REAL TIME UPDATING METHODOLOGY FOR MATHEMATICAL MODELS OF DECISION MAKING PROCESS

Sérgio Torres Sá Barretto, sa.barretto@petrobras.com.br
PETROBRAS - Petróleo Brasileiro S.A.

Carlos Arthur Mattos Teixeira Cavalcante, arthurtc@ufba.br
Luciana de Almeida Pacheco, luciana.pacheco@gmail.com
Adonias Magdiel Silva Ferreira, adoniasmagdiel@ig.com.br
Ricardo Santos Nascimento, engenheirocall@gmail.com
UFBA – Universidade Federal da Bahia

Abstract. *At the end of 20th century technological advances in the Information Technology (IT) and telecommunication areas allowed long-distance communication between the various elements of an organization. This has meant a considerable increase in the flow of information within a productive system, allowing the consideration of various possible operational scenarios, making the decision-making and management processes more complex. In this panorama, isolated and resolute solutions proposed by the universal mechanism no longer offer satisfactory results; only systemic solutions seemed to be capable of explaining this new, unexpected and uncertain environment. Such systemic solutions, developed in the light of the Complexity Theory, were called Complex Adaptive Systems (CAS). Given this context, the concept of mathematical modelling and optimization of productive processes supporting the analysis of decision-making has been calling attention. It is common to observe the development of various resolute mathematical models for the same productive system, each model attending a specific objective or a specific aspect of the modeled reality, which, in turn, is constantly altered. Such constant alterations cause undesired pauses in the production management systems for the updating of its models, impairing the decision-making process in a productive system.*

This research develops a methodology for the elaboration of mathematical models, which continually updated due to the alterations on the modeled realities, seeking to improve the decision-making process in a productive system. This work also incorporates software development, connected to the supervision layer of industrial plants which update its model in real time, within pre-established limits. The validation and critical analysis of the proposed methodology is occurring at a thermoelectric plant, located at a generating park belonging to Petrobras in Brazil.

Keywords: Mathematical Modeling; Decision Theory; Production Management; Optimization; Complex Adaptive System (CAS)

1. INTRODUCTION

According to Fidelis and Cândido (2006), the beginning of 21st century, known as the Information Age, has been characterized by an explosive increase in the information flow within the organizational environment, demanding an equally explosive increase in the organization's ability to collect, interpret and manage its resources.

This increase in the information flow in the productive organizations has promoted the generation and consideration of various possible operational scenarios, making decision-making processes more dynamic and complex for the operational management of productive processes.

The development of advanced technologies for efficient management of progressively complex and dynamic productive systems is imperative for the maintenance of excellence levels in world class companies. In this context, Decision Theory, defined as the field of knowledge that studies the development of rational methods for selecting the best among a set of possible alternatives, applied to the management systems of productive processes, is today one of the areas of knowledge in highest demand by several different segments of human activity. (Shimizu, 2006).

In order to ensure decision-making modeling in these complex operational scenarios, various authors suggest the management model development based on the Complexity Theory and the use of Decision Support Systems (DSS) (Anderson, 1999; Leite and Bornia and Coelho, 2004; Rebelo, 2008).

According to Anderson (1999), Complexity Theory, more specifically the theory of Complex Adaptive Systems, proposes management systems modeling in these complex and dynamic environments in the form of entities with the ability to learn and adapt themselves continually along with the environment changes.

Decision Support Systems (DSS) are interactive software-based systems designed to help decision makers solve problems using mathematical models, highlighting the consequences of different decision alternatives (Shimizu, 2006).

Mathematical Modeling is the area of knowledge that studies the means for modeling real systems. For a long time, man has been trying to portray the behavior of various types of systems through mathematical models. However, most common modeling techniques are based on the adjustment of the data observed to descriptive equations of the phenomenology of studied processes (Aguirre, 2007). A basic premise for this type of techniques is the previous and explicit knowledge of the cause and effect relationships among incoming and outcome variables of the observed processes.

Due to technological advances in data collection of productive processes since the 1990's a re-consolidation of the development of empirical modeling techniques has begun. These techniques are based on the observation of data and the establishment of relationships of mathematical dependency between incoming and outcome variables with no explicit reference to its cause and effect relationships (Aguirre, 2007).

The main objective of this paper is to present a methodology for updating mathematical models in real time, especially mathematical models to support managerial decision-making, by using empirical modeling methods. The update in real time is imperative to guarantee acceptable levels of semantic gap, that is, the level of the disagreement between model and reality.

The development of methodologies such as these is very promising because they can be used in Decision Support Systems, offering the necessary adaptability to speed up the decision-making processes in productive unities. In order to assure its effective practical use, the proposed methodology is being validated in the field, at a thermoelectric plant of Petrobras, installed in Brazil.

2. ORGANIZATIONS AS COMPLEX ADAPTIVE SYSTEMS

For almost 300 years the universal mechanism ordered the way we face reality in the form of finding immutable rules, or equations, highlighting its behavior. Elsewhere, at the end of the 19th century, Henri Poincaré announced the theory of chaos, postulating that the certainties in exact sciences are relative to the degree of depth of objective investigations. Poincaré's theory was the basis for the concepts of chaos established by Prigogine in the second half of the 20th century (Fróis, 2004).

Dutra and Erdmann (2007) classify the theory of complexity as an area of science that studies the emerging properties that arise from the interconnection of elements belonging to the same system. These relationships of order and disorder emerge in a level that does not exist at inferior levels.

According to Morin (1977, apud Dutra and Erdmann, 2007, p.409), the emergence of order in a complex and chaotic environment occurs because the relationship between the elements of the system appear in a tetralogic level of order/disorder/interaction and organization. From these interactions, a context of disorder may cause a new order in the organization within a cyclical process of incremental complexity.

The conclusion is that the universal mechanism is not capable of producing adequate solutions for complex problems because these kinds of problems require the solutions to have the capacity to adapt according to the environment they are in. The area of knowledge that studies solutions for these kinds of problems, in the light of the Complexity Theory, is called Complex Adaptive Systems (CAS) (Anderson, 2008).

In order to understand a CAS Rebelo (2004) says that it is necessary to analyze the differences between simple and complex systems. A CAS has the capacity to re-organize its components in response to stimulus derived from internal and external environments, or to stimulus generated in random situations. An organization is a complex adaptive system because it learns each time it is re-organized. CASs are composed of intelligent agents endowed with pre-determined cognitive schemes, hierarchically set, interacting between them with autonomy of action, continually learning, adapting and evolving.

A CAS cannot be analyzed by linear cause-and-effect scientific methods. Despite being globally complex, they present local simplicity. They are creative when operating within a space of transition or possibilities, that is, a paradoxical state, stable and unstable at the same time, guided by the antagonist dynamics of cooperation and competition, restriction and amplification, and exposure to creative tension. It is possible to say that CASs are creative when they operate on the limit between order and disorder, or even when they operate on the edge of chaos (Rebelo, 2004).

During the last two decades, various technologies of information have been developed, which have revolutionized and substantially increased the complexity of the business environment. World class corporations have started to base their decisions in flows of information, which has meant that one of the major challenges to be faced today is the capacity to rapidly adapt to this growing flow (Dutra and Erdmann, 2007).

Dutra and Erdmann (2007) also say that the universal mechanism cannot solve the organizational problems that arise in business environments anymore because it isolates the problems in smaller parts and solves them individually. Nowadays, the organizational problems have a high level of interconnection, and thus they are improper for the implementation of isolated solutions, only systemic solutions seem to work.

In this context an organizational structure can be considered as the grouping of agents. These agents can be represented by individuals or groups of individuals, each with a specific strategy and behavior. Each agent has a cognitive structure that determines a specific action according to a perspective of the environment in which it is found. This new context determines a complex and dynamic and why not say a chaotic organizational environment (Anderson, 2008).

3. PRODUCTION MANAGEMENT AND DECISION-MAKING MODELLING TECHNIQUES

Managing is to make decisions. Managers constantly face complex situations which present a myriad of possible solutions. The pressing question is the definition of which is the best solution to be implemented. When there is available data, the problem can be structured in a mathematical form. This formal analysis of the problem is nothing more than an abstraction of the contextualized reality. The area of knowledge that organizes data derived from a reality according to the formal needs of a mathematical model is known as modeling (Moreira, 1993; Ravindran et al., 2006).

Mathematical modeling is by no means a scientific method. The key for the successful resolution of certain problems depends not just a good mathematical formulation but to a great extent this formulation is an art (Ravindran et al 2006). Moore and Weatherford (2005), highlight that the judgment of the managers should permeate all aspects of the modeling process. According to them, a reality may be abstracted in the form of a mathematical model, however, by definition a model is a simplification of reality and inevitably some imponderable factors will be not part of the abstraction.

Though such imponderable factors are not included in the mathematical model they must be considered in the decision-making process. The decision will depend not only on the analysis of the results obtained from the model, but also on the managerial analysis of these factors. To a great extent these will depend on the experience and intuition of the decision-maker (see Fig. 1).

For Moreira (1993), the modeling process problem might be described by a sequence of five phases: 1) Problem Definition; 2) Model Development; 3) Data Analysis; 4) Model Solution; and 5) Solution Performing. All these phases are important and should be carried out in sequence until the implementation phase. Moreira (1993) also highlights the presence of factors which are imponderable or qualitative on the decision-making process that cannot be turned in a math model. On the other hand, in complex problems, the phase of mathematical modeling could suggest new aspects susceptible to structuring, which would not be identifiable using only qualitative analysis (see Fig. 2).

Reinforcing this issue, Moore and Weatherford (2005) say that the use of models as support for decision-making process does not necessarily imply the implementation of the best managerial solution, but enables the managers to obtain important and helpful insights for exploring alternatives, establishing contingency plans and reducing time responses.

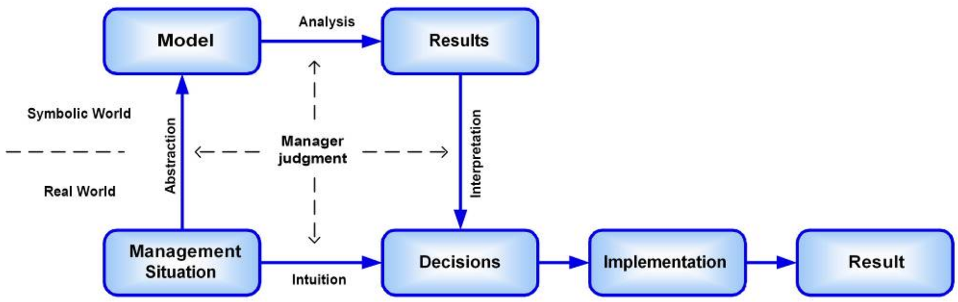

Figure 1. The role of judgment in the modeling process (Modified from Moore and Weatherford, 2005)

The solutions of mathematically modeled decision problems are generally found through the use of techniques and tools that optimize a managerial objective function. This could be translated as the maximization of profit or the minimization of cost or operation period in a productive process. In face of intense competitiveness and unpredictable scenario, the production function acquires a significant value regarding the main objective of firms because it starts to act as propelling strength to support and implement an organizational strategy (Hayes and Wheelwright, 1984; Slack and Chambers and Johnston, 2002).

According to Dutra and Erdmann (2007), the Production Planning and Control (PPC) can be considered the core of operational management in an organization, and deficiencies in the implantation of this activity have a right impact on the productive process performance. Dutra and Erdmann (2007) also define the PPC activity as a part of decision support system that commands and coordinates the productive process to accomplish the schedule and the processes in order to attend the requirements of time, quality and quantity of the production chain.

According to Dutra and Erdmann (2007), due to increasing unpredictability and consequently the complexity of organizations, the productive process should be modeled as a CAS or an open system: a system that interacts actively with the surrounding environment according to schemes or pre-defined rules.

Indeed, one of the main problems that limits the practical use of mathematical models developed to support the management of productive systems is that the modeled realities change over time causing discrepancies between model and reality, making models inadequate to simulate the studied realities. The increase of this semantic gap requires repeated human interventions to update the codified models. As a result, periods of time when the model is unavailable or inadequate to fulfill its main function of supporting the real decision-making process are frequent.

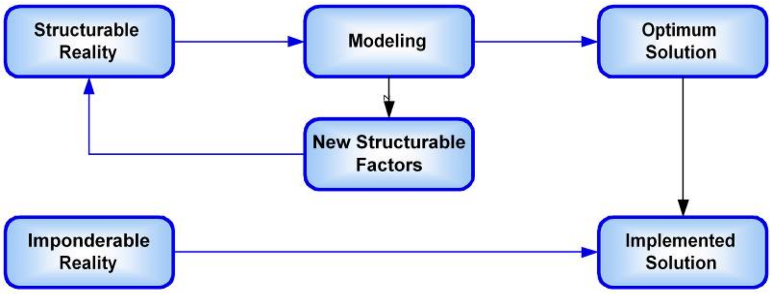

Figure 2. The process of Modeling Decision Problems

The technological advance of computational resources has greatly widened the horizon of modeling techniques, facilitating the resolution of problems which involve complex mathematical models. According to Aguirre (2007), mathematical modeling can be classified in three basic types: white-box modeling, gray-box modeling and black-box modeling.

In white-box or conceptual modeling, the whole physical behavior of the modeling target process is mathematically described in detail. This type of modeling requires that the modeler has a deep knowledge of the phenomenology of the modeled system. Depending on the complexity of the modeled reality this technique could turn out to be very costly and time-consuming.

As regards black-box modeling, also known as empirical modeling, it is not necessary to know the phenomenological relationships between the incoming and outcome variables of a process. In this kind of modeling technique, there is no obvious relationship between the structure and parameters of the models and the physical aspects of the reality. The main characteristic of this technique is that knowledge about the physical nature of the reality is not necessary.

Finally in gray-box modeling, the polarity white-box/black-box is reduced by the combination of the positive aspects of these two kinds of modeling techniques. In this case the relationships between variables obtained from the phenomenological knowledge of the reality is complemented by the use of auxiliary information from the time series of the system, allowing an association of the dynamics that they can produce with the structure of the model and its parameters.

Nowadays the technological advances of computational resources enable means for obtaining and storing data of the time series to support the development of black-box and grey-box modeling techniques. In fact, these kinds of approach have become viable due to factors such as the fall in price of computational resources and the availability of data acquisition technologies, among others. The study of the black-box and grey-box modeling techniques is known as Systems Identification (Aguirre, 2007).

4. INFRA-STRUCTURE OF DATA ACQUISITION

The development of the methodology was conducted at the Laboratório de Sistemas Integrados de Produção (LABSIP), in English Integrated Systems of Production Laboratory at the Universidade Federal da Bahia (UFBA), in English the Federal University of Bahia, in Brazil. The selected pilot-plant was the Thermo-Electric Plant (TEP) named Romulo Almeida. It is part of Petrobras' electrical energy generator park located in Camaçari in the state of Bahia. It is composed of three Gas Turbines (GT), each connected to a Heat Recovery Steam Generator (HRSG). The TEP also has an Auxiliary Boiler (AB) and a Steam Turbine (ST) connected to a generator, totaling a generating capacity of 137.0 MW of electrical energy and a production capacity of 265.7 tons of steam per hour. The diversity of possible operational scenarios makes the TEP attractive for developing and testing the methodology.

In order to support the methodology development activities, a Process Information Management System (PIMS) was used to keep the TEP's time series. A PIMS is nothing more than a temporal database or industrial process historian capable of storing great volumes of data for several years at a relatively low cost. With a PIMS it is possible to recover data from any specific variable extremely fast (Dang, 2007; Barr, 1994; Fras and Dang, 2004).

The installation of a PIMS at the plant was carried out in order to acquire the time series. Each essential variable was configured by the operational staff of the plant on the TEP's PIMS. The variables were configured from the addresses of the instruments installed in the productive process, which perform the measurement of the variables and are visualized by the supervisory layer of the TEP.

Another PIMS was set at LABSIP and connected to the plant historian. In a laboratory setting, the clients given by the PIMS supplier were used to import the values of the time series stored at the temporal base to a previously prepared electronic spreadsheet, and then exported to MATLAB and submitted to the algorithm that implements the updating methodology (Fig. 3).

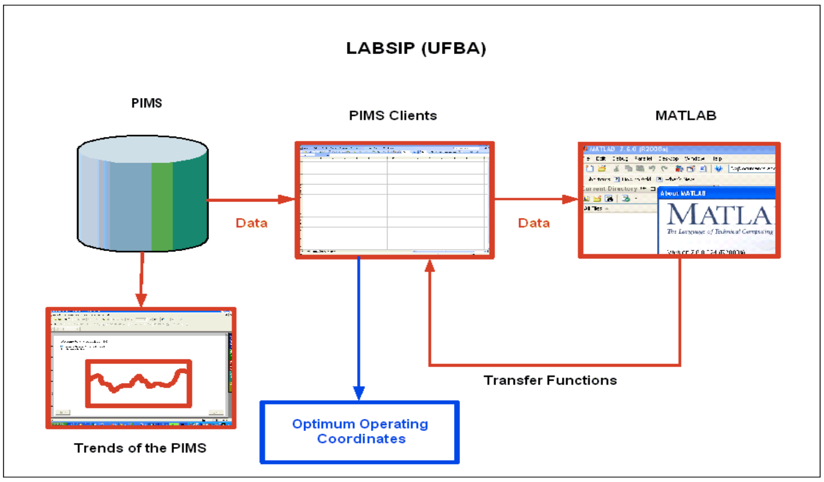

Figure 3. Architecture used in laboratory

The data obtained was processed using MATLAB's System Identification Toolbox in order to find a way to update the math model. The findings are sent back to spreadsheet where they feed the restrictions of a managerial decision-making mathematical model that optimize an objective function (in this case, the total operational cost of the unit). In a specific temporal context the coordinates for an optimum operational scenario are thus generated.

5. THE MODELED PRODUCTIVE PROCESS

The productive process selected for this research was conceptually divided into productive operation blocks, termed Production Blocks (PB). For each PB, the equations or transfer functions which express the outcome behavior corresponding to the pertinent incoming signal were inferred by empirical or black-box modeling techniques. The blocks shown in Fig. 4 were considered smart agents for the implementation of the abovementioned updating method. These updatable functions will compose the set of restrictions equations for the mathematical decision-process model of the TEP.

Given this, the transfer functions of the PB are determined by differences equations, as defined in Aguirre (2007). For such, appropriate techniques for identification of systems are used according to the behavior of the incoming and outcome signals of each PB.

The PB diagram presented in Fig. 4 was elaborated based on the analysis of engineering flow charts, equipment operation manuals and process plants, as well as interviews with managers and operators. Furthermore, the independent variables (under the control of operations and management) and the availability of data to compose the time series were considered.

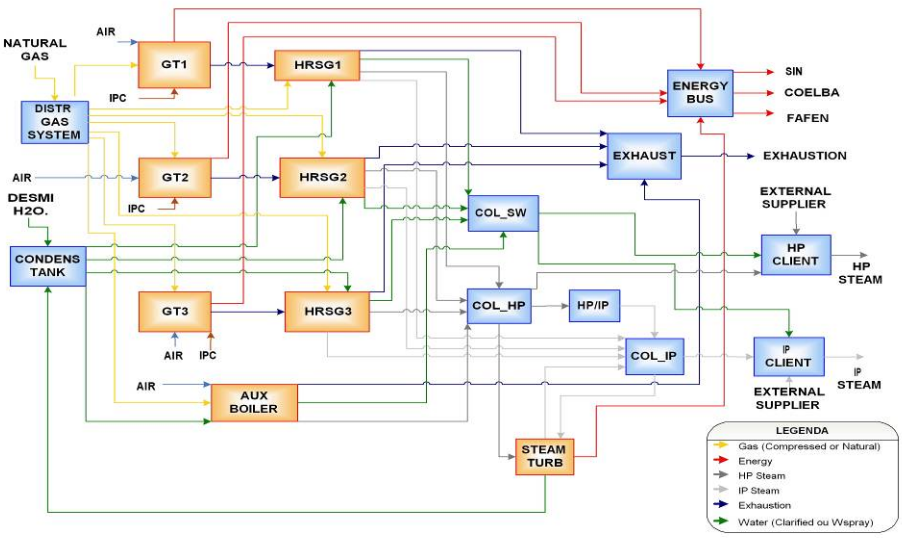

Figure 4. Block Diagram from the TEP

The function of the PB diagram is to represent the flow of the collected signals, the transfer function performed by each functional component and the relationship existing between each of them. The PB represent a black-box process or its transfer function, which relates the incomings and outcomes of each sub-process of the TEP.

6. DEVELOPMENT OF THE DECISION MODEL UPDATING METHODOLOGY

The development of a methodology for updating mathematical models in real time was conducted by means of Systems Identification techniques. The methodology assumes that the decision-making process will be modeled in the form of a managerial objective function and a set of restrictions equations, including operational, economic and environmental subsets. Each restriction is viewed as a dynamic black-box process that leads the incoming values of the input variables to the outcome values of the output variables.

The selected pilot-plant had its productive flow detailed and converted into a block diagram in such a way as to enable the elaboration of a model of decision-making process adopted by their decision makers. As well as the simple operational issues, this model also incorporates economic and environmental questions which affect the identified decision-making process in such way that restrictions such as raw materials disposal (fuel, for example) and environmental restrictions (such as NOX and CO2 emission limits) could been incorporated in the decision-making process model. The guiding rule was to identify the operational variables under the decision control of the pilot-plant's main manager.

The mathematical relationships between outcome and incoming values are established by empirical modeling techniques. The objective is to find a mathematical structure and its parameters that represent the left side behavior of each restriction equation. A computational procedure is then introduced in order to re-calculate each dynamic restriction equation for each significant time interval between managerial decisions. Thus, the mathematical structure and its parameters are maintained up to date in significant real time. Finally, the findings must be encapsulated in a computational application or DSS for supporting the decision-making process in a real scheme.

For the validation of the proposed methodology on the implementation of Decision Support Systems, a system named PROTEU 1.0 will be installed in the pilot-plant. This application will test and validate the positive and negative aspects of both the methodology itself and its applicability on the development of Decision Support Systems. PROTEU's development which incorporates the updating methodology proposed in this work aims to optimize of operational variables and the decision criteria adopted to support decision-making. The objective is to offer the decision-maker the coordinates for the optimum operational scenario that results in minimum cost, respecting environmental limits and equipment wear.

6.1. Empirical Modeling Flow

Figure 5 presents the empirical or black-box modeling flow developed to promote the updating of mathematical decision models applied to Decision Support Systems. The empirical modeling technique flow is based on regression and auto-regression concepts and was implemented and tested in the laboratory described and discussed below.

To create the time series, the initial assessment of the sample size was carried out to calculate the sample's level of statistical representation and consequently determine the interval of time used for discretization of the variables involved in the TEP's process. After this, an estimate for determining the representative size of the sample was calculated. The criterion of proportion in infinite populations from Spiegel (1977) was used to assess the size of the sample of data from the historical series of the TEP.

The acquisition of incoming and outcome signals of the PB (which were used to estimate the parameters of the transfer functions) required a procedure capable of offering maximum reliability to the performed analysis. Ratifying Aguirre (2007), the acquisition of data from the productive process proved to be an essential activity to perform the system identification activities. Among the problems related to the experimentation of these PBs, the choice of variables and the determination of the adequate sampling period are mentioned. After defining the sample size, it is necessary to recover it from the TEP process. A series of 10.080 values of all variables available from all PBs was acquired.

After the acquisition of samples from the data of variables pertinent to the block diagram shown in Fig. 4 a crossed-correlation analysis was made to verify which incomings data cause expressive variations on the outcomes data and vice-versa. The variables that show a significant crossed-correlating behavior were considered essential, and when the behavior is not found to be significant they were considered non-essential. All flows whose variables were considered non-essential were removed from black-box modeling.

During the development of the updating model all PBs were included as relevant operational restrictions. Therefore, for both left side (or input variables) and right side (or output variables) the operational limits were established, namely, the range of acceptable values within the industrial process.

For example, the electrical energy generated in a gas turbine at any time (the right side or the outcome data series) cannot be below or above of the minimum and the maximum values respectively specified by the manufacturer. Likewise the flow of gas and the flow of air at any respective time (the left side or the incoming data series) cannot be out of the operational range specified in the same manner. According to these operational limits, those values generated during the starting or deactivation of the gas turbine must be omitted from the data series acquired.

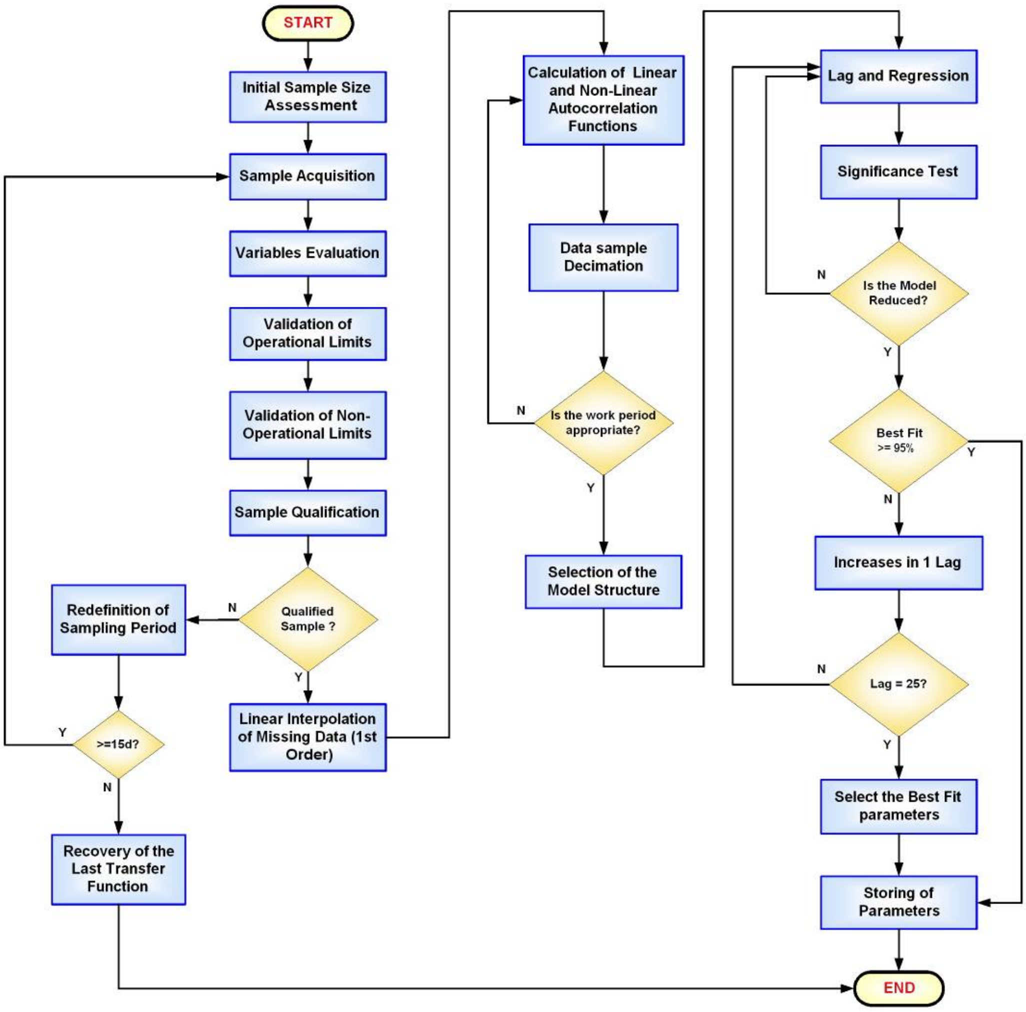

Figure 5. Transfer function updating methodology flow

In order to attend the plant's demands, the operation group of the plant set several distinct stationary states and normal fluctuations or dynamic evolutions. However, even at a stationary state unforeseen fluctuations coming from atypical occurrences, such as: suddenly variation in the turbine load and raw material properties and anomalies in equipment can occur. It was considered that these explosive variances do not accurately characterize the behavior of the system being analyzed therefore they were removed from the data series originally acquired.

After data recovery, the sample had to be qualified in order to determine whether it was considered valid or not. This occurred due to the fact that not all values desired were available at the supervisory layer of the TEP. Issues such as operational unavailability of equipment, or oscillations in the communication between the PIMS and the supervisory layer of the plant could cause invalid or contaminating values. *Bad input, shut down, bad values* are some of these missing or invalid values recovered from the PIMS.

The qualification phase is based on the division of the sample into 168 parts (each containing 01h00m of historical data), and posterior analysis of the standard deviation of the invalid data. Then, after using the sample size assessment for finite populations, the verification of whether the quantities of the valid parts fit the size assessment criterion is made.

If the series is not qualified at the moment of data recovery, the initial time reference must be displaced to the past in 24 hours, and from this point another 168 hours are recovered retroactively. This behavior is continually repeated until a qualified sample is acquired or until the maximum displacement of 15 days is reached.

For any variable of a PB if the maximum displacement of 15 days has been reached without reaching a properly approved time series, the process is forwarded to its final and the last valid transfer function is used in the plants' mathematical model.

After the removal of the contamined data, a first order linear interpolation is performed on the gaps left in the series through the removal of the spurious data filling it with supposedly typical data.

An important action to be taken regarding the sampling period is to determine what the period considered for the identification of the model should be. Aguirre (2007) recommends that this period should have values of response to the system concerning its normal behavior of operation, and in particular should contain the minimum and maximum values of responses possible to obtain within the pre-established functioning conditions. Shannon (apud Aguire, 2007, p. 463) says that a signal that does not contain frequency components above the half of time work of sampling.

Aguirre (2007) also defines a simple sample decimation process that starts with an acquisition of a signal with a very small sampling period that can be considered an over-sampled signal. Then the correlation is verified through adjacent observations of the sampled signal. In order to quantify the effects of the over-sampling in a signal, Aguirre (2007) refers to the calculation of the auto-correlation function.

The decimation process occurs in the following way: for each PB shown in Fig. 4, the minimum value for the auto-correlation function of the series acquired from the outcome signals is calculated. Then the period of work is progressively varied each 15 minutes in order to obtain the minimum point of the auto-correlation function within a lag interval between 10 and 20.

The decimated series is transposed to a matrix of differences, where it is re-written lagging in $t - 1$, $t - 2$ until $t - 25$ (lags). Then multi-varied linear regressions are carried out on the correlate orders to find the transfer functions. To compose the decision-making mathematical model of the pilot-plan, the transfer functions with the best-fit $\geq$ 95 % are selected as updated restriction equations.

Many kinds of mathematical representations can be structured by this procedure. In general the results of this procedure are models with polynomial coefficients that multiply the variables from their respective input and output states of an SD. It highlights that the variables are vectors of states of signals delayed in the lag *n*, for example: the vector $v\ (n-1)$, means vector in a delayed period of one lag.

7. PRELIMINARY RESULTS

For the structuring of models and updating of a transfer function of a PB, an array of data with the input variables in the current time ($x_1\ (t)$, $x_2\ (t)$, $x_3\ (t)$ and $x_4\ (t)$) and variable output ($v\ (t)$) was considered

As an example, with the values in real time, a matrix of states was created over which the method of least squares was applied, resulting in the following equation:

$$v(t) = p_1 + p_2 \cdot v(t-1) + p_3 \cdot x_1(t) + p_4 \cdot x_1(t-1) + p_5 \cdot x_2(t) + p_6 \cdot x_2(t-1) +$$
$$p_7 \cdot x_3(t) + p_8 \cdot x_3(t-1) + p_9 \cdot x_4(t) + p_{10} \cdot x_4(t-1)$$

Where:

$$p_1 = -9{,}1990;\ p_2 = 0{,}2432;\ p_3 = -0{,}1482;\ p_4 = 0{,}3545;\ p_5 = 3{,}2994;\ p_6 = -0{,}5278;$$
$$p_7 = -0{,}0063;\ p_8 = 0{,}0018;\ p_9 = -0{,}0404;\ p_{10} = 0{,}0025$$

According to Aguirre's classification (2007), this model is known as Autoregressive Model with Exogenous Input (ARX) and presents an explanation degree of 95.34%. For the given example, the adjustment to the original series can be seen in Fig. 6.

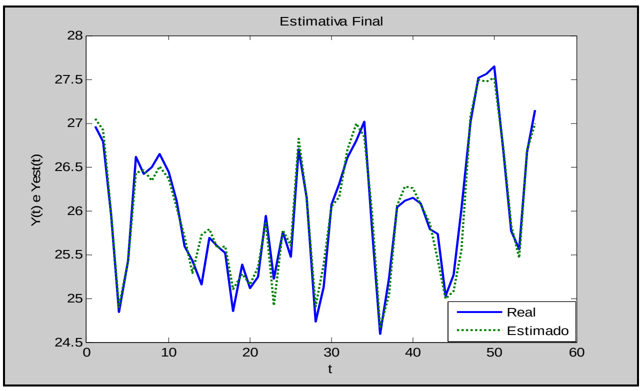

Figure 6. Time series real and estimated

It is observed that this model presents a noise with a distribution similar to the Gauss curve: white noise (see Figure 7).

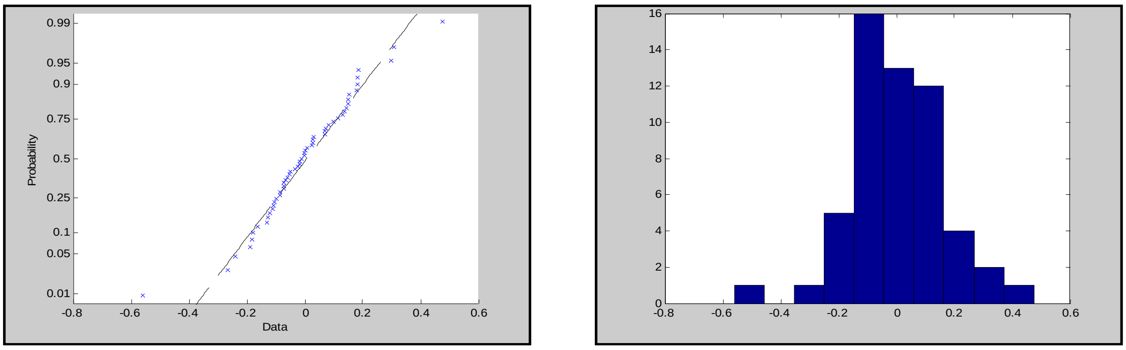

Figure 7. Noise analysis and noise distribution

Thus, the identification of the computational process of TEP was carried out by MATLAB using the input-output of each PB. The historical data were used to generate a mathematical model that reflects the observed behavior.

Moreover, the absence of explicit knowledge about the system's dynamics, and considering that the TEP's system usually presents significant non-linearity; the proposition of a dynamic model has proved a very complex task.

A more realistic approach was opted for with a simple symbolic representation but with white noise and a high degree of model explanation. Another aspect is that the model has a representative parameter (p_1) which eliminates the systematic error between the actual and observed values (offset).

As proposed, the partial results obtained so far show that the developed methodology is appropriate for updating models in real time.

During the updating methodology development, the ARX, ARMAX, BJ and OE structures were investigated as possible structures representing the dynamic behavior of the systems under consideration (PBs). However, the ARX structure presents more consistent results.

One of the aspects raised by colleagues and critics who have followed the development of this work is its interdisciplinary character, particularly the unifying aspect of techniques and methods from control theory applied to problems of production management.

Depending on the work period resulting from decimation of the outcome signals, in some cases it was noted that there was a loss of some information regarding the dynamics of the incoming signals. This information loss regarding the dynamics of the incoming signal occurred with the signal of the gas pressure variable on GT3. This is apparently not very representative as can be observed by the smoothness of the signal shown in Fig. 6. Thus, it is suggested that a crossed-correlation analysis be performed between the incoming and outcome signals of each PB, establishing the satisfactory index for this correlation. If the established limit is reached, the sampling period can be progressively reduced until a good crossed-correlation is achieved.

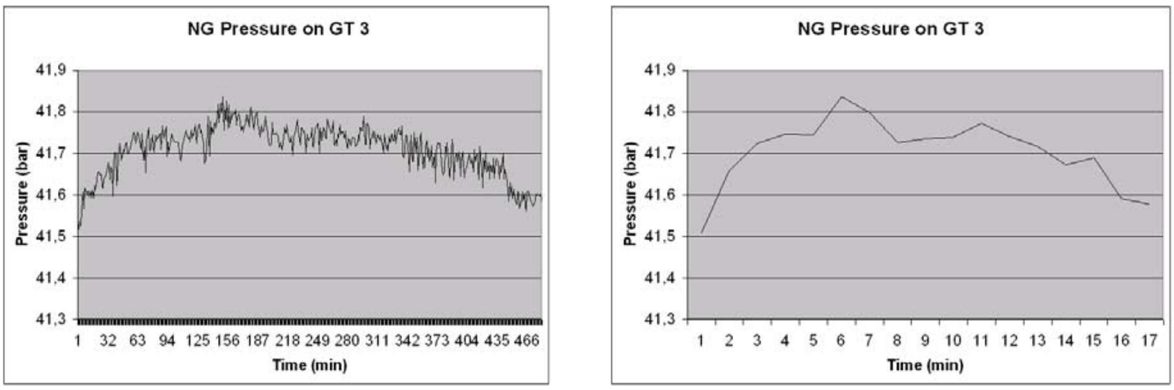

Figure 6. Gas pressure on GT 3 with decimation range of 01 and 30 minutes

As above mentioned, the methodology development and tests are being carried out in a laboratory with field data through the use of an infra-structure described in Fig. 4. The PROTEU 1.0 system is being modeled, which aims to encapsulate the methodology proposed in this research and will incorporate adaptive agents and implement the behavior of a CAS.

The interaction with managers and operators of the selected TEP Pilot confirms the value and importance of the updating methodology and the PROTEU 1.0 in support of decision making. Moreover, the intense participation of this people in the development of this work, has allowed the testing of simplified versions of this application containing an experimental model of the problem.

8. REFERENCES

Aguirre, L. A., 2007, “Introdução a Identificação de Sistemas Técnicas Lineares e Nao-Lineares Aplicadas a Sistemas Reais”, 3.ed. Ed. UFMG, Belo Horizonte, Brazil.

Anderson, P., 1999, “Complexity Theory and Organization Science”, Organization Science, Vol.10, pp. 216-232.

Dang, T., 2007, “Integration of Power Plant information system with Business information system in the open electricity market: challenges and solutions”, IEEE - 5th International Conference on Industrial Informatics. Vol.2, pp. 1209-1213.

Dutra, F. A. F., Erdmann, R. H., 2007, “Análise do planejamento e controle da produção sob a ótica da Teoria da Complexidade”, Revista Produção, Vol.17, São Paulo, Brazil, pp. 407-419.

Fidelis, J. R. F., Cândido, C. M., 2006, “Administração da Informação Integrada às Estratégias Empresariais”, Perspectivas em ciência da informação, Vol.11, Belo Horizonte, Brazil, pp. 424-432.

Fras, A., Dang, T., 2004, “Improving industrial application's performances with an Historian”, IEEE - International Conference on Industrial Technology (ICIT), Vol.2, pp. 718-721.

Fróis, K. P., 2004, “Uma breve história do fim das incertezas ou o Paradoxo de Janus”, Cadernos de Pesquisa Interdisciplinar em Ciências Humanas, n. 63.

Hayes, R., Wheelwright S., 1984, “Restoring our Competitive Edge Competing through Manufacturing. Nova Iorque: John Wiley.

Leite, M. S. A., Bornia, A. C., Coelho, C. C. S. R, 2004, “Os conceitos de dialógica e sistema adaptativo complexo (SAC) aplicados à cadeia de suprimentos: uma contribuição da ciência da complexidade”, Revista Pesquisa e Desenvolvimento Engenharia de Produção, n. 3, p. 27-42.

Moore, J.H., Weatherford, L.R, 2005, “Tomada de Decisão em Administração com Planilhas Eletrônicas”, 6.ed. Ed Bookman, Porto Alegre, Brazil,.

Moreira, D.A, 1993, “Administração da Produção e Operações”, Ed. Pioneira, São Paulo, Brazil.

Ravindran, A., Ragsdell, K.M. and Reklaitis, G.V., 2006, “Engineering optimization: methods and applications”. 2.ed. Ed. John Wiley & Sons, Inc, Hoboken, New Jersey, USA.

Rebelo, L. M. B., 2008, “A dinâmica do processo de formação de estratégias de gestão em universidades: a perspectiva da teoria da complexidade”, Tese de Doutorado em Engenharia de Produção – PPGEP, Universidade Federal de Santa Catarina, Florianópolis, Brazil, 278 p.

Shimizu, T., 2001, “Decisão nas organizações”, Ed. Atlas, Campos Elísios, Brasil.

Slack, N., Chambers, S. and Jonhston, R., 2002, “Administração da Produção”, 2.ed, Ed. Atlas, São Paulo, Brazil.

Spiegel, M.R., 1994 “Estatística”, 3.ed, Ed. Makron Books, São Paulo, Brazil.