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Load Forecast under Uncertainty: Accounting for the Economic Crisis Impact

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***Abstract*-- This paper presents a novel model for the Load Forecast under uncertainty specially designed for markets under permanent evolution. The proposed approach does not rely on statistic models designed to reproduce the past. Instead, we make extensive use of intelligent models able to explain consumers' behavior and its specific characteristics. This model has gained importance in the present days, where the risks associated to the economic crisis lye underneath any decision and require a reliable and complete to support every decision. A comprehensive case study with the Southeastern Brazilian market is presented and discussed, enlightening the dependencies between load consumption and international economic indices.**

***Index Terms*-- Load Forecast, Uncertainties, Risk Analysis**

I. Introduction

LOAD forecast has been a challenge [1-3] for young energy markets, still under evolution and far from stability. Each important fact (a shortage, a political event, an economic plan) may produce a severe impact on the consumption patterns, defining sometimes a whole new reality. In these cases, past information is no longer valid, and history becomes data without information.

References [4-7]] present a new model, based on Hilbert spaces, specially designed for evolutionary markets, where statistical models fail to yield a reliable forecast. Contrary to most known approaches, it does not rely on past data statistical analysis – actually mostly obsolete due to extreme consumer change in habits dynamics.

The proposed model looks for "understanding" these dynamic changes, based on special "explaining variables", using innovative tools based on evolutionary functional analysis and Hilbert Spaces. Prediction follows from evaluating the unknown function (daily, weekly, monthly, etc loads) projections on the "explaining variables".

One of the algorithm plus is its evolutionary characteristic. Possible errors, that may eventually occur, are not removed as bad, off curve, or anomalous data. The model must face reality, not the other way around. Unexpected behavior must be fully explained and absorbed, improving its prediction capacity. This learning ability makes the approach adapt in time; evolution not obsolescence.

This approach, initially applied to non-stationary dynamics, gained a new importance with the recent economic crisis – which produced, in most markets (even the previously stable), a significant impact. Many old consumption dynamics were broken, and a "best-medium-worst" scenario forecast is not enough. If it is not possible to control the future, it is crucial to understand its uncertainties. A good forecast must include the analysis of the (sometimes not explicit) connections between load and global economy and a complete risk evaluation.

Under these requirements, this paper extends the initial model to accommodate two necessary extensions:

1- the ability to perform forecasts under uncertainties, mapping the complete region of possible future scenarios

2- the possibility of accommodating different, related variables (such as industrial production, Gross Product, Employment rate, etc).

The next sections describe the developed model and a realistic application to the Brazilian Southeastern System.

II. The Model

The modeling objective is more than just prediction itself; in fact, we aim a complete characterization of the variable under study. The final objective is to explain variable dynamics, uncertainty and possible short, average and long range evolutions. The model might, therefore, be used for any decision in a variety of horizons.

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A. Projection Theorem

Functional Analysis has been extensively applied to optimization processes [8]. It might be used on a statistical basis, as it is often found in communications, or on a deterministic point of view, the latter usually associated to Hilbert Spaces.

It is common refer to Hilbert Space elements as vectors, or, in our computerized world, data sequences representing loads, temperatures, economy index, etc. The Hilbert Space is a complete metric space [9,10], being able to approximate any given vector, such as always satisfying the Projection Theorem and the Orthogonality Condition [9-11]. This is shown in Fig.1, where a given load vector is approximated by the addition of three "explaining variable" vectors, V_{e1}, V_{e2} and V_{e3}.

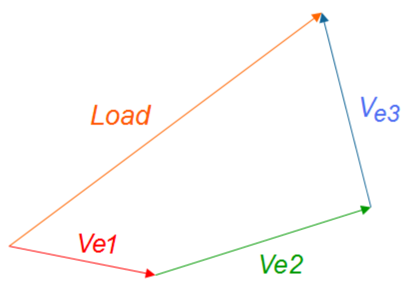

Fig. 1 – Hilbert Space Decomposition

One observes the original vector (in this case a Load or Market) is approximated by the vector sum of its "explaining variables". The process is developed recursively, as may be noticed in Fig.2 for just one "explaining variable". The original vector is projected (from this the Projection Theorem) over the "explaining variable" vector. The projected vector is a scaled version of the first "explaining variable" vector, say V_{e1} in Fig.1.

The other vector corresponds to the original vector unexplained part, or in other words; the approximation error vector. The desired vector is the sum of V_{e1} (Explained Vector) and the Error Vector (Unexplained Vector).

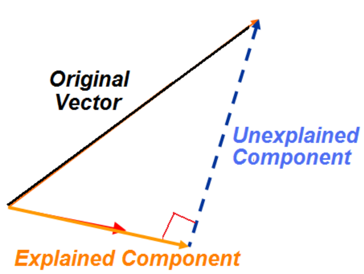

Fig.2 – Original Vector decomposition over just a first "explaining vector"

B. Sequential Algorithm

The procedure is sequential. The Error Vector is now approximated by the second "explaining variable", leading to V_{e2} (Explained Vector) in Fig.1 and a second Error Vector.

This latter is to be further decomposed, leading to V_{e3} (Explained Vector) in Fig.1, while a third Error Vector is generated. The third Error Vector in Fig.1 is the zero vector, indicating a perfect match, always possible in an ideal complete metric space as should be our Hilbert Space.

In practice, however, this is not to happen, since, having achieved a sufficiently small or known error vector, implies further decomposition of this last error would have negligible contribution to the original vector understanding. Fig.3 displays a sequence of decompositions emphasizing the decomposition process as a sum of approximations (projections) and a final error (residue).

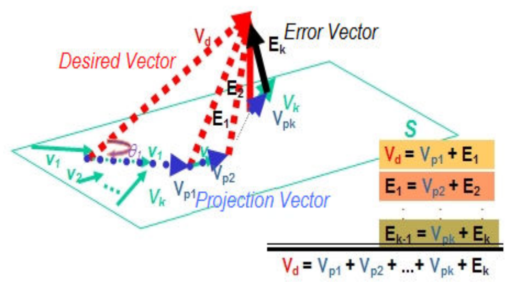

Fig.3 – Sequence of Decompositions

C. Parallel processing model

Naturally, the described sequential optimization approach is dependent on the sequence of chosen "explaining variables" and a straight procedure would be appreciated, especially when a large number of possible "explaining variables" is available - a very common situation when a problem is initially faced.

Let $\underline{C}$ be the desired vector to be decomposed by the set of "explaining variables-vectors" $\underline{S_1}, \underline{S_2}, \dots, \underline{S_N}$. Therefore, one should look for the optimum combination of these "basis" vectors

$$\underline{C} \cong \underline{\underline{S}}\,\underline{\alpha} = \left[\underline{S_1}, \underline{S_2}, \dots, \underline{S_N}\right]\,\underline{\alpha} \qquad (1)$$

such as to minimize the error norm

$$\min_{\underline{\alpha}} \underbrace{\left\|\underline{C} - \underline{\underline{S}}\,\underline{\alpha}\right\|}_{\|\underline{\varepsilon}\|} \qquad (2)$$

The Projection Theorem states the optimum approximation error is orthogonal to the space of "explaining vectors" and, therefore, to any of its elements, such as

$$\underline{\varepsilon}^t \underline{S_i} = \underline{C}^t \underline{S_i} - \underline{\alpha}^t \underline{\underline{S}}^t \underline{S_i} = 0 \quad \text{for} \quad i = 1,2,\dots,N \qquad (3)$$

or, for all "explaining vectors"

$$\underline{C}^t \underbrace{\left[\underline{S_1}, \underline{S_2}, \dots, \underline{S_N}\right]}_{\underline{\underline{S}}} = \underline{\alpha}^t \left[\underline{\underline{S}}^t\right] \underbrace{\left[\underline{S_1}, \underline{S_2}, \dots, \underline{S_N}\right]}_{\underline{\underline{S}}} \qquad (4)$$

leading finally to the unique [9] optimum set of coefficients

$$\underline{\alpha} = \left(\underline{\underline{S}}^t\,\underline{\underline{S}}\right)^{-1}\,\underline{\underline{S}}^t\,\underline{C} \qquad (5)$$

The method is now able to work with large sets of "explaining vectors" in a very efficient way. Moreover, it solves the "co-integration" problem, automatically accommodating inter-correlated explaining variables, finding the best fit while eliminating possible "double counting" effects due to the interdependencies.

Figure 4 illustrates the overall scheme of such optimum decomposition approach as a Recomposition System identification method. Here, a set of "explaining variables" are the system's inputs, while a market or load function correspond to its output. As stated, the Recomposition System simply produces the desired output as a weighted (optimal) ($\underline{\alpha}$) sum of its inputs ($\underline{\underline{S}}$).

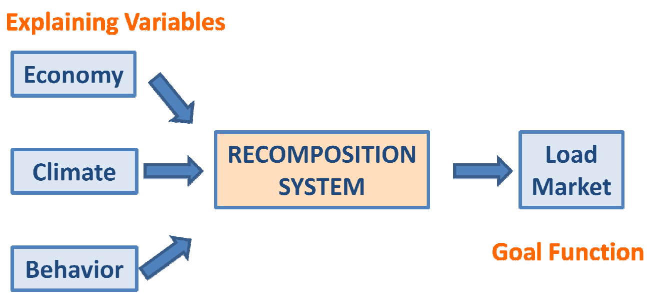

Fig.4 – System Identification Interpretation

D. *The Approach Errors*

It is important to notice that the concept of error, here, is different from the classical models. Classical approaches take the error as the forecast uncertainty; the described method, in fact, aims a *complete* characterization. Residual values are effectively aggregated in the composition of the final function as "unexplained" part of the total output. These unexplained values may not even be small: a constant (not negligible) residual component is frequently found as a consequence of constant consumption patterns (pump units, street lights, etc.).

E. *The Recursive Algorithm*

The recomposition system is able to produce a market/load forecast based on explaining variable forecasts – not always available or reliable. In this case, the same system may be used to forecast input variables – and the recursion may go as far as necessary to obtain a consistent result. Figure 5 illustrates a possible recursive scheme, applied to the chain "economy-load", where the economic scenarios are explained by external and internal indices (industrial production, exchange rates, Gross National Product, etc.)

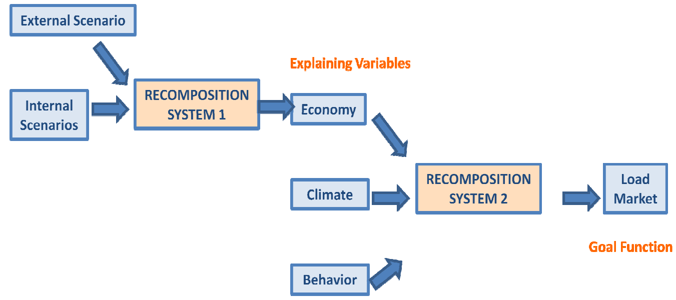

Fig. 5 – Recursive Forecast Scheme

F. *Uncertainties*

As previously discussed, the proposed model yields a complete result – residuals are treated as unexplained components, not approach errors. This paper focuses on the uncertainties associated to the explaining variables. The recomposition system will apply convolution methods to "propagate", for instance, possible international economic scenarios into consistent economic indices and finally load or energy market forecasts.

III. Case Study

This model was applied to the load forecast of S. Paulo state region (the economical center of Brazil, responsible for almost 40% of the country load).

A. *The Static Forecast*

The first step is to "understand" the region load, performing a static (deterministic) forecast. As Brazil faced a severe shortage in 2002 and the new energy market rules began effectively to be applied around 2004, historical records before this "mark" are not consistent with actual dynamic. Our history is therefore composed of mere four years (48 months) of representative data – too small for classical algorithms, based on statistics or neural networks.

This paper will represent the studied variable (load) by three components: economy, climate and consumer's behavior (associated to holidays, vacation, seasonal events, etc.).

Figure 6 illustrates the load components: as expected, the economic component dominates, confirming the heavy industrial park.

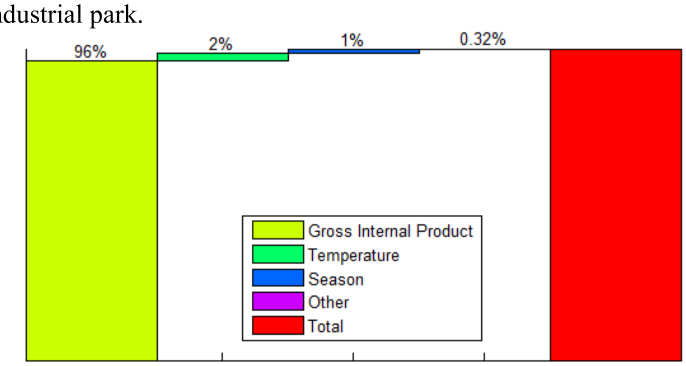

Fig.6– Load Components

Figure 7 shows the errors offered by the model throughout this year – small, considering all the unforeseen impacts of the crisis accommodation and the atypical climate experienced.

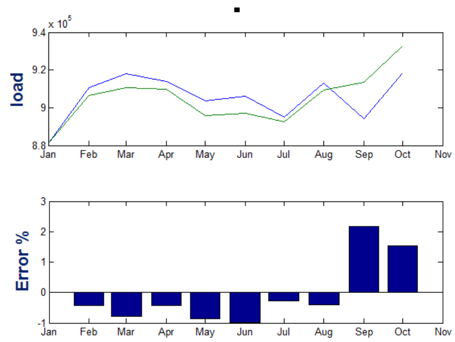

Fig.7– Actual Forecast errors (observed in blue and predicted in green)

B. The Recursion: economic model

The extreme dependence of the economy growth requires the forecast of future economic scenarios. To accomplish this goal, it will be necessary to explain the Gross National Product as a function of new variables. Knowing that, living in a globalized world, all economies are, in fact, interconnected, next intuitive step was to try some international indices. The automatic (parallel) model described in the previous section tried a set of different indices until coming to the final result: the best explanation for the Brazilian Gross National Product was found to be the Domestic American Investments (non residential), found in the set of economic indices available in [12]. Figure 8 shows the final composition and Figure 9 presents the load function synthesized by the main variables: American investments and seasonal behavior.

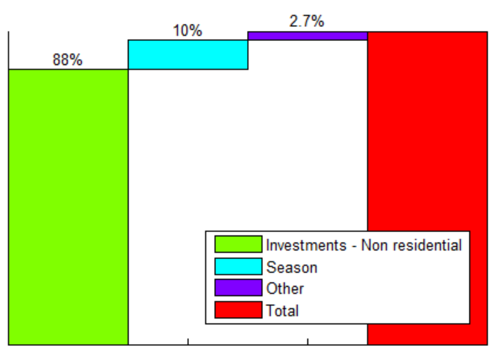

Fig.8– Gross National Product explanation

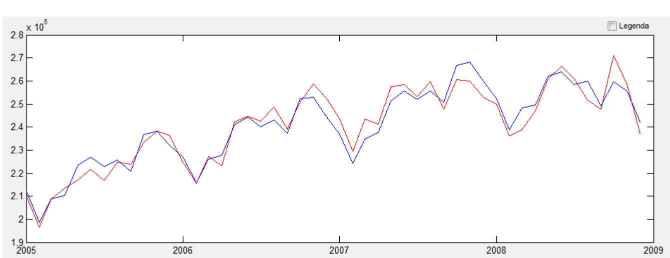

Fig.9– Gross National Product: real (red) and synthesized (blue)

The extreme dependence between the Brazilian most important load and the American investments (non residential) is clear and impressive. It is important to notice that we do not state here that American Domestic Investments have a direct influence on the Brazilian load. However, this index may be seen as a "thermometer" of the American consumption, which "injects" resources in the global economies – including Brazil.

Although the complete model would accommodate some less significant variables (exports, employment), we feel this simplified model will be adequate to this paper purposes: small enough to provide simplicity, realistic enough to provide complete understanding of the process.

C. The Risk Analysis

The last step corresponds to "map" future uncertainties, following the propagation scheme illustrated in Figure 10:

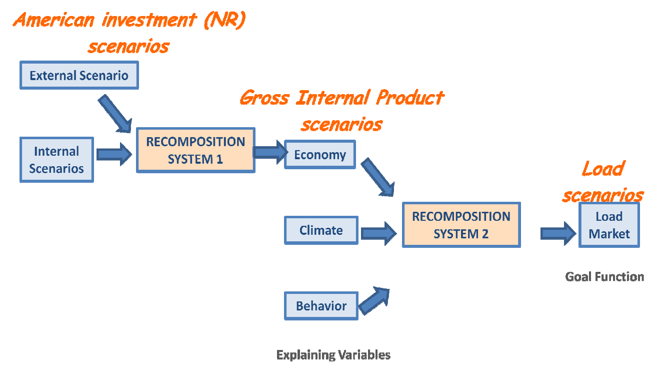

Fig.10– Uncertainty Propagation

We will not aim, in this paper, to produce reliable forecasts for the American evolution; each analyst will have his/her perceptions, and any result would be questionable. Instead, we *assumed* the set of possible future scenarios presented in Figure 11 – ranging from optimistic to pessimistic; each one is associated to a corresponding probability. It must however be stressed that the algorithm is general, and able to accommodate from scenario probability distributions to fuzzy sets.

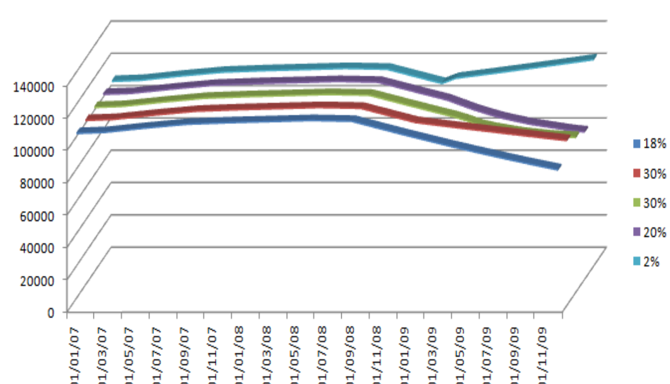

Fig. 11 – Possible scenarios for the American Investment (Non residential)

The associated Gross National Product and Load forecasts are displayed in Figures 11 and 12 as tridimensional figures (interpolated for better visualization), completely describing the probability density function of Gross National Product and Load for year 2009. The initial months are more delicate: from February to may, for instance, a relatively small economy contraction resulting in a severe load reduction.

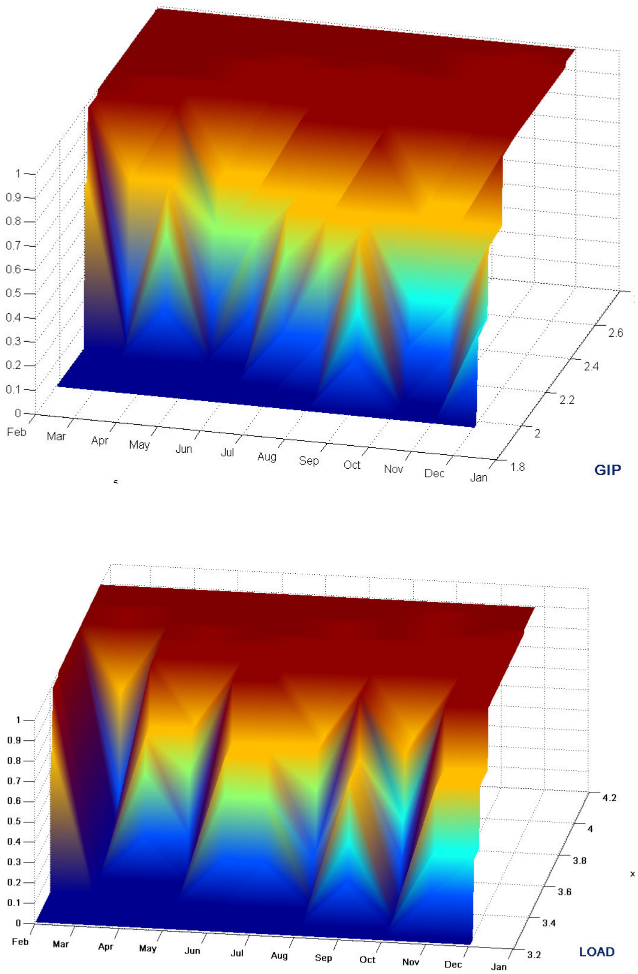

Fig. 12 – Probability Density Function for GNP and Load, 2009

IV. Conclusions

This paper presents a novel approach for the Load Forecast under Uncertainties. This approach is especially useful to address an important problem, affecting most energy utilities across the globe: the evaluation of impact of the recent economic crisis in a country, region or company's load.

The model is able to easily "map" recursively the connections (not always clear) between energy consumption and any kind of explaining variable – from economy to climate or behavior. The effects of any special event – from an economical crisis to social/political facts – may be easily detected and analyzed.

Finally, it is possible to construct the region of possible scenarios with any desired degree of precision – providing the necessary information for a reliable decision.

V. References

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