propto \phi \cdot (1 - \%_{SOC}) \,. \tag{15}$$

In the same way, according to [26], V2G energy directly depends on the probability of remaining in the state j during a time unit, that is:

$$E_{V2G} \propto \psi \cdot W_{demanded}. \tag{16}$$

The knowledge of the evolution of both types of energies lets CSCC estimate the G2V/V2G energy flow during each day. The results obtained to estimate the G2V power supply in the network of CS in the city are shown in the Figure 4. The test was performed in the same scenario as that of result in Figure 3.

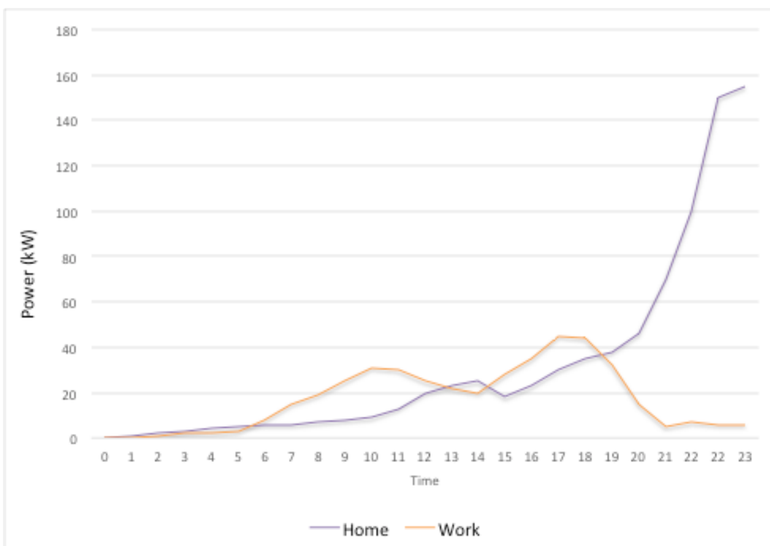

Figure 4. Estimation of G2V power flow in a day.

Analyzing the beginning of the obtained graph, it is observed that G2V energy is approximately null. This behaviour is due to the fact that the FEV are fully loaded before the first trip around 5:00 am. Therefore, it is consistent with the actual behavior.

In terms of V2G energy, the availability profiles show a similar pattern to that of the probabilities of transition and arrival at home and the working states, as we present in the following Figure 5.

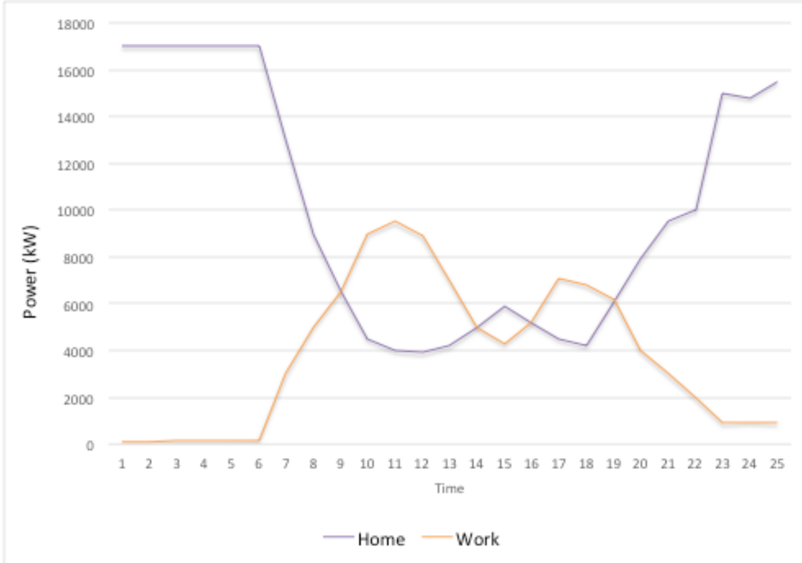

Figure 5. Estimation of G2V power flow in a day.

It is during working hours (8:00-12:00 and 15:00-18:00) on working days and during the night and in the morning on holidays, when the FEV seems to collaborate more effectively with the network, transferring energy (V2G service) that FEV do not need and helping the CS network to satisfy the need of charging. Thus the network will be able to self-control and increase its efficiency, satisfying the needs of the FEV fleet.

As a consequence of these results and its correct integration in the CSCC, the system gives information to the CSCC about the estimation of the G2V/V2G energy transfer for the day. This information leads to the integration of this type of services in the energy market. Moreover, this information is combined with other available data sources to plan the signals of possible intervention of the energy supplier, which are used to produce the different control action for the regularization of the load in all the CS network.

7. TRAFFIC PREDICTION SYSTEM.

To ensure that travel planning, and mobility in general, is not affected by causes such as traffic, it is of paramount importance to make decisions in advance. Hence we need to analyze how to design a traffic prediction algorithm to be integrated in the mobility model for the Smart City. This problem posed an innovative challenge to the entire European society, and has been solved by following the next steps:

1. Prediction problem: formalization and resolution model.

   The formulation of the problem requires a mathematical representation of the traffic in the city at each time t and to analyze how this measure of traffic at t depends on the previous moments. Recurrences in the measurement of traffic allows us to define patterns whose similarities are measured with statistical tools such as analysis of correlations between the patterns obtained. We obtain the traffic at a later time (prediction) based on the traffic measured at the current time and before.

   To obtain this prediction, denote by Y_t the random variable representing the traffic forecast at time t. It leads to a family of continuous random variables depending on time (moment at which we get the traffic forecast).

Since it is impossible to know exactly the traffic in each future moment, we proceed to discretize this family of continuous random variables. To do this, we make traffic forecasts only at certain times of the day, represented by slots. Let $I = \{k \in \mathbb{Z}\}_{k \le t}$ be the set of indexes representing these slots, that is, the different observations of traffic throughout the day, where t is the observation of the traffic we want to predict. In this way, we have a series of random variables $\{Y_t\}_{\mathrm{t} \in \mathrm{I}}$ temporarily ordered and dependent on each other.

Since the traffic forecast at time t, Y_t, depends on the traffic at time *t-k, k>0*, we can express it as a recurrence dependence on the series of random variables that represent the traffic at the moments before t, that is, $\{Y_{t-i}\}_{i \ge 1}$. Therefore, we can approximate Y_t by a linear combination of $\{Y_{t-i}\}_{i \ge 1}$:

$$\boldsymbol{p}\left(\{Y_{t-i}\}_{1 \le i \le p}\right) = a_0 + \sum_{i=1}^{p} a_i \, Y_{t-i} \, . \tag{17}$$

being $\{a_i\}_{1 \le i \le p}$ the dependency coefficients between the current traffic forecast and the previous one. It is necessary to ensure that the linear dependence between Y_t and $\{Y_{t-i}\}_{i \ge 1}$ is valid for a prediction of traffic as close as possible to reality. Using the so called simple and partial autocorrelation functions, we do it in the next point (ii).

When approximating $\mathrm{Y_t}$ for $\boldsymbol{p}\left(\{Y_{t-i}\}_{1 \le i \le p}\right)$ we can express the error of this approximation as follows:

$$\mathrm{e_t} = \mathrm{Y_t} - \left(\mathrm{a_0} + \sum_{\mathrm{i}=1}^{\mathrm{p}} \mathrm{a_i} \, \mathrm{Y_{t-i}}\right) . \tag{18}$$

Hence $\mathrm{Y_t}$ can be expressed as the time series

$$Y_t = a_0 + \sum_{i=1}^{p} a_i \, Y_{t-i} + e_t \, . \tag{19}$$

This formulation defines the estimation model of Y_t, which is called autoregressive of order p, since our random variable Y_t depends on the p observations before. The mathematical basis of this formulation is the theory of time series, whose detailed study can be found in [27].

The (p+1) parameters $\{a_j\}_{j=0}^{p}$ define the lineal regression function $\boldsymbol{p}\left(\{Y_{t-k}\}_{k=1}^{p}, \{a_j\}_{j=0}^{p}\right)$ which best approximates the traffic measurements of the day Y_t from $\{Y_{t-k}\}_{k=1}^{p}$, that is, $Y_t = \boldsymbol{p}\left(\{Y_{t-k}\}_{k=1}^{p}, \{a_j\}_{j=0}^{p}\right)$. In order to obtain the value of these parameters it is required that the mean square error when approximating Y_t for $\boldsymbol{p}\left(\{Y_{t-i}\}_{1 \le i \le p}\right)$ is minimum, as it is explained below.

Let N be the number of data obtained from the traffic measurements in previous slots. The mean square error is expressed as follows:

$$\mathrm{MSE(p)} = \sqrt{\frac{1}{\mathrm{N}} \sum_{\mathrm{t}=1}^{\mathrm{N}} \left(\mathrm{p}(\mathrm{Y_{t-i}}, 1 \le \mathrm{i} \le \mathrm{p}) - \mathrm{Y_t} \right)^2} = \sqrt{\frac{1}{\mathrm{N}} \sum_{\mathrm{t}=1}^{\mathrm{N}} \left(\mathrm{a_0} + \sum_{\mathrm{i}=1}^{\mathrm{p}} \mathrm{a_i} \, \mathrm{Y_{t-i}} - \mathrm{Y_t} \right)^2} \, . \tag{20}$$

Instead of minimizing the mean square error, we minimize its square to simplify the associated calculations:

$$E = \frac{1}{N} \sum_{t=1}^{N} \left(p(Y_{t-i}, 1 \le i \le p) - Y_t \right)^2 = \frac{1}{N} \sum_{t=1}^{N} \left(a_0 + \sum_{i=1}^{p} a_i \, Y_{t-i} - Y_t \right)^2 = E\left(a_0, a_1, \ldots, a_p\right). \tag{21}$$

To minimize this several variables expression, we calculate the partial derivatives with respect to each variable a_i and match the gradient of this function E to zero to obtain the critical points of E.

$$\frac{\partial \mathrm{E}}{\partial \mathrm{a}_0} = 0 \rightarrow \sum_{t=1}^{N} 2\left(\mathrm{a}_0 + \sum_{i=1}^{p} \mathrm{a}_i \mathrm{Y}_{t-i} - \mathrm{Y}_t\right) = 0$$

$$\frac{\partial \mathrm{E}}{\partial \mathrm{a}_k} = 0 \rightarrow \sum_{t=1}^{N} 2\left(\mathrm{a}_0 + \sum_{i=1}^{p} \mathrm{a}_i \mathrm{Y}_{t-i} - \mathrm{Y}_t\right)\mathrm{Y}_{t-k} = 0 \tag{22}$$

Developing the equations, we obtain the next system of (p+1) linear equations with (p+1) variables. Solving the system, the weights $(a_0, a_1, \dots, a_p)$ are obtained.

$$\left\{\begin{array}{r} \mathrm{N}\,\mathrm{a}_0 + \sum_{i=1}^{p} \mathrm{a}_i \left(\sum_{t=1}^{N} \mathrm{Y}_{t-i}\right) = \sum_{t=1}^{N} \mathrm{Y}_t \\ \mathrm{a}_0 \sum_{t=1}^{N} \mathrm{Y}_{t-k} + \sum_{i=1}^{p} \mathrm{a}_i \left(\sum_{t=1}^{N} \mathrm{Y}_{t-i}\mathrm{Y}_{t-k}\right) = \sum_{t=1}^{N} \mathrm{Y}_t\mathrm{Y}_{t-k} \quad, 1 \le k \le p \end{array}\right\}. \tag{23}$$

2. Methodology to validate the proposed model: simple and partial autocorrelation functions.

It is important to note that the error in predicting traffic at t also depends on the error in predicting traffic in previous slots. In order to study the relationship between the traffic prediction at a given slot k and the prediction k slots before, we calculate the coefficient of simple autocorrelation of order k, as expressed below. Moreover this coefficient also allows us to validate that this dependence is linear:

$$\rho_k = \frac{\sum_{t=1}^{N}(\mathrm{Y}_t-\mu)(\mathrm{Y}_{t-k}-\mu)}{(n-k)\sum_{t=1}^{N}(\mathrm{Y}_t-\mu)^2/n}, \tag{24}$$

where μ is the average of the random variable Y_t. This average is obtained from the historic traffic data that we will have, as we see in the next point, where we describe the prediction algorithm designed.

This set of coefficients ρ_k forms the so-called simple autocorrelation function (SAF), that is, SAF(0)= ρ_0=1, SAF(k)= ρ_k, $1 \le k \le p$. As correlations, the value of ρ_k are in the range [-1,1], where 1 means a perfect correlation.

It is not enough to calculate the simple autocorrelation in order to validate the model proposed for the calculation of Y_t (and with it the prediction of traffic at slot k). We also need to analyze the dependence between the errors in the different predictions but eliminating the possible effect of the intermediate results between two given predictions. We define the partial autocorrelation coefficient of order k, R_k, as the correlation between two samples separated in k slots when the linear dependence between the two samples is suppressed due to intermediate values. These coefficients R_k are the values of the partial autocorrelation function (PAF).

Once calculated the simple autocorrelation coefficients ρ_k, the Yule-Walker equations ([27]) allow us to state that these ρ_k are a linear combination of the smallest order autocorrelation coefficients, that is, $\{\rho_i\}_{i<k}$.

$$\rho_k = \sum_{j=1}^{p} \alpha_j \rho_{k-j} \quad, \quad 1 \le k \le p\,. \tag{25}$$

The proportionality constants α_j and, with them, the partial autocorrelation coefficients R_k can be calculated as follows:

$$
\begin{gathered}
\mathrm{R}_1 = \rho_1 \, , \\
\begin{bmatrix} \rho_0 & \rho_0 \\ \rho_1 & \rho_1 \end{bmatrix}^{-1} \begin{bmatrix} \rho_1 \\ \rho_2 \end{bmatrix} = \begin{bmatrix} * \\ \alpha_2 \end{bmatrix} , \mathrm{R}_2 = \alpha_2 \, , \\
\begin{bmatrix} \rho_0 & \rho_1 & \rho_2 \\ \rho_1 & \rho_0 & \rho_1 \\ \rho_2 & \rho_1 & \rho_0 \end{bmatrix}^{-1} \begin{bmatrix} \rho_1 \\ \rho_2 \\ \rho_3 \end{bmatrix} = \begin{bmatrix} * \\ * \\ \alpha_3 \end{bmatrix} , \mathrm{R}_3 = \alpha_3 \, .
\end{gathered}
\tag{26}
$$

Thus the coefficients R_k, which define the partial autocorrelation function PAF(k)= R_k, can be obtained recurrently.

The fact that the SAF coefficients do not cancel out quickly while the first PAF coefficients form a rapidly convergent recurrence to zero implies that the behaviour of the time series considered follows a linear autoregressive model of at least order 2 (as a consequence of the equations of Yule-Walker, [27]), that is, $p \geq 2$. Both functions, SAF and PAF, thus validate the autoregressive model of order p.

3. Design of the traffic prediction algorithm.

Factors influencing the traffic behaviour (temperature during the day, tourist movements, school holidays, winter, etc.) define initial and/or boundary conditions to determine the prediction tasks. Through direct observation, we can see that the traffic presents a repetitive daily pattern:

- In the night it reaches levels approaching zero. This ensures a stationary behaviour from a statistical point of view.
- Traffic behavior is similar in the week. That is, the same pattern can be observed in traffic during working days, for example.

Once obtained the time series $\mathrm{Y_t} = \mathrm{a_0} + \sum_{\mathrm{i=1}}^{\mathrm{p}} \mathrm{a_i}\, \mathrm{Y_{t-i}} + \mathrm{e_t}$ and designed the way to validate its linear dependence by studying the SAF and PAF associated functions, the next step is to separate $\mathrm{Y_t}$ into two components, one with stationary information and the other one related to stochastic information. The last part of $\mathrm{Y_t}$ is what characterizes the variable behaviour and traffic variations between apparently similar days. The smaller this stochastic component (impossible to calculate accurately) is, the smaller the mean squared error results. Let us see how to obtain, or compose, the prediction of the final data series.

The next figure shows the processes we have carried out to predict the traffic at t. These processes make up the traffic prediction algorithm.

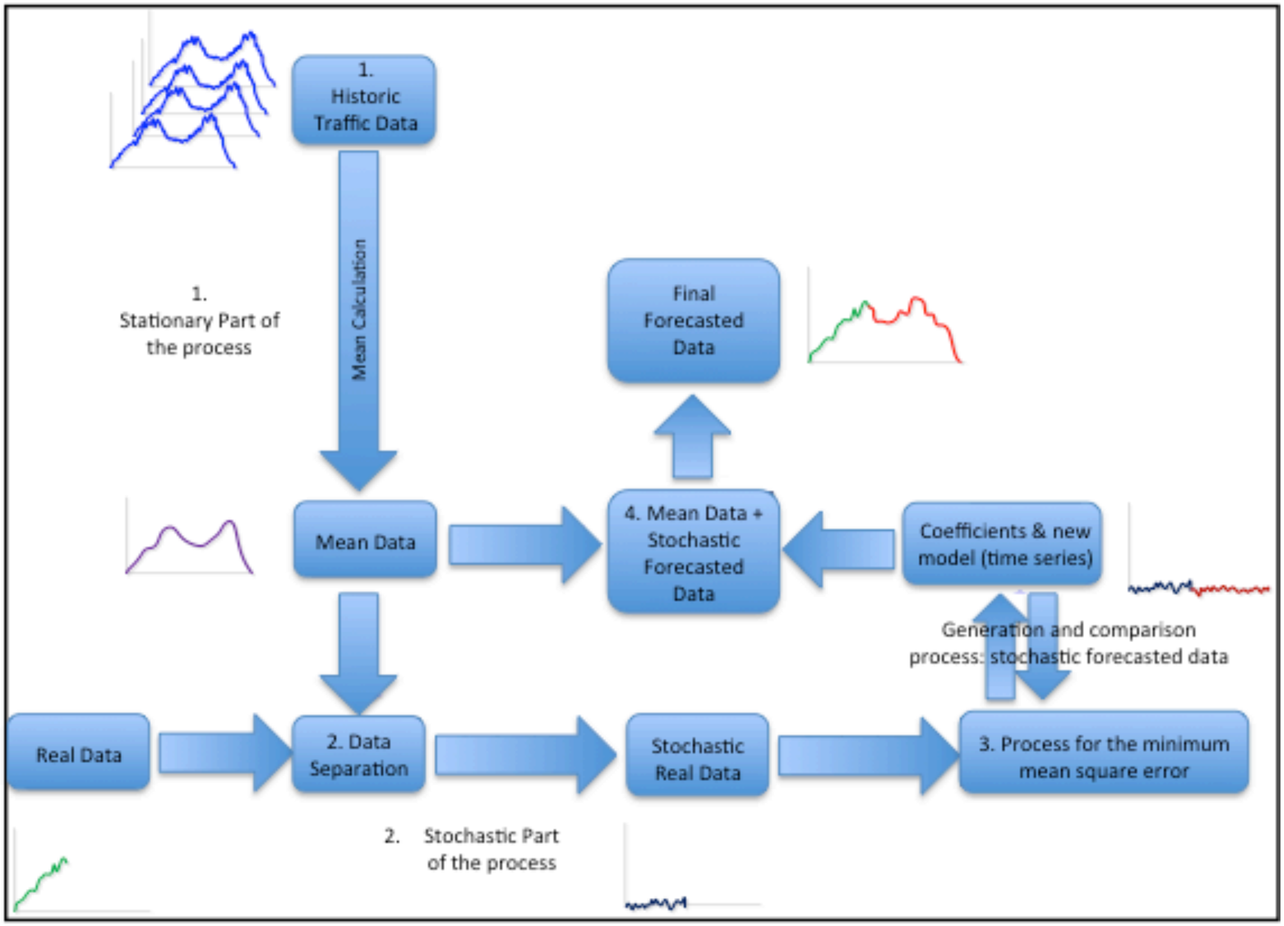

Figure 6. Traffic prediction algorithm.

i. First, based on historic traffic data, we obtain the mean values at each moment of the day. It is the stationary or deterministic part of the process.

ii. Subtracting these mean values from the (real) data that we have at t, we obtain the traffic variations (stochastic traffic data) occurring at each time t of the day.

iii. From these stochastic data, we approximate the value of the traffic variations in the next slots. We do it by taking the developed model and minimizing the mean square error between the traffic variations at time t and those calculated by the model.

The results allow us to calculate the coefficients that generate a new model. With this new model a new series is generated to compare with the previous ones, and so on. In this way we obtain the stochastic time series related to different slots of the day.

iv. Finally we add the stochastic part to the deterministic part obtained in the first step. Thus, we get the final series that predicts traffic at t from the previous ones.

4. Test to calculate the simple and partial autocorrelation for the model validation.

The next figure shows the time series related to a full day (April 2, 2018), with the original data (in pink), the stationary data (in blue) and the resulting stochastic data (in red):

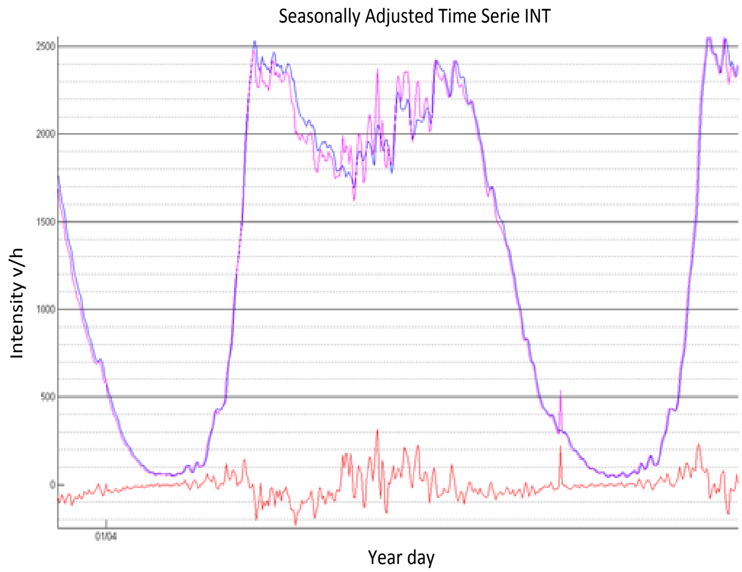

Figure 7. Instance of traffic prediction time series obtained.

For this day we first calculate the simple autocorrelation (SAF) function of our series Y_t and obtain the next figure. In this figure 8 we show the range (between blue lines) where the values of the SAF should not be considered significant, according to Yule-Walker equations ([27]).

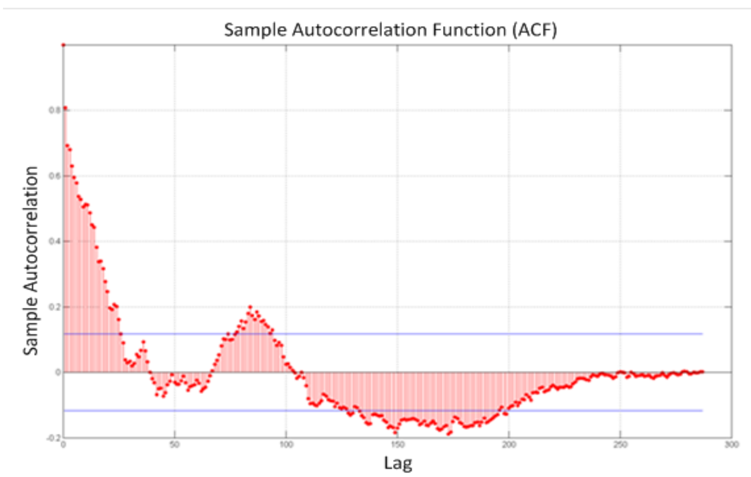

Figure 8. Simple Autocorrelation Function (SAF).

This SAF presents a slow convergence and too many significant terms. The SAF coefficients do not converge rapidly to zero. This means (as we have already anticipated) that the dependency model has to be linear autoregressive. We must know the order of dependency or autoregression. Therefore, it is necessary to carry out an additional analysis by means of the partial autocorrelation function (PAF) in order to fix the order of the model, generally less than 5. The next figure shows the PAF, where it can be seen that the coefficients of higher value are the first and the third ones. From them, the relatively rapid cancellation of the PAF coefficients implies that the time series has, at least, a second-order autoregressive model behaviour.

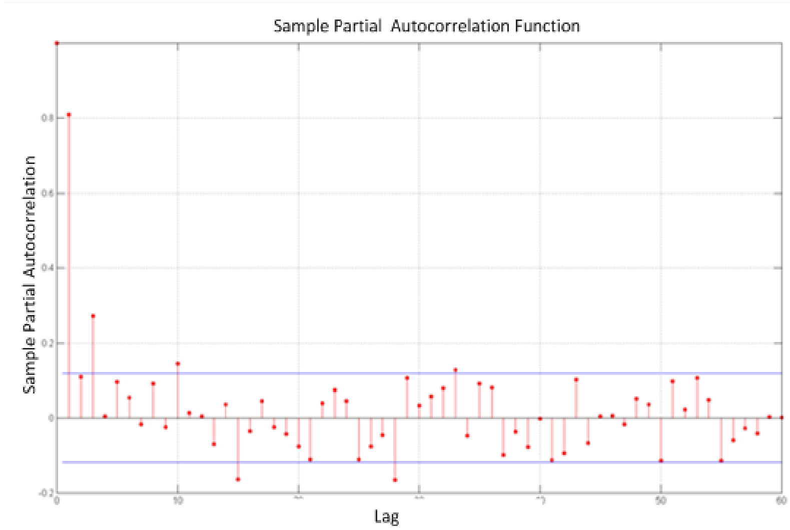

Figure 9. Partial Autocorrelation Function (PAF).

5. Estimation of the error in the predictions to improve the system continuously.

   To describe how to estimate the prediction error, we have taken a practical case. We select a second-order autoregressive model (p = 2) given by:

$$y_t = 0.8y_{t-1} - 0.4y_{t-2} \tag{27}$$

   This model generates the series of the next figure:

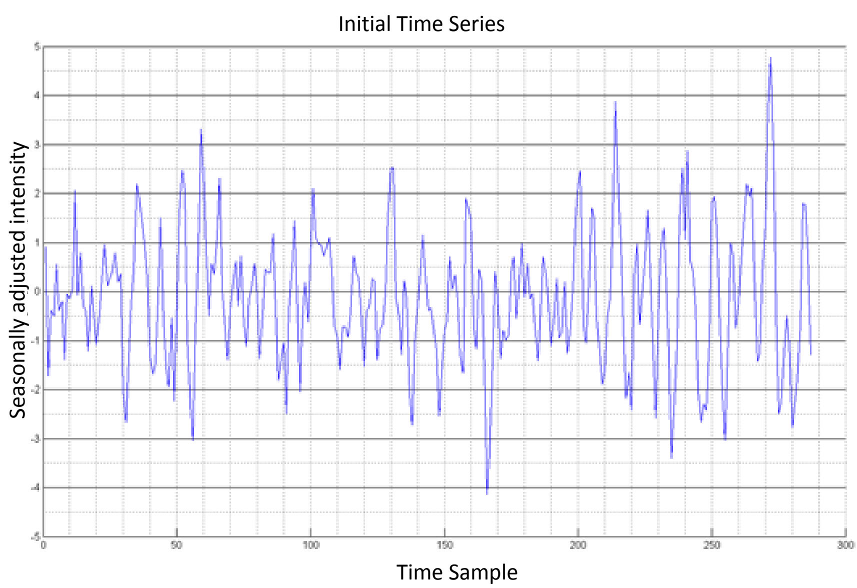

Figure 10. Initial model generated, autoregressive of order 2.

According to the algorithm designed, the coefficients of the new time series are calculated. This is done by taking the model and minimizing the mean square error, as described previously. These new coefficients generate a new model with which a new series is generated to be compared with the previous one. The resulting model is the next one:

$$y_t = 0.7452\, y_{t-1} - 0.3092 y_{t-2} \tag{28}$$

This model allows us to generate new data series, which are shown in the next figure (the initial time series in blue and the results after the application of the obtained model in red):

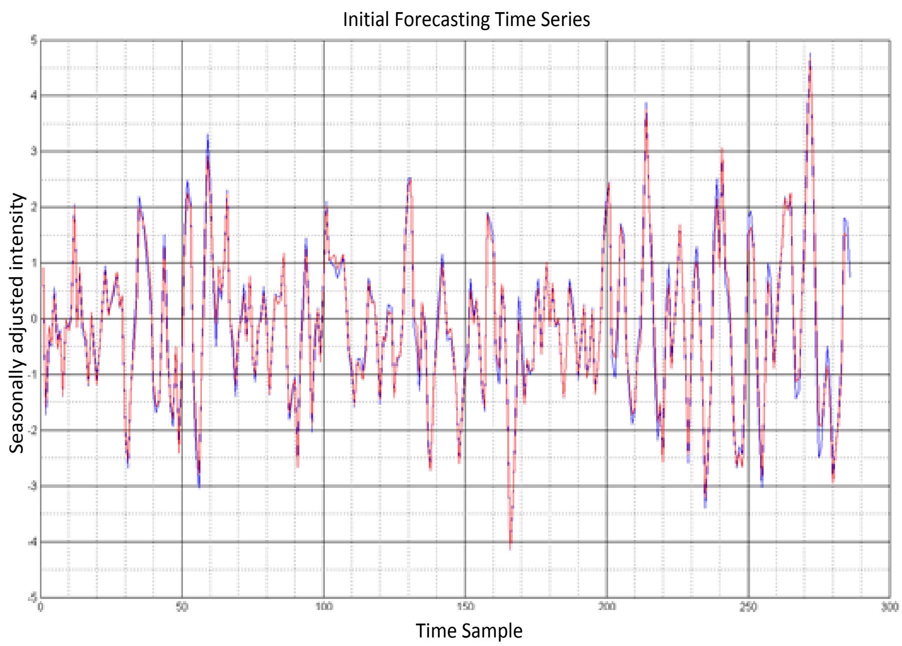

Figure 11. Initial time series vs. resulting time series.

The difference between both time series gives us the mean square error, as shown in the next graph.

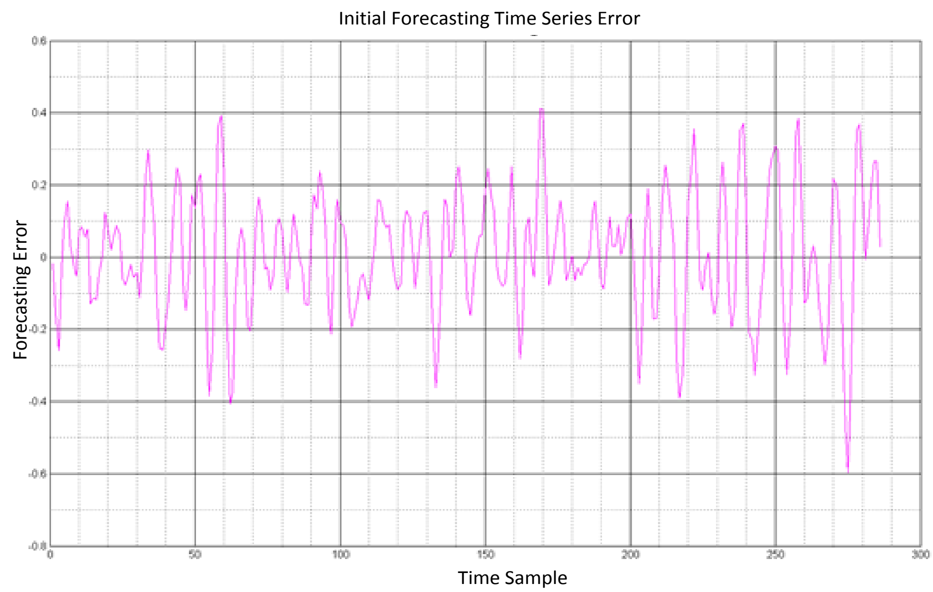

Figure 12. Prediction error related to the time series generated by an autoregressive model of order 2.

It can therefore be concluded that the prediction error is in an acceptable range of values and that, although it can be improved, this case allows us to illustrate how to calculate the prediction error in a real situation. To minimize the error in this case, it is required that the dependency value p be higher than 2. The larger the amount of historic data is, the better our prediction will be. This is how we proceed to continuously improve the traffic prediction.

8. CONCLUSIONS AND FUTURE WORK

We have designed an interoperability network model for FEV power supply management within the Smart City. It includes the proposal of a model to predict the traffic in order to prevent our future cities from issues which can damage the mobility. This model is based on different algorithms which allow us to track the FEV autonomy, to estimate the G2V/V2G energy flow in the city and to forecast future traffic behaviour in the city.

The model, developed to integrate the FEV in the mobility network, allows the CSCC to plan the interoperability between the FEV and the smart grid, which is a solution to efficiently control the energy availability from a centralized information system as we have proved with our tests in Ljubljana ([17]). Currently the European Commission continues promoting the development of new solutions and evolutions of existing ones in the context of the Smart City.

The work presented here is ready to be implemented in practice and some initiatives are already underway. The development and implementation of a project of this nature would only require the support of local institutions, energy suppliers and vehicle manufacturers, especially focused on FEV. The rest would involve working to implement the results achieved.

Future research actions include the evolution of this model, applying it to high power vehicles (buses, vans and electric trucks). Moreover, integration of FEV loading system into the smart home and implementation of FEVs in other economic areas such as agriculture are necessary to ensure the best distribution of energy in the Smart City, as an evolution of what we achieved in the associated working package of FiSpace ([28]), a Fiware-based project.

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