Load forecasting scheme based on energy efficiency for planning the expansion of electrical systems

J. L. Cerda Arias *Student Member, IEEE* and D. Westermann**,** *Senior Member, IEEE*

***Abstract*: A fundamental phase in the electrical systems planning is the temporal and spatial load forecasting. By changes in the structures of electricity markets and implementing policies for energy optimization, it is necessary to consider new variables that detail of better form the behavior´s forecasting and expansion of the electrical consumption to medium and long time. This work proposes a global load forecasting scheme to long-time, covering the topic temporal and spatial. The load forecasting proposes based in the influence of macroeconomic variables, implementing energy efficiency policies and the entry of new technologies that optimize their consumption. The proposed strategy combines load forecasting methods based on traditional methodologies with the implementation of the wavelets transformed and is validated through a sensitivity analysis for a real data set. Also, the model is applied to a real distribution system showing the potential for their use.**

Index Terms **Temporal & spatial load forecasting, Energy efficiency, Transmission and Distribution system planning model, Wavelets Transform, Identification systems.**

I. Nomenclature

ESP	:	Electrical system planning.
LFM	:	Load forecasting model.
PEC	:	Primary energy consumption.
EE	:	Energy efficiency.
GDP	:	Gross domestic product.
GDP_{pe}	:	*GDP* pro person.

II. Introduction

In the area of the *ESP* is essential used in the initial phase a *LFM*, being one of the objectives to tackles in the expansion of electrical system. This load forecasting should guide the growth of the electrical system. For this reason and due to the entry of new technologies and changes in the structures of electricity markets, it becomes necessary to consider new variables to give details best the forecasting of load's behavior and expansion in the medium and long time. Actually have developed various loads forecasting methods, using regressive methodologies, neural networks or fuzzy logic, generating an important range of forecasting's tools. However, to exist other mathematics methodologies little explored in the load forecasting as the wavelets theory, which is used to analyze the variation frequency signals, considering its ability to detect variations of signals or variables that influence the load´s behavior.

On the other hand, growth from load historically has been strongly linked to a country's economy. The load forecasting have been used as variables influencing their behavior various indexes that describe "*why?"* consume a certain amount of energy, between these variables are considered climatic, socioeconomic status, macroeconomic variables such as *GDP*, population level, etc. However this has changed in recent decades, mainly by the shortage of energy resources and the fluctuation in the price of these. Thus, since 1990, energy consumption per *GDP* unit, globally, has been reduced at a rate of 2% per year [4].

Because this is now appreciates that one of 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 has influenced the decoupling between economic growth and the load produced largely by the introduction of *EE* policies motivated by a shortage of resources and by caring for the environment globally. This has generated the intuitive idea that there is a link between sustainable economic growth of a nation and implementing *EE* policies. This influence of the optimization of resources is reflected in the relationship between growth of a country or city and *EE* indices.

This work proposes a procedure for the load forecasting, which incorporates a *LFM* in the medium and long time, considering the behavior of macroeconomic variables, optimization of energy resources and implicitly the influence of climatic variables.

For the construction of the model used different math methodologies, exploring the use of wavelets transform as tools for forecast signals combined with linear regression models and processes grouping by cluster, in order to obtain a temporal and spatial growth forecast of the expansion of consumption.

III. State of the Art

The *LFM*s have been extensively developed during the last four decades, especially since the 80's, a product of structural changes in the electricity sector, associated with the introduction of competitive markets [13].

According to the objective of *ESP*, it is necessary to consider two components of these models: temporal forecast (*how much?)* and the spatial forecast (*where?*).

J. L. Cerda Arias is with Faculty of Electrical Engineering and Information Technology, Department of Power System - Technology University of Ilmenau. Gustav-Kirchhoff-St. 01, D-98693 Ilmenau.
(e-mail: jose-luis.cerda-arias@tu-ilmenau.de).
D. Westermann is with Faculty of Electrical Engineering and Information Technology, Department of Power System - Technology University of Ilmenau. Gustav-Kirchhoff-St. 01, D-98693 Ilmenau.
(e-mail: dirk.westermann@tu-ilmenau.de).

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A. Temporal Load Forecasting

Current *LFM*s are composed of different methodologies. The traditional procedures or commonly used to develop a *LFM* used: collect a certain amount of data, identify certain trends or particular forms in them express these relationships in mathematics forms and test the model [13].

LFM developed can be grouped according to various characteristics, e.g. according to the time horizon to consider, there are models of short-time, which helps operate the system and programming tasks of daily or weekly, also exist models of medium and long time, which are used in the *ESP*.

Among the methods called traditional are the multiple linear regression, time series, exponential decay and Kalman filter, in others. Additionally, between the methods currently used massively in investigating this theme, highlighting the expert systems, neural networks and implementations of models combined. There are a considerable number of works that have implemented some of these techniques, or combinations [13].

In short, to exist a number of applications those are presented in the literature [13] - [27].

B. Spatial Load Forecasting

In addition to the temporal load forecasting, there is an area of the forecast essential in the *ESP*. This referred to as spatial distribution forecast consumption. Since the 70's have develop various programs and methods of solution, considering various factors influencing its distribution, as is the installation of a new consumption, a new industry, the relocation of the population, trade installation, among others.

The indices used to special forecast is the energy consumed per capita, distribution from type of consumption and analysis of behavior, consumer density on the area to analyze. To solve this type of problem has been further developed various software presented in the literature [1].

IV. Variable To Consider

For the *LFM* it is necessary to consider classifying the type of consumption and variables that are used.

A. Load profiles

According to the classification of the consumption in Germany [5], the load profiles are available:

TABLE I
LOAD PROFILES

Consumption characteristics	Annual energy consumption	VDEW-Load profile
House/ Trade	< 8.000 kWh	House H_0
	≥ 8.000 kWh	Trade ($G_0 – G_6$)
Agriculture / Trade	< 16.000 kWh	Agriculture ($L_0 – L_2$)
	≥ 16.000 kWh	Trade ($G_0 – G_6$)
House / Agriculture	< 8.000 kWh	House H_0
	≥ 8.000 kWh	Agriculture ($L_0 – L_2$)

B. Macroeconomic variables

The load's growth historically has been linked to a country's economy, which is why it is possible to make an *LFM* from economic behavior of a country or state.

The indices that represent a country's growth are the *GDP* und GDP_{pe}. *GDP* includes the value of all within an economic area during a certain period produced. It corresponds to the gross value added of all economic sectors, plus taxes and less subsidies on products [6].

The methodologies used to *GDP* forecast are models *ARIMA*[1] [7] - [10].Its specifications are based on the last 12 and 36 months.

Returning to the relationship with this index of load's growth, due to shortages and price levels of fuels, and the care of the environment, have implemented policies that encourage use of equipment with better technology, both in industry and in homes, this influence can be seen in the development of more efficient technology, which optimize energy consumption.

Because of this relationship and current decoupling of macroeconomic variables is necessary to incorporate into the analysis the *PEC* level and *EE* indices.

C. Energy efficiency

In order to follow up on changes in the efficiency with which countries use energy, construction of the *EE* indicators. Among the most commonly used to describe this process are: economic indices, the techno-economic indices and saving energy. Below are some of them.

- *Energy intensity (EI)* [4] is defined as the relationship between energy consumption and the level of activity generated in one country, sector or sub sector and can be expressed in reason: *Tcal/MM€, TJ/MM€* or *kwh/MM€* sector:

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

Where, $EI_t = EI$ in period t.
EC_t = Energy consumption in t, in energy units, *Tcal* or *TJ*.
GDP_t = in money units, *MM€*.

In conducting an analysis of trends in *EE* through *EI* indicator, should take into account the evolution of the amount of energy consumed depends on changes in: Economic activity (value added, population, area built, Ton-km transported) and the structure of the economy (industrial structure, structure modal transport, household appliances saturation degree).

- *Specific consumption (Ce)*, Techno-economic index, is used when the analysis was performed at levels sufficiently disaggregated (by sub-Branches or end-uses) and related energy consumed with activity levels measured in physical units (*Ton*, *passenger-km*, m^2 of housing or heating buildings).
- *Methods of decomposition (IMD)*. [4] This indicator allows separate the effect of *EE* and other effects as structural changes that might otherwise lead to wrong conclusions.

EE can be accomplished by choosing a representative sample from *PEC* nationally or per sector. Consider the entire energy consumption improves analysis but requires a larger amount of information associated.

V. Load Forecasting Scheme

According to previously released, the proposed procedure for *LFM* is presented in the following schedule:

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[1] *ARIMAX: autoregressive integrated moving average*

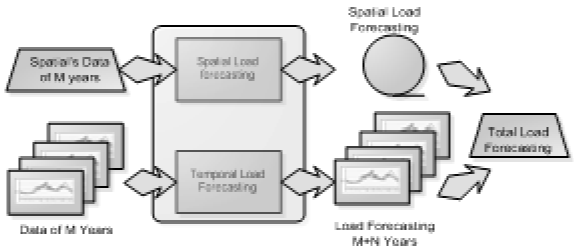

Fig. 1. Load forecasting Scheme.

This scheme considers the temporary and spatial *LFM*, considering *M* periods as a basis for forecast *N* periods [1]. The following describes these two modules.

A. Temporal load forecasting

The temporary *LFM* considers consumption measured at each point independent of their location with similar behaviors to other consumption, it can be grouped in order to make a forecast of the best representative of the group and then extrapolate the results. Fig. 2 presents the methodology used.

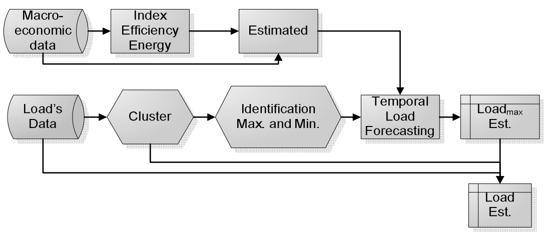

Fig. 2. Temporal load forecasting Scheme

Its composition is presented below:

- *Initial classification and choice of representatives*, data are classified according to their consumption's type presented in point *IV.A.* They are grouped and categorized according to the seasons: summer, winter and spring-fall. These data are grouped in the matrix load *L*.

$$L = \lfloor Ho_{i,j} \quad Gk_{i,j} \quad Lk_{i,j} \rfloor \text{ ,Size } (k{\cdot}j) \times i \tag{2}$$

Where, i = n° samples; j = n° customer or measurement; and k= consumption's type

This methodology used cluster data is as follows:

- The data are reduced to three values representing: *maximum, minimum* and *average*. These data characteristic associated data sets of customers with similar behavior, discarding erroneous data in the analysis.
- *Representative's election*. - is used *Fuzzy K-mean* methodology [24], which associates a membership function of each data to a cluster defined. The methodology is as follows:

a. *Centroid's calculation of each cluster.*

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

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

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

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

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

c. *Objective function*

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

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

With matrix *L*, is the choice of load representatives of each consumption's type, obtains a representative matrix of *L*.

$$L' = \lfloor Ho_{i,\alpha} \quad Gk_{i,\beta} \quad Lk_{i,\gamma} \rfloor \; (\alpha + k\beta + k\gamma)\cdot\, i, \tag{7}$$

Where, i = n° samples; α, β, γ = n° customer selected < j; and k= consumption's type

The separation of data from matrix *L'* in summer, winter and spring-fall each year is as follows:

$$L'' = \begin{bmatrix} Ho\_s_{i,\alpha} & G\_sk_{i,\beta} & L\_sk_{i,\gamma} \\ Ho\_w_{i,\alpha} & G\_wk_{i,\beta} & L\_wk_{i,\gamma} \\ Ho\_s-f_{i,\alpha} & G\_s-fk_{i,\beta} & L\_s-fk_{i,\gamma} \end{bmatrix} \tag{8}$$

From this matrix are chosen maximum values per year, obtaining a new matrix with the maximum values of each period and each year.

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

- *Macroeconomic variables and EE*, Because the model is to carry out medium and long time, the group 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.
  - GDP_{pe} in the region or the city to analyze.
  - *PEC* Index by sector.
  - *EE* Index by sector.
- *Forecasting model*, a sign to identify are the highest annual winter referring to each load representative. Is necessary forecast the variable that influence in the load.

The following forecast methods are present, using various mathematical tools. It should be noted that the identification, are developed on the basis of representation from a signal with orthogonal functions, creating a forecast based on the combination of these [2], [27], [29].

The forecast have two stages. Each stage is independent and used different methodologies.

- *The model's structure:* The choice of the model's structure is referring to the identification of variables and the delay forming the identification's model. This presents two methodologies:

a. *Stepwise Multiple Regression (SMR)* [2], [13], [30]. 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:

$$y(t) = X^T\theta + w(t) \tag{9}$$

where, $\theta = [\theta_1 \ldots \theta_k]^T$, $X(t) = [x_1 \ldots x_k]^T$ and $w(t)$ is white noise, being x_i the model components that can be autoregressive variables $y(t-j)$ or measured variables $u(t-i)$.

b. *Heuristic method, based on fuzzy algorithms (HM)* [31], In this case, for a diffuse structure of a model is defined as the selection of input variables significant. Similarly to the *SMR*, *HM* is to select some input variables in all the variables of entry candidates, increasing the number of entry in one at one, according to some criterion laid down in comparison [33].

- *Parameters identification.* Once identified the model's structure and certain variables that compose it, can be used to parameters identification. Various methods are presented:
  - Applying differential equations [13], [22], [24], [29].
  - Models based on fuzzy logic (*Takagi &Sugeno*) [31].
  - Neural networks applications [29].
  - Implementation of wavelet's theory in parameters identification [3], [34].

Implementation of the Wavelet's theory in parameters identification. The wavelet transforms allows a description of signals that include local features. His expression for discrete Wavelet transform is as follows:

$$g(t) = \sum_{k=0}^{2^{j0}-1} C_{j0,k}\varphi_{j0,k}(t) + \sum_{j=j0}^{N-1}\sum_{k=0}^{2^{j}-1} d_{jk}\psi_{jk}(t) \quad j,\, k \in Z+ \qquad (10)$$

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

The mother wavelet function $\psi(t)$, always brings with it a function associated scale $\varphi(t)$. With this tool, it may represent a signal by a number of coefficients.

The wavelet transform application in signal's identification can be used in two ways:

a. *Parameter identification, if parameter is variant in time* [34]. Is a system represented by the following model:

$$y(t) = \alpha u_1(t-i) + \beta(t)u_2(t-j) + K + w(t) \qquad (11)$$

Where $\beta(t)$, it's parameter variant in time.

To identify the parameter $\beta(t)$ aims at transforming wavelets coefficients. That $\beta(t)$ was represented expression for discrete wavelet transform. The long finite data recording [$0, M$]. With this representation function $\beta(t)$ is replaced by coefficients to estimate and functions known.

The advantage of this transformation, it is possible to transform a model with time-varying parameters of complex modeling on a simple model of fixed parameters, which can then apply the rules for identifying parameters [13], [22], [24], [29].

The disadvantage is the large number of variables to calculate because the system is transformed into a group of systems related to the number of coefficient [34].

b. *Signal processing and coefficients wavelets identification*. Considering the same model of the system $y(t)$, but with constant parameters ($\beta(t)$= constant).

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 figure below shows this calculation.

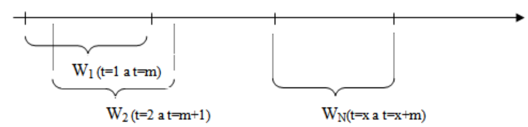

Fig. 3. Construction of coefficient's samples.

The coefficient's numbers is half the length of the sample's windows (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:

$$\begin{aligned} C^{y}_{j,k}(W) &= \alpha_{cw}C^{y}_{j,k}(W-i) + \beta_{cw}C^{U_1}_{j,k}(W-r) + \gamma_{cw}C^{U_2}_{j,k}(W-q) + K_{cw} \\ d^{y}_{j,k}(W) &= \alpha_{dw}d^{y}_{j,k}(W-i) + \beta_{dw}d^{U_1}_{j,k}(W-r) + \gamma_{dw}d^{U_2}_{j,k}(W-q) + K_{dw} \end{aligned} \qquad (12)$$

To model structure's identification of each coefficient and forecast the parameters of this system are used methods previously appointed. Then proceeds to calculate inverse discrete wavelet transformed (*IDWT*) from coefficients forecasting of $y(t)$.

$$\left(\begin{bmatrix} \hat{C}^{y}{}_{01} \\ \vdots \\ \hat{C}^{y}{}_{ck} \end{bmatrix}, \begin{bmatrix} \hat{d}^{y}{}_{01} \\ \vdots \\ \hat{d}^{y}{}_{jk} \end{bmatrix}\right) \Rightarrow \hat{y}(t) \qquad (13)$$

The 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 disadvantage is the large number of variables necessary.

- *Reconstruction consumption*, with the previous phase, is aimed at representative load forecasting of each cluster. With the membership function calculated in the formative stage of cluster extrapolate the load forecasting to all members of each cluster, according to their membership function.

$\hat{L}^{k}_{i}(t)$ is load forecasting from consumption type k and representative from cluster i, in t; $\hat{L}^{k}_{Ci}(t)$ is load forecasting from centroid from cluster i; and μ^{k}_{ij} membership function representative from cluster i in the cluster j.

The consumption type k have N cluster:

$$\begin{bmatrix} \hat{L}^{k}_{1}(t) \\ \vdots \\ \hat{L}^{k}_{N}(t) \end{bmatrix} = \begin{bmatrix} \mu^{k}_{11} & \cdots & \mu^{k}_{1N} \\ \vdots & \ddots & \vdots \\ \mu^{k}_{N1} & \cdots & \mu^{k}_{NN} \end{bmatrix} \begin{bmatrix} \hat{L}^{k}_{C1}(t) \\ \vdots \\ \hat{L}^{k}_{CN}(t) \end{bmatrix} \Rightarrow \hat{L} = \mu L_c \Rightarrow \mu^{-1}\hat{L} = L \qquad (14)$$

And each consumption forecasting (M) is:

$$\begin{bmatrix} \hat{L}^{k}_{1}(t) \\ \vdots \\ \hat{L}^{k}_{M}(t) \end{bmatrix} = \begin{bmatrix} \mu^{k}_{11} & \cdots & \mu^{k}_{1N} \\ \vdots & \ddots & \vdots \\ \mu^{k}_{M1} & \cdots & \mu^{k}_{MN} \end{bmatrix} \begin{bmatrix} \hat{L}^{k}_{C1}(t) \\ \vdots \\ \hat{L}^{k}_{CN}(t) \end{bmatrix} \qquad (15)$$

The results are applicable to distribution spatial.

B. Spatial load forecasting

The spatial *LFM* 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.

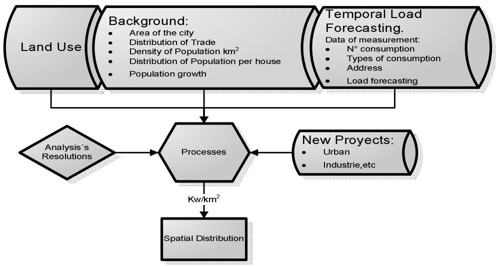

Fig.4. Spatial *LFM*

Fig. 4 presents the information flow and processes to develop. The main objective is to obtain a value of consumption for area and the location in the map city.

- *Temporal Load Forecasting.* Considers the results obtained by type of consumption (H_0, G_i or L_i) and its location.
- *Background of City*. It must have the characteristics of the city and its habitants. The following information is needed on this point:
  - City´s area
  - Population density (hab/km^2)
  - Density trade($Trade/km^2$)
  - Population distribution per family or home (Hab_{hause})
  - Population growth.
  - Land Use ($Land_{use}$).
- *New Projects*. When considering a new project in the city should have the following information: that type of project (housing, industrial or commercial), area, load forecasting and certain locations and areas according to land use.

With this information it is possible consider to long time the influence of a new project in the load.

- *Resolution´s analysis*. 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 per area unit (kw/km^2).

- Non-populated areas in the city identification and division by sections. To identify non-populated areas such as parks, parking lots or airports, it is necessary to first analyze the city's image or his map. The city map is used in binary form (1= not populated area and 0 = populated area or to settle possible), denoted as image these areas as white & black [28]. This matrix will receive the name of M_{princ}.

Later M_{princ} is divided by N^2 sections and obtained the city's area in each section ($Area_{sec}$).

- *Number of residents and trade in each section*, with the data hab/km^2, $Trade/km^2$ and division by sections, gives us an index of habitants per section (hab_{sec}). Similarly obtained the number of commercial (G_{sec}), industries and farms (L_{sec}).
- *Number of residents and trade in each measurement in each section*, Considering specifically the residential measurements type, using the number of residences $H_{0\ mes}$ and the number of people's distribution per household (Hab_{house}), gives the following relation of habitants by measuring:

$$Hab^i_{mea} = Hab^i_{house} \cdot H^i_{0\_mea} \left[Hab / mes \right] \quad i = \sec tion \tag{16}$$

A particular case in residential measurements, which also include these small trades. This are considered as the number of trade by measuring, G^i_{mea} for each section i.

The rest of the commercial and industrial measures are considered as a single consumer located in their respective coordinates.

- *Consumption by residents and trade in each section*, considering $\%H_0$ and $\%G$:

$$Load^i_{hab} = \frac{P_{H0}^{\ mea} \cdot \%H_0^{mea}}{Hab^i_{mea}} \left[kw / hab \right] \quad i = \sec tion \tag{17}$$

$$Load^i_G = \frac{P_{H0}^{\ mea} \cdot \%G^{mea}}{G^i_{mea}} \left[kw / Trade \right] \quad i = \sec tion \tag{18}$$

In the case of commercial and industries is the same as the load's value.

- *Load per area in each section,* according to the area *($Area_{sec}$)*, is considered hab_{sec} or $trade_{sec}$ and *Load* of each section. Thus, it is calculated the load per km^2, to the maximum and minimum per capita consumption.

$$Load\_a^i_{H0} = Load^i_{hab} \cdot \left(\frac{hab^i_{\sec}}{area^i_{\sec}} \right) \left[kw / km^2 \right] \quad i = \sec tion \tag{19}$$

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

$$Sec\_a_j = \left[Sec \;\; Load\_a_{j\_\max} \;\; Load\_a_{j\_\min} \;\; (x,y)_{\max} \;\; (x,y)_{\min} \right] \qquad j = H_0, G_i, L_0 \tag{20}$$

- *Spatial Distribution*. 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 $N(x,y)$ with maximum magnitude V_{max}, focusing on (x_{max},y_{max}) and a variance that $N(x_{min}, y_{min}) = V_{min}$.

In the second scenario, is considered the same situation before, but without V_{min}, is 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.

To unite all these sections, is considered the maximum value of all sections in the city map, forming a matrix of kw/km^2 values. 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 of kw/km^2 values $=0$ for values in the matrix $M_{princ}(i,j)=1$, otherwise maintaining the value. This vector is the final result graph of the spatial *LFM*.

VI. Scheme Apply

A. System Precedents.

Consider measurements residential H_0 and commercial Gi ($i=1{:}6$) between the years 2000 and 2004. Also have the following information: how many houses or trade connected to the point measured and addresses.

Fig. 5. Real and binary map City [36]

Fig 5 shows the binary map city [35] with added values and land use. The area of the city is 297.6 km^2 [12]. According to information from the city which is registered in [11], is used population and trade density; habitants per house and used Laden.

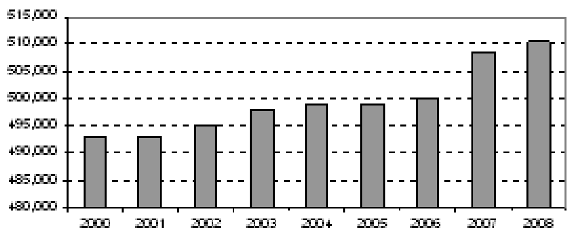

Fig. 6. Expected growth of the city

Fig. 6 shows the level of the population [12]. There are no new projects for this analysis.

B. Temporal Load Forecasting Apply

Fig. 7 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.

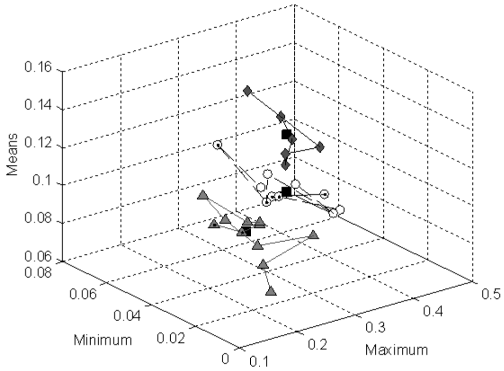

Fig. 7. Groupings of consumption H_0.

Then determine the annual maximum from each load near to centroid of each cluster, separated by season. Fig. 8 below shows the curves of the annual maximum load.

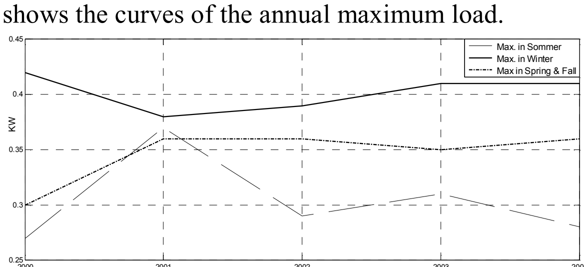

Fig. 8. Annual maximum load H_0.

As macroeconomic variables, given *GDP*, GDP_{pe}, *PEC* and *EI*, between the years 1991 - 2007, 1991 and 2005 and 1991 - 2004 respectively.

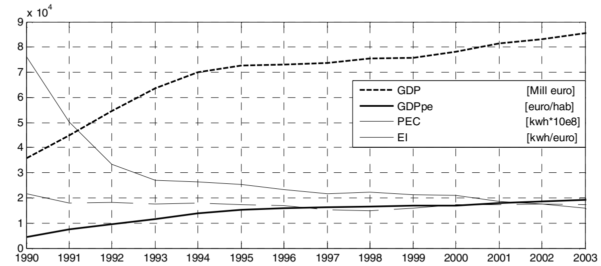

Fig. 9. *GDP*, *GDPpe*, *PEC* and *EI*.

- *Variable's forecasting models*. For forecast *GDP* and GDP_{pe}, will be used for the structure's identification the methodology *SMR*. And the parameter's identification is performed with a *ARIMAX* model. The structure gained is as follows:

$$GDP\ (t) = \sum_{i=1,2,3,4,5,6,8,10} \alpha_i GDP\ (t-i) + K \tag{21}$$

For the *PEC* forecasting is used the same procedure before.

$$PEC\ (t) = \sum_{i=1;3;5;6;7;9;10} \alpha_i PEC\ (t-i) + K \tag{22}$$

The error mean quadratic (E_{RMS}) between 2002 and 2007 is 1,7% and 1,3% in that period respectively.

To *EI* forecasting was used wavelets transformation, in order to model the effect that can cause a change in the *GDP* or *PEC*.

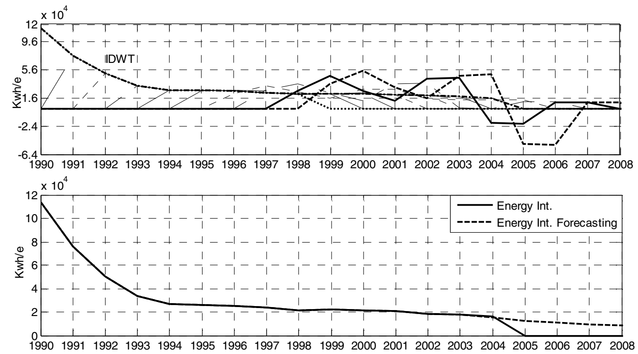

Fig. 10. - *EI* forecasting.

Fig. 10 shows the *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 2008.

Each representative load is forecast at independently, because each cluster has a different behavior and different variables influential.

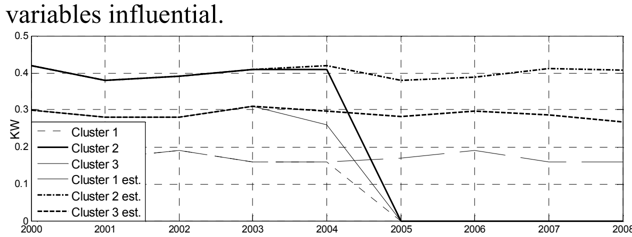

Fig. 11**.** Load forecasting H_0.

Fig. 11 shows the load forecasting of the representatives of the cluster residential. E_{RMS} obtained in the models is 1,3% for residential and 2,1% for commercial load.

- *Reconstruction of consumption*, the results for the candidates from each clusters are extrapolated to all measurements used. Fig. 12 shows the load forecasting residential measurements

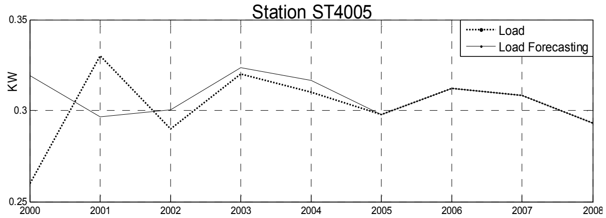

Fig. 12. - Load H_0 forecasting

C. Spatial Load Forecasting Apply

According to the results from temporal *LFM* and the city's information, is to make the methodology for spatial *LFM*.

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

The spatial location of index kw/km^2 for each section is associated with the coordinates of the measures, settled the normal function in these points.

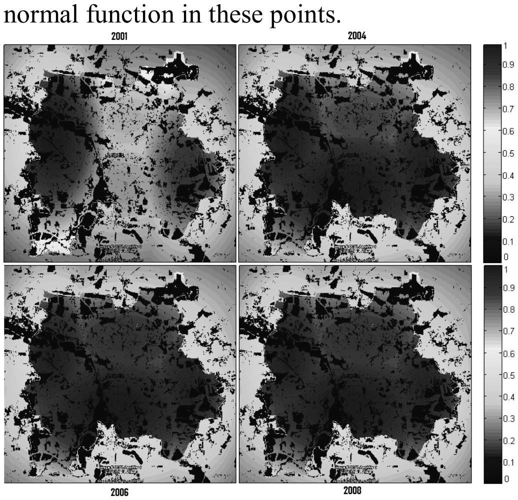

Fig. 13. Spatial load residential forecasting.

Fig. 13 shows the residential load distribution °/*1* (respect to maximum limit for each year between 2000 and 2008) for the years 2001-2004-2006-2008. There is a variation in the distribution of consumption linked strongly with the number of habitants.

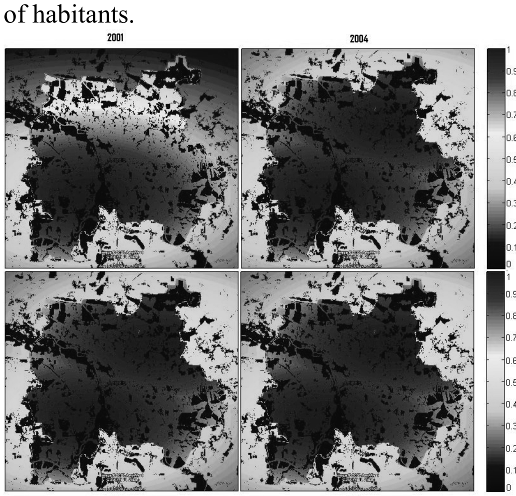

Fig. 14. Spatial load commercial forecasting.

Fig. 14 shows the commercial load distribution in °/*1* for the years 2001-2004-2006-2008. There is a distribution of consumption stabilized since the year 2004.

This methodology is possible to analyze the entry of a new consumption and as influences in the behavior associated with area's use and to residents of nearby areas that are affected.

VII. Conclusions

Methodologies current of *ESP* 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.

The new scheme propose a temporal and spatial *LFM* in medium and long term for *PSE*, incorporating the macroeconomic variables effects, optimization of energy consumption expected reflected in *EE* indices and *PEC*.

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 *LFM*. Besides adding the spatial *LFM* and its expansion into a physical location.

Using a *LFM* is essential for decision-making at the time to optimize the resources available in planning. Currently, there are a large number of studies *LFM* [13]-[27] that are used and implemented according to the needs and requirements submitted to cover. In particular, the study of the implementation of wavelets transformed in the *LFM* is based in his little exploration in implementing the identification system and its 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 spatial *LFM* is based in relate the area and the number of habitants with the forest consumption level, then projects in normal functions in the city's map analyzed, which is divided into sections according to the number of existing measurements.

The validation of the strategy proposed was based on real data measures in a Germany's city. The temporary *LFM* resulting in E_{RMS} average of 1,3% and 2,1% for residential and commercial consumption respectively. The spatial *LFM*, the result of the index kw/km^2 used has a behavior consistent with the decline in *PEC* and *EI* forecasting. Its application space was performed according to the measurements obtained satisfactory results showing according to the scope of the tool presented. Using these models presented and implementing a forecasting temporal and spatial strategy, it is possible to incorporate the effect to long time a new project in the city as an industry, trade, hospital or residential project, considering their level of consumption and spatial distribution.

In summary, the results of this study allow establish the importance in the load forecasting in the area of *ESP*, exist benefits economic and technical referring to the projection of new electrical facilities necessary.

Future work on this theme are focused on the study of new variables for measuring consumption and the incorporation of new policies aimed at optimizing the power consumption in the *LFM* und association to the grid.

VIII. Acknowledgment

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IX. References

Books:

[1] Lee Willis, H. "*Spatial Electric Load Forecasting*", Second Edition, Marcel Dekker, Inc. ISBN: 0-8247-0840-7
[2] Ljung, Lennart, ".*System identification: theory for the user",* 2nd ed. Upper Saddle River, N.J.: Prentice Hall PTR, c1999.
[3] Mallat, S. "*A Wavelet Tour of signal processing*", Second Edition, Academic Press. ISBN-10: 0-12-466606-X

Technical Reports:

[4] National Energy Commission of Chile, "*Estimating the potential for energy savings, through improvements in energy efficiency in different sectors of consumption in Chile*", Santiago, 4. October 2004.
[5] Ing. Otto Kalab, Wirtschaftskammer OÖ. Standard Load profile. *"By the VDEW-Load profile".* http://www.vdn-berlin.de/lastprofile.asp
[6] *http://www.vgrdl.de* "Volkswirtschaftliche Gesamtrechnungen der Länder".
[7] Statistisches Bundesamt, "*Methoden – Verfahren – Entwicklungen"*, Ausgabe 2/2005
[8] Statistisches Bundesamt, *"Bruttoinlands-Produkt 2007 Für Deutschland",* Additional material to the press conference on 15 January 2008 in Frankfurt am Main.
[9] Statistisches Bundesamt, "*Statistisches Jahrbuch 2007 Für die Bundesrepublik Deutschland"*, Statistical Yearbook 2007 For the Federal Republic of Germany.
[10] Statistisches Bundesamt, Nachrichten aus dem Statistischen Bundesamt.
[11] *Websites:http://www.leipzig-sachsen.de/leipzig-stadtchronik/statistik-einwohner.html*
[12] *http://www.leipzig.de/statistik* & *http://www.leipzig.de/wahlen*, "*City of Leipzig Office for Statistics and elections*", 2002-2007.

Papers from Conference Proceedings (Published):

[13] Cerda, J.L., Palma, R., "*Strategies for Control of Demand-based Distributed Generation Company for Distribution*", Engineer's Institute of Chile, Chilean Engineering magazine vol.118 N°1, April 2006.
[14] D. W. Bunn, "*Forecasting Loads and Prices in Competitive Power Markets*", Proc. of the IEEE, N°2, February 2000.
[15] Kyung-bin S., Young-sik B, Dug hun H., and Gilsoo J, *"Short-term load forecasting for the holidays using fuzzy linear regression method",* IEEE Transactions on power systems, vol. 20, N°1, February 2005
[16] Derekw B," *Forecasting loads and prices in competitive power markets*", Proceedings of the IEEE, vol.88, N°2, February 2000
[17] M. kandil, S. El-debeiky, and N. Hasanien *"Long-term load forecasting for fast developing utility using a knowledge-based expert system"*, IEEE Transactions on power systems, vol.17, N°2, May 2002
[18] Otavio A Carpinteiro, Rafael C Leme, Antonio C De Souza, Carlos A Pinheiro, Edmilson M Moreira "*Long-Term Load Forecasting Via A Hierarchical Neural Model With Time Integrators*", Electric Power Systems Research, Vol. 77, No. 3-4. (March 2007), Pp. 371-378.
[19] A. carpinteiro, I. Lima, R. Leme A. Zambroni, E. Moreira and C. Pinheiro*, "A hybrid neutral model in long-term electrical load forescasting".* Icann, part II, lncs 4132 pp. 717-725, 2006
[20] Khaled M. El-naggar, and Khaled A. Al-rumaih, "*Electric load forecasting using genetic based algorithm, optimal filter estimator and least error squares technique: comparative study",* Proceedings of world academy of science, vol. 6, June 2005 ISSN 1307-6884
[21] K.Karabuluta, A.Alkanb, A.Yilmazb, *"long term energy consumption forecasting using genetic programming",* Mathematical and computational applications, vol. 13, N°2, pp. 71-80, 2008.
[22] Hiroshi I. and Bahman K., "*Long-term load forecasting using neural nets",* electronics & information engineering Dept., Tokyo University.
[23] H. Najafi, S. Javadi, Z. Asherloo, *"distribution networks load forecasting using improved clustering method with particular software",* Proceedings of the 7th international conference on systems theory and scientific computation, Athens, Greece, August 24-26, 2007
[24] Haydari, Z., Kavehnia, F., Askari, M. and Ganbariyan, M., "*Time-Series Load Modelling and Load Forecasting Using Neuro-Fuzzy Techniques"* 9th International Conference. Electrical power Quality and utilization. Barcelona, 9-11 October 2007
[25] Ly Fie, S. and Xue-Bing Lu, "*Demand Forecasting in the Deregulated Market: a bibliography survey",* School of Business Systems P O Box 63B, Monash University 3800 Victoria, Australia.
[26] Chaturvedi, D., Satsangi, P. and Kalra, P., "*Fuzzified neural network approach for load forecasting",* Eng. Int. Syst (2001) 3–9
[27] Zhao-Yang Dong, Bai-Ling Zhang, Qian Huang, *"Adaptive Ne real Network Short Term Load Forecasting with Wavelet Decompositions"*; IEEE Porto Power Tech Conference; 10 - 13 September 2001, Porto, Portugal.
[28] Francesc Oliva, Miguel de Cáceres, Xavier Font, Carles M. Cuadras, "*Contributions from a perspective based on near Fuzzy K-Means clustering",* XXVI National Congress of Statistics and Operations Research, Ubeda, 6-9 November 2001.
[29] González G., Orchard M., Cerda J.L., Casali A. and Vallebuona G., "*Local models for soft-sensors in a rougher flotation bank*", Minerals Engineering, Vol. 16, pp. 441-453, 2003.
[30] Casali, A., González G., Agusto, H., Vallebuona, G., "*Dynamic simulator of a rougher flotation circuit for a cooper sulphide ore*", Minerals Engineering, Vol. 15, pp. 253-262, 2002.
[31] Sugeno, M. and Yasukawa, T. "*A fuzzy-logic-based approach to qualitative modeling*", Fuzzy Systems, IEEE Transactions on. ISSN: 1063-6706, February 1993
[32] Takagi, T. and Sugeno, M. "*Fuzzy identification of systems and its application to modeling and control*" IEEE Transactions on Systems Man and Cybernetics, 15(1):116-132, 1985.
[33] Sáez, D. and Cipriano,A. "*Design of Fuzzy Model based Predictive Controllers and its Application to an Inverted Pendulum".* Proceedings of the Sixth IEEE International Conference on Fuzzy Systems, FUZZ-IEEE'97, Barcelona, July 1-5 1997, pp. 915-919.
[34] G. D. Gonzalez, G. Ceballos, R. Paut, D. Miranda, P. La Rosa, "*Fault Detection and Identification Through Variance of Wavelet Transform of System Outputs*," 7th WSEAS CSCC. Corfu Island, Greece, July 7-10, 2003.

Patents:

[35] The MathWorks, Inc. "*MATLAB Function Reference*", © 1984-2007
[36] http://earth.google.de , "Google Earth 4.3.7284.3916 (beta)".

X. Biographies

José Luis Cerda Arias Received the Electrical Engineer diploma in 2002 from the Universidad of Chile**. He obtained his M.Sc** electrical enginee**ring from the** Universidad of Chile in 2007, **Santiago from Chile. I**n present student of Dr.-Ing. Program from Technology University of Ilmenau, Ilmenau, Germany

Dirk Westermann (M'94–SM'05) received his diploma degree in electrical engineering in 1992 and his Ph.D. in 1997 at the University of Dortmund, Germany. In 1997 he joined ABB Power System division where he hold several positions in R&D and Technology Management. He became full time professor and director of the institute of electric power and control technologies at the Ilmenau University of Technology, Germany in 2004. His current research interests are power system control and operation including wide area measurement, renewable in feed and demand side management, energy management systems.