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PLANNING THE EXPANSION OF THE ELECTRIC SYSTEM, CONSIDERING THE EFFECT OF THE INTRODUCTION OF ELECTRIC AND HYBRID VEHICLES

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ABSTRACT

Since the beginning of the automotive industry, has been studied using electrical energy as alternative source to diesel in vehicles. Today it is necessary to execute an analysis of the massive entry of this type of technology and its effect forecasting on the planning future electricity networks, determining the amount and location of these consumption. On account of this, changes in the electricity market's structure and the implementation of energy policies, it is necessary to consider new variables that detail the best way of entry new consumption and system growth in the medium and long term. This paper proposes a load forecasting strategy based on the influence of energy policies and new technologies. The proposed strategy combines load forecasting methods with the Wavelets transformed and is validated through a sensitivity analysis for a real data set and sales forecast of electric vehicles, showing the potential for their use.

Index Terms - Electric vehicle, Spatial load forecasting, Supply control, Energy efficiency, Transmission and Distribution system planning model, Wavelets transform and Identification systems.

1. INTRODUCTION

Since the beginning of the automotive industry about 1895, many inventors use electricity as the energy base for vehicles, but the development of the components have not had a competitive development. Already in the year 1912 experts predict that prices are rising and that oil reserves are limited [1]. At present has continued research on the use of electricity as energy source for vehicles, focusing primarily on developing batteries as a source partial or total, alternative source of oil.

Complementary to the development of the vehicles, there is at present the real resource shortages and environmental problems, which have accelerated the use of electricity as an alternative source to oil and its derivatives. On the care of the environment, international agreements to reduce emissions, the reduction of oil reserve and the new rules in Europe to increase alternative energy sources [2]-[7], have promoted the development of exploration for new resources, generating changes in the use of new technologies and the use of electrical systems. One of these developments is the electric and hybrid vehicles, with the growing need for a real alternative source of energy competitive with current oil prices. Electric and hybrid vehicles are offering major advantages due to the efficiency transformation that has the electricity and utilization of supply networks, especially in cities.

Whereas the incorporation of such consumption on the electrical system, it is essential to analyze its impact on existing electrical networks, both in the operation of the electrical system at critical times of consumption.

In the area of power system planning is essential counting in the initial stage with the load forecasting and identify the variation in subsequent periods to make the behavior change and consumption level, being one of the objectives to be considered in the expansion of electrical system. On account of this; the entry of new technologies and changes in the structure of electricity markets, it is necessary to consider new variables that detail the best way to estimate the behavior and growth of electricity consumption in the medium and long period.

Currently have developed various load forecasting methodologies, using regressive models and computational methods such as neural networks, fuzzy logic and other mathematical tools used such as the theory of Wavelets [8]-[10].

Furthermore, growth of electricity consumption has historically been regarded as influential variables: climatic, socioeconomic variables such as macroeconomic growth of a country or city (*GDP*) and population level. However this has been changing in recent decades mainly because of scarce energy resources and price fluctuation of these [11]. The variables that currently affects the load's behavior is the use of equipment with better technology, both in industry and in homes, this influence can be seen in the development of technology efficient, to optimize energy consumption. This variable influenced the decoupling between economic growth and load, caused in large measure by the introduction of energy efficiency policies.

This work proposes a procedure for the load forecasting and new consumption forecast, specified in the entry of a new type of consumption such as the use of electric and hybrid electric vehicles, which incorporates a load forecasting model in the medium and long period, considering the behavior of macroeconomic variables, optimization of energy resources and implicitly the influence of climatic variables. The proposed model combines load forecasting methods based on traditional methodologies and the wavelet transform application.

2. VARIABLES TO CONSIDER

For purposes of analysis, the load forecasting of electric vehicles connected to the electrical system shall be considered as a new type of consumption that are joining the growing consumption of natural system.

To a load forecasting model and the effect of a new type of consumption, it is necessary to consider the classification of the load type and variables that are used for forecast.

2.1. Load profiles

According to the classification of the consumption in Germany [29].

2.2. Macroeconomic variables

The growth of electricity consumption has historically been linked to a country's economy, which is why it is possible to load forecasting from indexes that represent a country's economic as *GDP* [8] & [30]. The methodology used to forecast the *GDP* models were *ARIMA* (autoregressive integrated moving average) [31] - [33].

However, due to the implementation of policies that encourage use of facilities with more technology, both in industry and in households, it is possible to see a development of more efficient technologies, which optimize energy consumption. On account of this relation and decoupling current of macroeconomic variables are considered in analyzing the level of primary energy consumption and energy efficiency index [8].

2.3. Energy Efficiency

In order to track changes in the efficiency of energy use, are built energy efficiency indicators. Among the most commonly used to describe this process include: economic indicators, Technical-economic and indicators of energy efficiency [8]. The index used in this analysis is the energy intensity (*EI*), economic index used in the evaluation of energy efficiency at the aggregate level. EI is defined as the ratio between energy consumption and the level of activity generated in a country, sector or sub sector and the reason can be expressed in: *MWh/MM€:*

$$EI_t = \frac{EC_t}{GDP_t} \qquad (1)$$

Where, $EI_t = EI$ in period t.

EC_t = Energy consumption in t, in energy units, *MWh*.

GDP_t = in money units, *MM€*.

2.4. Levels of C02 emissions and level of vehicles sales

Since the Industrial Revolution and mainly due to intensive use of fossil fuels in industrial and transportation activities, there have been noticeable increases in the amounts of $C0_2$ released into the atmosphere, among others, with the aggravation that other human activities such as deforestation, have limited regenerative capacity of the atmosphere to eliminate the $C0_2$, the main responsible for the greenhouse effect. Reducing emissions of $C0_2$ of vehicle is a variable directly proportional to the use of technology more efficient and less polluting.

In addition, a variable to consider is the level of vehicle sales, which also reflected the entry of new technology and is directly related to the economic level of country or city to analyze.

3. LOAD FORECASTING SCHEME

According to previously released, the proposed procedure for load forecasting model is presented in the following schedule:

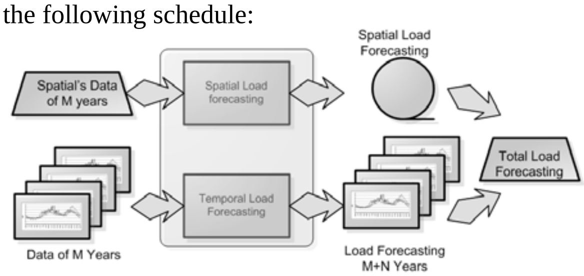

Figure 1. - Load forecasting Scheme

This scheme considers the temporary and space load forecasting, considering *M* as a base period, to estimate *N* periods [28].

Below are two modules that make up the total forecast.

3.1. Temporal Load Forecasting

Temporal load forecasting measured at each point regardless of its spatial location and behavior similar, this can be grouped according to their peak values, minimums and averages, to make a forecast of better representative of the group and then extrapolate the forecast results.

The groups of variables that influence its behavior are:

- *GDP* in the region to analyze, in more detail can be done analyzing the region where they belong data and thus separated by the productive sector.
- *PEC* Index by sector.
- *EE* Index by sector.

Whereas as a sign to identify the maximum annual (winter) relating to each load representative, is the forecast for the variables that influence the load and the load itself.

The identification methodologies are based on a signal representation of orthogonal functions each other, creating a forecast based on the combination of these. The forecast is comprised of two stages:

The model's structure: Stepwise Multiple Regression (*SMR*) is used. The *SMR* allows to determine which is the best structure to model to a variable *y(t)* based on selected components of a variable candidates set [34]-[36].

Parameters identification. Once identified the model's structure and certain variables that compose it, can be used to parameters identification, used models described by equations of difference, using models as regressive *ARMAX* [2] or the Implementation of the theory of Wavelets in identifying factors [9], [10]. Detailed development of this methodology is presented in work [8].

3.2. Spatial Load Forecasting

The spatial load forecasting model considers a series of data necessary to know the behavior of a city for its expansion and distribution. Several factors influence this behavior, considering own behaviors and variables to analyze each city.

The main objective is to obtain a value of consumption for area, the location and the distributed in the map city. This index considered the temporal load forecasting by type of consumption, distributed per capita or per Trade km^2.

$$Load\_a^{i}_{H0} = Load^{i}_{hab} \cdot \left(\frac{hab^{i}_{sec}}{area^{i}_{sec}} \right) \left[kw / km^2 \right] \quad i = section \qquad (2)$$

Detailed development of this methodology is presented in work [8]

4. LOAD FORECASTING SCHEDULE OF A NEW PROJECT

The effect of a new project or load projected is generally identified the location and spatial distribution in the electrical system, however there are new consumption to be temporal und spatial forecast.

4.1. Temporal Load Forecasting

The temporal load forecasting of a new consumption is independent of its spatial location. If there are different measurement techniques used for grouping, determining a representative measurement of each cluster and then extrapolate the results to all simples.

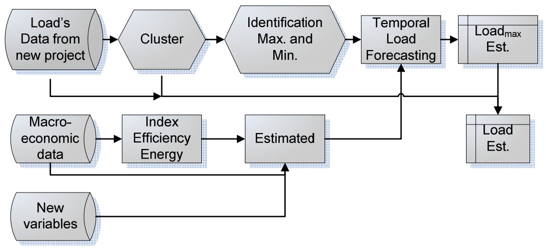

Figure 2.- Temporal load forecasting Scheme

Fig. 2 presents the methodology used. Its composition is as follows:

<u>*Initial classification and election of representatives*</u>, the process of grouping and identification of representative data is the most important process in this phase. This uses data clustering methods [8]. When considering the values of those data is limited to three load representative: maximum, minimum and average [28]. These characteristic data, associated data sets of customers with similar behavior.

It is considered the point of minimum distance (*Single-Link*) for the initial association of cluster [37]. For the election of the representatives used the methodology *Fuzzy K-mean* [37], which associates a function of belonging to a cluster each data set. As initial condition is considered earned in the previous point. The methodology is as follows:

a. Calculating centroids of each cluster.

$$C_{k,i} = \frac{1}{n_k} \sum_{j=1}^{n_k} x_{j,i} \qquad (3)$$

Where, C_k = cluster's centroid *k;* n_k = element in cluster *k*; and *i* = Component of the entry vector, in this case is 3-D.

b. Calculating distance points to centroids and membership functions.

It is calculating the Euclidean distance between points. It is considered the point of minimum distance (*Single-Link*) for the association's initial cluster [28]

$$e_i^2(k) = (x_i - C_{k,i})^T (x_i - C_{k,i}) \qquad (4)$$

$$\mu_i(k) = \frac{1}{\sum_{l=1}^{k} \left[\frac{e_i(k)}{e_i(l)} \right]^{\frac{2}{(m-1)}}} \qquad (5)$$

Where, *k* = cluster*;* *m* = parameter referred to the overlap of cluster; and *i* = Component of the entry vector.

c. *Objective function*

$$FO(k) = \sum_{i=1}^{K} \sum_{j=1}^{N} U_j(i) \cdot e_j^2(i) \qquad (6)$$

The objective function should be minimized according to groups that are conducted in each iteration.

It considers annual data due to the timing of the data used as input variables. For example *GDP* or *EE*.

Variables that influence, because the model is to make medium and long period, the group of variables that influence its behavior and to explore are:

- *GDP* in the region to analyze, in more detail can be done analyzing the region where they belong data and thus separated by the productive sector.
- *PEC* Index by sector.
- *EE* Index by sector.
- *Remis$_j$* index of $C0_2$ emissions associated with the direct emission of vehicles in the year *j*.
- *Vv$_j$* index of vehicle sales in the year *j*.

Forecasting model of variables that influence consumption in the new consumption is resolved in the same form presented in IV.1.

The model's structure: *utilize SMR* allows to determine which is the best structure to model to a variable *y(t)* based on selected components of a variable candidates set.

- ***Parameters identification.*** Once identified the model's structure and certain variables that compose it, can be used to parameters identification, used models described by equations of difference, using models as regressive ARMAX [2] or the Implementation of the theory of Wavelets in identifying factors [9], [10] , [38].

1-Implementation of the Wavelet's theory in parameters identification, the wavelet transforms allows a description of signals that include local features. This property is very useful to determine what moment a disturbance occurs in a signal that is whether or not affected by noise. His expression for discrete Wavelet transform is as follows:

$$g(t) = \sum_{k=0}^{2^{j0}-1} C_{j0,k}\varphi_{j0,k}(t) + \sum_{j=j0}^{N-1}\sum_{k=0}^{2^j-1} d_{jk}\Psi_{jk}(t) \quad j,\, k \in Z+ \qquad (7)$$

Where, $\psi_{j,k}(t) = 2^{2/j}\psi(2^{jt} - k)$

The mother wavelet function *ψ(t)*, always brings with it a function associated scale *φ(t)*. With this tool, it may represent a signal by a number of coefficients. Considering the model of the system:

$$y(t) = \alpha u_1(t-i) + \beta u_2(t-j) + w(t) \qquad (8)$$

If applied discrete Wavelets transformation to the functions is obtained following the transformation of them:

$$y(t) \Rightarrow \left(\begin{bmatrix} C^y{}_{01} \\ \vdots \\ C^y{}_{ck}\end{bmatrix}, \begin{bmatrix} d^y{}_{01} \\ \vdots \\ d^y{}_{jk}\end{bmatrix}\right) u_1(t) \Rightarrow \left(\begin{bmatrix} C^{u_1}{}_{01} \\ \vdots \\ C^{u_1}{}_{ck}\end{bmatrix}, \begin{bmatrix} d^{u_1}{}_{01} \\ \vdots \\ d^{u_1}{}_{jk}\end{bmatrix}\right) \text{ and } u_2(t) \Rightarrow \left(\begin{bmatrix} C^{u_2}{}_{01} \\ \vdots \\ C^{u_2}{}_{ck}\end{bmatrix}, \begin{bmatrix} d^{u_2}{}_{01} \\ \vdots \\ d^{u_2}{}_{jk}\end{bmatrix}\right)$$

The calculation of these parameters depends on the length of the window samples, which must be mobile in order to generate a sweep of the signal and thus test the behavior of each parameter.

The coefficient's numbers is half the length of the sample's window (*m*), namely *m/2* $C_{j,k}$ parameters and *m/2* parameters $d_{j,k}$. The window's number defines the coefficients sample's numbers, namely *N> m/2*.

This creates a system in which the coefficients wavelet are identification of the signal *y(t)* depending on the behavior of the coefficients of signals autoregressive *y(t)* and the input variables. With this system have in following:

$$\begin{aligned} C^y_{j,k}(W) &= \alpha_{cw} C^y_{j,k}(W-i) + \beta_{cw} C^{U_1}_{j,k}(W-r) + \gamma_{cw} C^{U_2}_{j,k}(W-q) + K_{cw} \\ d^y_{j,k}(W) &= \alpha_{dw} d^y_{j,k}(W-i) + \beta_{dw} d^{U_1}_{j,k}(W-r) + \gamma_{dw} d^{U_2}_{j,k}(W-q) + K_{dw} \end{aligned} \qquad (9)$$

Then proceeds to calculate the inverse discrete Wavelets transformed (*IDWT*) from coefficients forecasting of *y(t)*.

$$\left(\begin{bmatrix} \hat{C}^y{}_{01} \\ \vdots \\ \hat{C}^y{}_{ck}\end{bmatrix}, \begin{bmatrix} \hat{d}^y{}_{01} \\ \vdots \\ \hat{d}^y{}_{jk}\end{bmatrix}\right) \Rightarrow \hat{y}(t) \qquad (10)$$

The biggest advantage of this method is the detection of changes in frequency signals and modeling in each independently stretch of the signal, and then consolidates all these variations.

The disadvantages of this model is the large number of variables to calculate because the system is transformed into a group of systems related to the number of coefficient., It is necessary to have a sufficient number of measures.

Reconstruction consumption, with the previous phase, is aimed at representative load forecasting of each cluster. With the membership function μ^k_{ij} calculated in the formative stage of cluster extrapolate the load forecasting to all members of each cluster, according to their membership function. And of each load forecasting (*M*), is:

$$\begin{bmatrix} \hat{L}^k_1(t) \\ \vdots \\ \hat{L}^k_M(t)\end{bmatrix} = \begin{bmatrix} \mu^k_{11} & \cdots & \mu^k_{1N} \\ \vdots & \ddots & \vdots \\ \mu^k_{M1} & \cdots & \mu^k_{MN}\end{bmatrix} \begin{bmatrix} \hat{L}^k_{C1}(t) \\ \vdots \\ \hat{L}^k_{CN}(t)\end{bmatrix} \qquad (11)$$

The results are applicable to distribution spatial.

4.2. Spatial Load Forecasting

The spatial load forecasting models considers a data of new consumption and the behavior of a city for its expansion and distribution. The main objective is to obtain a value of consumption for area, the location and the distributed in the map city.

Background of new project and area. It must have the characteristics of new project, city and its habitants. The following information is needed on this point:

- Area of the new project
- Population density (*hab/km^2*) or Density trade(*Trade/km^2*) and growth
- New load distribution.
- Type of consumption.
- Land Use, (*Land$_{use}$*) this division may be in the following:

Housing-Trade-Parks-Parking-Airport-Industry-Agriculture-Services.

It is necessary to locate information in the map city; his analysis is performed through the level of resolution used. This resolution *(N)* is defined as the level of division of the city into "sections" in which develops in the process of data analysis in an independent manner, and then add all sections and obtain the total distribution in the map.

The process of obtaining the consumption's distribution in the city map is calculated the load for area (kw/km^2).

The spatial load forecasting of the new consumption can be approached in two ways:

1. *New consumption in a specific area not covered by any city or area to be analyzed.*

In this case it is necessary to distributed the load forecasting of the city or area according to the methodology presented in [8], obtaining a distribution kw/km^2.

For the new load forecasting, it is necessary to obtain an index kw/km^2 in the specified area, which may be an area adjacent to the city or one belonging to the city. The methodology for this case considers the consumption per capita or trade distribution in the area to analyze and its growth.

The data obtained were subsequently representing each section of the area to be analyzed and considered maximum & minimum with their respective coordinates.

$$Sec = \left[Sec \quad Load_{hab\_\max} \quad Load_{hab\_\min} \quad (x,y)_{\max} \quad (x,y)_{\min} \right] \qquad (12)$$

Is considered habsec and Load of each section en el area. Thus, it is calculated the load per km2, to the maximum and minimum per capita consumption.

$$Load\_a^i = Load^i_{hab} \cdot \left(\frac{hab^i_{\sec}}{area^i_{\sec}} \right) \left[kw/km^2 \right] \quad i = section \qquad (13)$$

In the same way for other consumption's types. This will finally get the matrixes to model in the map.

$$Sec\_a = \left[Sec \quad Load\_a_{\max} \quad Load\_a_{\min} \quad (x,y)_{\max} \quad (x,y)_{\min} \right] \qquad (14)$$

This analysis is by consumer type and year. Consider the scenarios regarding the number of available measures.

1. Where there is more than a measure by section
2. Where there is only one measure by section
3. Where there is not measure in the section

In the first scenario, the section *i,j*, has a maximum value V_{max} with coordinates (x_{max},y_{max}) and a value V_{min} with coordinates (x_{min},y_{min}). The proposed distribution is a normal distribution *Y(x,y)* with maximum magnitude V_{max}, focusing on (x_{max},y_{max}) and a variance that $Y(x_{min}, y_{min}) = V_{min}$.

If V_{min} is near V_{max}, the demand on the board of the section is not well represented by *Y(x,y) and* not continuous in the other section. For this it considers the distance between consumption (*x* & *y*), if this distance is >25% of the length section *(d).* Otherwise considering the V_{min} at the ends of the section, namely the minimum distance between (x_{max},y_{max}) and the section's boards, in order to represent between the two values all the values of the section.

In the second scenario, is considered the same situation before, but without V_{min}, is necessary to consider the maximum distance between (x_{max},y_{max}) and the section's boards.

In the third scenario is considered the effect of the analysis in adjacent sections in the project's area.

Later considering the matrix M_{princ}, which contains the pattern of land use is to identify places where no-show this growth.

Is considered in the matrix *kw_area (i,j)=0* for values in the matrix $M_{princ}(i,j)=1$, otherwise maintaining the value of *kw_area,(i,j).* This vector is the final result graph of the spatial load forecasting model..

2. *New consumption distributed in the city or area.*

The index Kw/km^2 of load forecasting according to the methodology presented in [8], add to what obtained by the new project or consumption. For the new load forecasting is necessary to obtain an index Kw/km^2 in the same area analyzed. The methodology for this case considers the load forecasting distribution per capita or trade and growth.

The data obtained were subsequently representing each section of the area to be analyzed and considered maximum & minimum with their respective coordinates. This will finally get the matrixes to model in the map.

This analysis is by consumer type and year. Consider the scenarios regarding the number of available measures.

1. Where there is measure
2. Where there is not measure in the section

Case 1 is presented same as cases 1 and 2 in the scenario above. In case 2, a distribution is made considering the maximum value of the section.

Later considering the matrix M_{princ} y el vector *kw_area* which contains the pattern of land use is to identify places where no-show this growth.

5. APPLICATION SCHEME

5.1. System Precedents

New consumed corresponds to the entry of electricity and hybrid vehicles that is connected to the electrical system and will be added to the projected consumption of natural growth residential and commercial consumption.

Consider measurements between 2000 and 2004. These measurements are residential H_0 and commercial G_i (i=1:6).

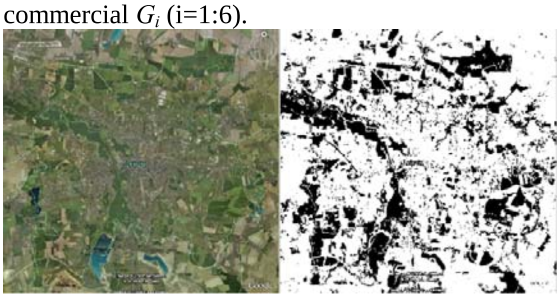

Figure 3.- Real and binary map City [45]

Fig 3 shows the binary map city [44] with added values and land use. According to information from the city [43], the area of the city is 297.6 km^2

As described variables that influence *GDP*, *GDPpe* and *EI*, between the years 1991 – 2008 and 1991 - 2005 respectively.

Besides includes the level of $C0_2$ emissions product of vehicles, respecting agreements made [12] and the number of vehicles purchased in the city.

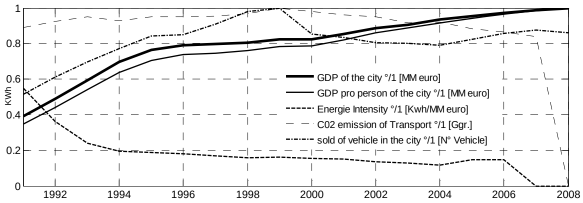

Figure 4. - GDP, GDPpe, EI, $C0_2$ and sale of vehicles.

However, it is possible to consider a consumption of 15 kWh per recharge of vehicle, 8 hours average. According to the proportional forecast and hypothetical in the city in the amount of electric vehicles in Germany [41], [43], obtains a curve which delivered maximum electrical power consumption as shown in Fig 5.

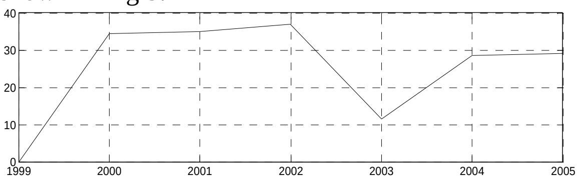

Figure 5. – Consumption KW

In the case of massive entry of electric vehicles, fig 8 represents the actual consumption of electricity for recharging electric vehicles.

5.2. Temporal Load Forecasting Apply

The load forecasting for consumption H_0 and G_i, Fig. 6 shows consumption grouped into clusters, with *Fuzzy K-means* methodology. The consumption H_0 was grouped in 3 cluster and consumption G_i in 2 clusters.

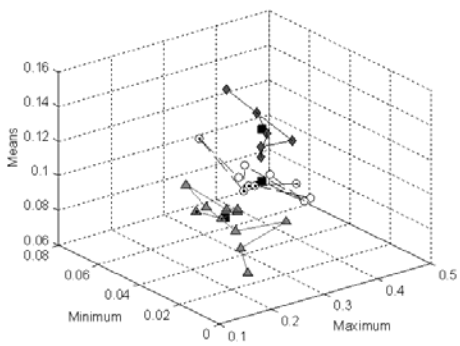

Figure 6. - Groupings of consumption H0.

With respect to the variables that influence the behavior of consumption and new consume projected as product income for electric and hybrid vehicles, for forecast GDP, will be used for the structure's identification the methodology SMR. And the parameter's identification is performed with an ARIMAX model. The structure gained is as follows:

$$PIB\ (t) = \sum_{i=1,2,3,4,5,6,8,10} \alpha_i PIB\ (t-i) + K \tag{16}$$

The error mean quadratic between 2002 and 2007 is 1,7% from index's average in that period.

To EI forecasting was used Wavelets transformation, in order to model the effect that can cause a change in the GDP or PEC, e.g. the admission of new technology, more efficient or introduction of political decisions that affect the GDP's trend.

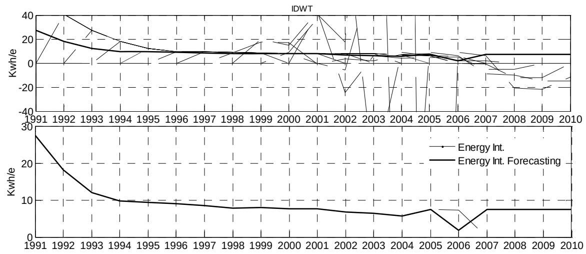

Figure 7. - EI forecasting.

Fig. 7 shows the inverse discrete wavelets transformed (*IDWT*) applied to the parameters Wavelet's identifications in each interval (fig. top), in the figure below shows the final EI forecasting by the year 2010.

Similarly wavelet transform is applied in the estimation of $C0_2$ emissions and selling vehicles in the city. Fig. 8 shows the *IDWT* applied to the wavelet's parameters identifications in each interval in the final shows the $C0_2$ emissions (top figure) and sales of vehicles (figure below) forecasting by the year 2010.

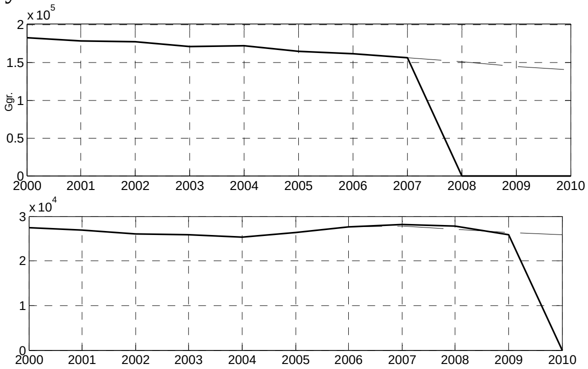

Figure 8. - C02 Emissions and sales of vehicles forecasting.

The error mean square average obtained in the models is 1.2% and 1.3% respectively.

With these variables is forecast the growth of load representatives from each cluster of the types of demand. Each model is forecast at independently, because each cluster has a different behavior and different variables influential. The error mean square average obtained in the models is 1.3% for residential and 2.1% for commercial load.

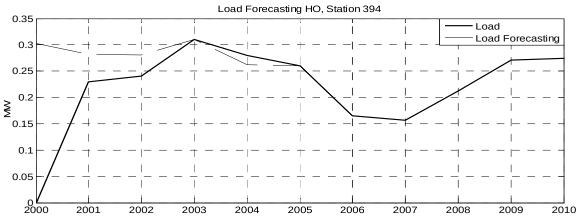

Figure 9.- Load H0 forecasting

Fig. 9 shows the load forecasting of one residential measurement (stations).

In the case of temporal load forecasting from electric vehicles, the results are presented in the following figure.

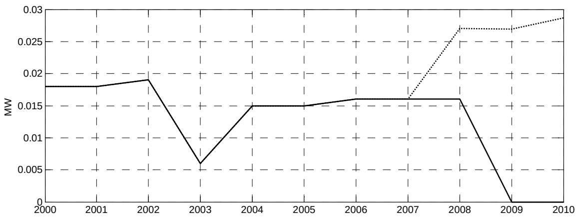

Figure 10.- Load forecasting of electricity vehicles

Fig. 10 shows the new load forecasting that less than 10% of residential consumption (*Fig. 9*). Due to the low level of penetration of this technology, it is not possible to have a representative number directly in the future, but to present their forecast this methodology. As we penetrate more cities in this technology will allow better forecast its temporal behavior.

5.3. Spatial Load Forecasting Apply

According to the results obtained from temporal load forecasting is to make the methodology for spatial load forecasting.

The map city is divided into 64 sections (resolution=8). In making the calculation of new consumption by area.

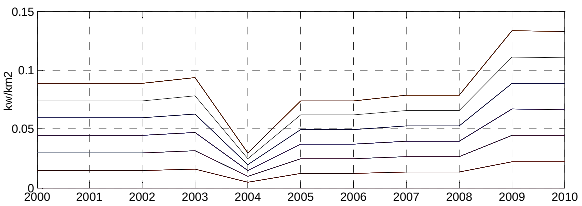

Figure 11.- kw/km2 by section of new consumption.

Fig. 11 shows the index *Kw/km²*, it emphasized to the behavior of consumption (growth) consistent with the reduction of $C0_2$ emissions and the sales of vehicles trend.

Spatial Distribution. The spatial location of index *Kw/km²* for each section is associated with the coordinates of the measures, focusing on the normal function of these points according to the natural rate of consumption of the city. One hypothesis is that to implement consumption refers to the vehicles is more likely to coincide with the minimum residential load, however the case of coincidence with peak demand, can design an electrical system with a degree of security related to its ability supply.

Fig 12 (top) shows the spatial distribution related to battery charging for electric and hybrid vehicles. Fig 12 (below) presents the maximum residential load.

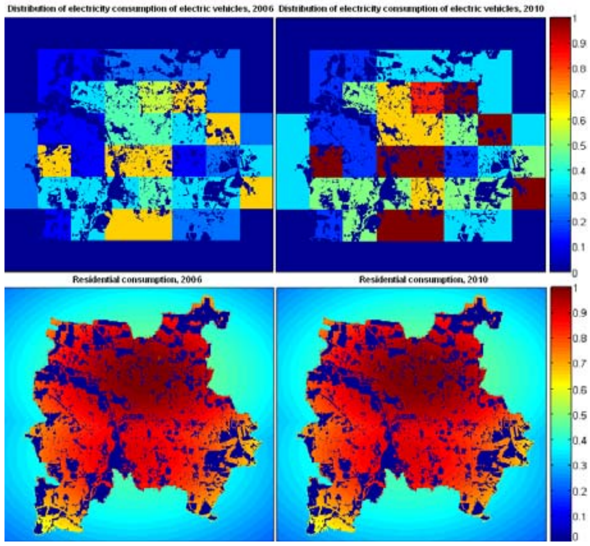

Figure 12.- Spatial distribution of new consumption und residential load

The values are presented in °/1 (with respect to the maximum for each year between 2000 and 2010 for each type of consumption analyzed independently) for the years 2006 and 2010. According to the residential load, this presents an almost constant distribution and intensity, due to low population growth and the influence of energy efficiency registered. However the consumption is growing anger that the registered consumption of electric vehicles. According to records obtained, the consumption will increase as we enter a larger number of vehicles, and their distribution is forecast according to what presented in Fig.12, where there are areas of higher number of vehicle in the area.

Fig. 13 shows the distribution of the sum of the residential consumption and the new consumption in °/1 for the years 2006-2010.

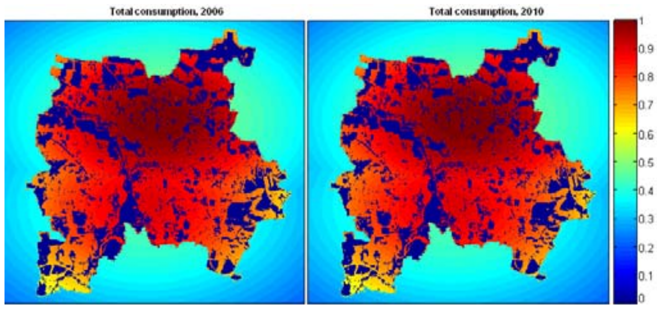

Figure 13.- spatial distribution of total load.

The sum of the distribution of the new consumption and the distribution of residential load, actually fails to reflect a significant increase in consumption is less than 10% of maximum between 2000 and 2010.

According to the results obtained are presented the load forecasting and location of the critical consumption of a city and the network, at certain times, also the effect of new consumer do the massive entry of electric vehicles will be judged as slightly increased .

The load forecasting strategy and analysis of new project proposes a new method to temporal and spatial load forecasting. Furthermore, it is noteworthy that the use of a load forecasting model is essential for making decisions in time to optimize available resources and schedule its use.

With this methodology it is possible to analyze the entry of a new consumer and influences behavior associated to the surface and uses the inhabitants of nearby areas that are affected.

6. CONCLUSIONS.

The implementation of new regulations aimed at reducing CO_2 emissions and exploring alternative sources to oil as an energy source of transportation, has encouraged the study new technologies in the automotive area as hybrid systems that use electricity or 100% electrical systems.

As increase this development of transport is coupled to the current energy supply systems such as gas, electricity or other source. In the case of electricity networks, the new consumption may affect the size of the existing electricity networks, its planning, new connections and the entry of new components capable of supplying the demand to required deliver the level of safety and quality requirements [39] [40].

Furthermore, the current methodologies of electrical system planning area are mainly based on macroeconomic variables the long time to load forecasting. The implementation of policies on the optimization of consumption energy, scarcity of fuel reflected in the prices of these, the entry of new technologies and changes in the electricity markets structures, make it necessary to consider new variables to give details of the best estimate of behavior and expansion of electricity consumption and new consumption.

The new scheme propose a temporal and spatial load forecasting model in medium and long term for PSE, incorporating the macroeconomic variables effects, optimization of energy consumption expected reflected in energy efficiency index and primary energy consumption, adding the new consumption forecasting related with CO_2 emissions and sales of vehicles in an area or city.

The strategy presented in this study is built on the base of a range of methodologies for forecast and classic grouping of signals combined with a novel use of Wavelets transformed for phase temporary load forecasting model. Besides adding the spatial load forecasting model and its expansion into a physical location.

Using a load forecasting model is essential for decision-making at the time to optimize the resources available in planning. Currently, there are a large number of studies load forecasting model [13]-[27] that are used and implemented according to the needs and requirements submitted to cover..

The implementation of Wavelets transformed in the load forecasting model is based in his property as a tool of analysis sections of the signal to analyze behaviors not expected a signal, that due to the influence of macroeconomic variables which have an estimate very sensitive to changes produced by externalities or political decisions of each country or city

The validation of the proposed strategy is based on actual load data and estimated data of electric vehicles in the city analyzed. According to the estimate of new consumption and the temporal residential load forecasting delivery a mean square error of 2% on average. The spatial distribution, according to data distribution in the city considered as population, vehicles and people by land use, has a spatial and temporal distribution concordant with the rate of growth of population in the city, the utilization efficiency energy and reducing CO_2 emissions, this is reflected in the remarkable increase of new consumption and constant level of residential consumption.

These results may be associated to the network according to the location of distribution station, determining the ability of the system at peak load, transfers load into the system before a failure and in planning the expansion of the system.

In summary, the results of this study allow establish the importance of forecast the effect of the massive entry of electric vehicles like load of the system and determine its distribution in the particular on the electrical system planning area, exist benefits economic and technical referring to the projection of new electrical facilities necessary.

Future work on this theme are focused on determining the study of new variables new variables that influence the massive entry of electric vehicles and the incorporation of new policies aimed at optimizing the power consumption in the load forecasting model.

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