Mobility Network Model for Full Electric Vehicles to Interoperate with the Smart Grid and Efficiently Manage the Power Supply in the Smart City

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ABSTRACT

Information technologies offer an excellent framework to integrate the Full Electric Vehicle (FEV) in the future European city ecosystem. In this paper we present a model of the mobility in a city in order to allow FEV to interoperate with the smart grid and a way to design an infrastructure to efficiently control and manage the energy availability and supply in the network of charge stations in the city.

CCS CONCEPTS

• Applied computing~Information integration and interoperability
• Software and its engineering~Software design engineering

KEYWORDS

Interoperability; power supply; Full Electric Vehicle (FEV); energy availability; Smart City; mobility model; Markov processes; applied mathematics; information systems

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1. Introduction

Sustainable development of urban areas is a challenge of highest interest at global level. Nowadays, 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 provide us with a large number of resources to manage the data generated by the city and make urban areas evolve. This is what will make the current concept of city change towards the intelligent city or *Smart City*.

The new model of the city we are going to face is characterized by a higher connectivity and interaction among all the services that determine an urban center. 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. A very relevant element in this context is the Full Electric Vehicle (FEV).

In this work we present the design of an interoperability system to integrate the FEV in the Smart City. Our aim has been to optimize the energy supply to the FEVs. It has required to model the mobility of the FEVs in an area, to analyze the power consumption of the vehicles, to forecast the power demand in the city and to study the power supply availability in the network of charge stations.

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

As far as related work is concerned, there are several research activities in the literature that deal with energy management in Smart Cities, its assessment and optimization.

Ploussard et al. [1] discuss in their work 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 power grid reduction technique to optimize the transmission expansion planning using a weighted signed graph model. These results are relevant for our smart charging infrastructure to be improved.

Papastamatiou et al. [2] 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 important to outline what Abdennahder et al. [3] present in their work. They propose a decision approach for energy distribution adaptation in the Smart City taking into account the energy network efficiency and users' comfort. Their results aim to increase the satisfaction of the users which is measured by their energy demands according to their criticality degrees.

2. Problems to be addressed and architecture

Our work was developed under the Smart Vehicle to Grid project [4], 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 to solve the following problems:

1. 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.
2. 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.
3. Analysis of how the smart grid can continue providing power by the time there is a big demand from the users. This is required to improve the efficiency of the charging infrastructure and to reduce costs.

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 (Figure 1).

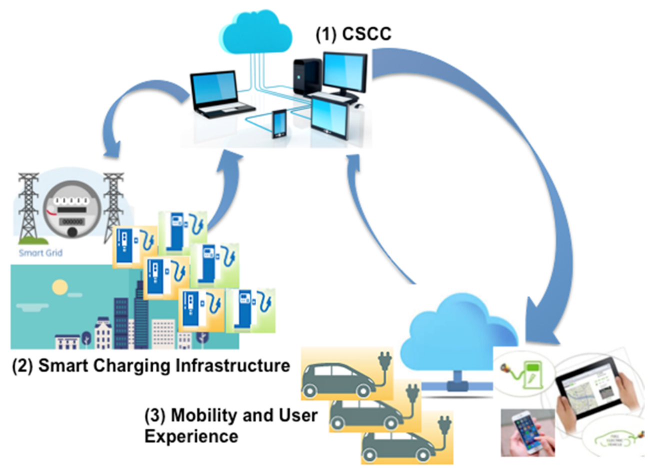

Figure 1: Interoperability System Architecture for FEV integration.

We see that it consists of three parts:

1. Charge Station Control Center (CSCC). It is the core component of the architecture, the responsible of 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 [5] 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 the relational model we needed to implement it. This model has been developed and tested, but it is not included in this paper as it does not contain research work. Its code is available at the url www.esystec.es/victorfdez/PhD.anexos/.

3. Tracing FEV autonomy in the city

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

- After knowing the route, Open Street Map database [6] provides us with APIs which are used to generate a matrix (route matrix) composed by the different steps in XML format to get our destination.

- Regarding the FEV battery, we have used the model of Hosseini-Badri-Parvania [7] 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.

Hence we estimate the consumption of power of FEV by using the data provided by the route matrix and the FEV battery model. In addition to this, speed variation is needed to be known as it is relevant to compare the different results.

Matlab libraries provided by the FEV simulator of Cerero-Tejero [8] and our estimation of the FEV power consumption have let us design the algorithm which develops the procedures to obtain the evolution of the SOC in the FEV once the arrival trip point has been reached. Figure 2 shows the Matlab implementation of this algorithm.

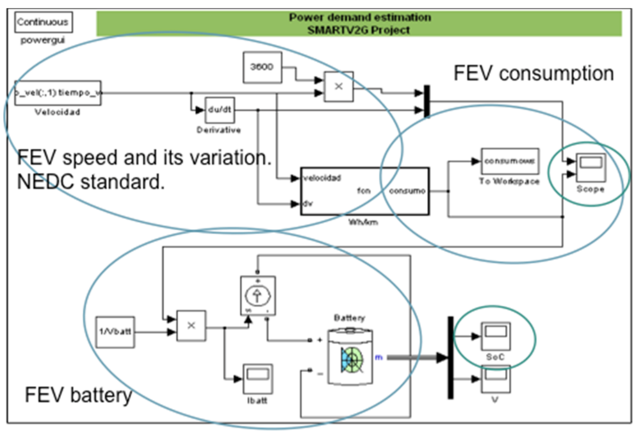

Figure 2: Matlab process to trace the evolution of FEV SOC from CSCC.

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 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), [9], 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.

4. Global FEV energy demand forecasting 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, often historical traffic data are not available. In that case, they must be simulated. We used Momoh-Wang artificial neural network [10] 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 $\{X_n\}_{n=0}^{\infty}$ 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 tendency which characterizes each time unit depending on its position on the week. Then, we obtained a function which best approximated 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 (workday or holyday, for instance).
    -
    - Type of charge: fast or slow, depending on the modes allowed by the CS.

    Figure 3 shows the different scenarios we have tested on Matlab. The last column represents the percentage of fast charges in a day.

	Number of FEV	Type of day	% fast charges
Scenario 1	1.000	Workday	0.25
Scenario 2	1.000	Workday	0.50
Scenario 3	1.000	Workday	0.75
Scenario 4	1.000	Holiday	0.25
Scenario 5	1.000	Holiday	0.50
Scenario 6	1.000	Holiday	0.75
Scenario 7	10.000	Workday	0.25
Scenario 8	10.000	Workday	0.50
Scenario 9	10.000	Workday	0.75
Scenario 10	10.000	Holiday	0.25
Scenario 11	10.000	Holiday	0.50
Scenario 12	10.000	Holiday	0.75
Scenario 13	50.000	Workday	0.25
Scenario 14	50.000	Workday	0.50
Scenario 15	50.000	Workday	0.75
Scenario 16	50.000	Holiday	0.25
Scenario 17	50.000	Holiday	0.50
Scenario 18	50.000	Holiday	0.75

Figure 3: Test scenarios to foresee the power demand energy in the city.

The algorithm was tested in different scenarios. The results obtained in Ljubljana (Slovenia) are shown in Figure 4, where a comparison between forecasted data and real data can be seen.

The average of the mean squared 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.

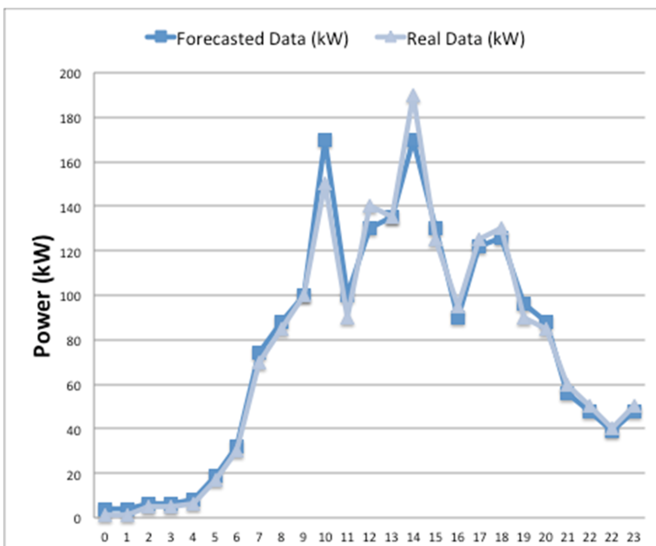

Figure 4: 24-hours charging load forecasting.

5. Modelling the estimation of power supply availability in the network of CS

Several research activities, such as [11], 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 can then consider the CS network as a system with a finite number of states $I = \{1,2,\ldots,m\}$ that randomly evolves in discrete time. Let J_n be the random variable representing the state of the system after the n-th transition. The sequence of random variables $(J_n, n \geq 0)$ is a Markov chain. For every i, j in I we have that

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

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:

$$P(J_n = j) = \sum_{k=1}^{m} P(J_n = j|\, J_{n-1} = k)\, P(J_{n-1} = k) = \sum_{k=1}^{m} p_{kj}\; P(J_{n-1} = k)\,, \tag{2}$$

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

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{m1} \\ p_{12} & p_{22} & \cdots & p_{m2} \\ \cdots & \cdots & \cdots & \cdots \\ p_{1m} & p_{2m} & \cdots & p_{mm} \end{bmatrix} = [p_{ij}]. \tag{3}$$

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

2. Let us include the time in the Markov chain. We define a sequence $(X_n, n \geq 0)$, where X_n is a random variable that 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 $F_{ij}(x)$ defines the probability of a transition from state i to j in a time x:

$$F_{ij}(x) = P(X_n \leq x|\, J_n = j,\, J_{n-1} = i). \tag{4}$$

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

If the next state is not relevant, the probability is given by the following distribution function:

$$H_i(x) = P(X_n \leq x|\, J_{n-1} = i) = \sum_{j=1}^{m} p_{ij} \cdot F_{ij}(x). \tag{5}$$

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:

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

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 foundation 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:

$$R_{ij} = E[N_j(t) | J_0 = i] = \sum_{n=0}^{\infty} n \cdot P\left(\frac{N_j(t)=n}{J_0=i}\right). \quad (7)$$

   Hence, developing this expression we get the next results:

$$R_{ij} = \sum_{n=0}^{\infty} n \cdot \sum_{k=1}^{n} \int_0^t H_i(k,\tau) \cdot Q_{ij}(k, t-\tau)\, d\tau. \quad (8)$$

$$R_{ij} = \sum_{n=0}^{\infty} n \cdot \sum_{k=1}^{n} H_i(k,t) * Q_{ij}(k,t) = \sum_{n=1}^{\infty} Q_{ij}^{n}(t), \quad (9)$$

   where k represents the k-th FEV of the fleet for which probabilities are calculated 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 $R = [R_{ij}]$.

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:

$$\phi_{ij}(u, k) = \sum_{l=1}^{m} \sum_{\tau=1}^{k} \phi_{lj}(\tau, k)\, b_{il}(u, \tau), \quad (10)$$

   Where

$$b_{ij}(u, k) = \begin{cases} Q_{ij}(u, u) = 0, & \text{if } k = u \\ Q_{ij}(u, k) - Q_{ij}(u, k-1) = 0, & \text{if } k > u \end{cases}. \quad (11)$$

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

$$\psi_{ij,(u,k)}(x) = \sum_{\tau=u}^{k} \left(1 - H_j(\tau, x)\right)\left(R_{ik}(u, \tau) - R_{ik}(u, \tau - 1)\right) \quad (12)$$

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

5. As far as the solution of these equations is concerned, we divided a day in ninety-six time units and we used iterative numerical methods [12] in discrete time. The required input data were 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 needed to operate with huge dimension arrays (96 x 96 x 2) to calculate the probabilities defining the mobility model, we used 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 (G2V energy) 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 (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:

$$E_{G2V} \propto \phi \cdot (1 - \%_{SOC}). \quad (13)$$

   In the same way, according to [13], V2G energy directly depends on the probability of remaining in the state j during a time unit, that is:

$$E_{V2G} \propto \psi \cdot W_{demanded}. \quad (14)$$

   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 5. The test was performed in the same scenario as that of result in Figure 4.

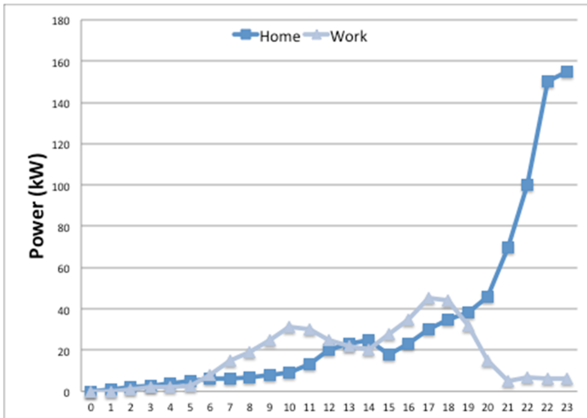

Figure 5: Estimation of G2V power flow in a day.

In terms of V2G energy, the availability profiles show a similar pattern with respect to the probabilities of transition and arrival at home and the working states, as we present in the following Figure 6.

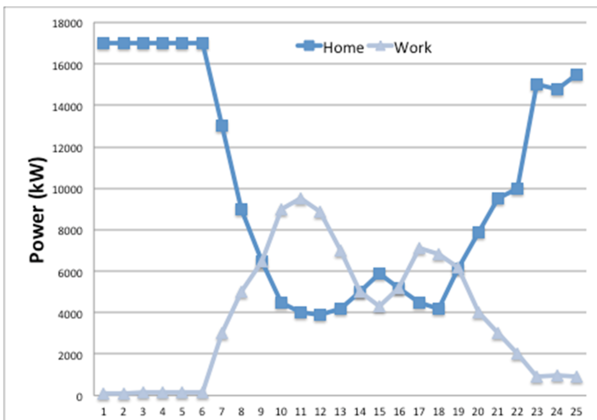

Figure 6: Estimation of V2G power flow in a day.

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 before starting to go out to enjoy the day, when the FEV can collaborate more effectively with the network, transferring energy (V2G service) that FEV do not need and allowing the CS network to control 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 this algorithm 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 will lead 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 that are used to produce the different control action to all the CS for the regularization of the load.

6. Conclusion and future work

We have designed a mobility model in a city and different algorithms to track the FEV autonomy, to forecast the global energy demand and to estimate the G2V/V2G energy flow in the city. It allows the CSCC to plan the interoperability between the FEV and the smart grid. It is a solution to efficiently control the energy availability from a centralized information system as we have proved with our tests in Ljubljana. Currently the European Commission continues to promote the development of new solutions and evolutions of existing ones in the context of 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 be work to implement the results achieved.

Future research actions include the evolution of this model applying to high power vehicles (buses, vans and electric trucks). Moreover, integration of FEV loading system into the smart home and implementation of FEVs in 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 [14], a Fiware-based project.

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