UNCERTAINTY ESTIMATE OF THE TEMPERATURE DYNAMIC MEASUREMENT BY SYSTEM IDENTIFICATION METHODS

Pablo Andrade Grossi
Centro de Desenvolvimento de Tecnologia Nuclear, ZIP: 30.123-970 - Belo Horizonte, Minas Gerais, Brazil.
pabloag@cdtn.br

Ricardo Alberto Neto Ferreira
Centro de Desenvolvimento de Tecnologia Nuclear, ZIP: 30.123-970 - Belo Horizonte, Minas Gerais, Brazil.
ranf@cdtn.br

Roberto Márcio de Andrade
Departamento de Engenharia Mecânica da UFMG, ZIP: 31.270-901 - Belo Horizonte, Minas Gerais, Brazil.
rma@ufmg.br

Abstract: *the determination of thermophysics properties of materials by the Flash Laser Method depends, fundamentally of the dynamic temperature measurement quality. The available standards for temperature measurement systems calibration just evaluate uncertainties for static measurements. The resulting uncertainties estimation of the dynamic process can be made basing on the transfer function, resulting from systems identification methods. In this work was determined the transfer function of an infrared temperature measurement system using the Least Square and the Instrumental Variables techniques for the system identification. The knowledge of the dynamic characteristics of this measurement system, allowed obtaining a better estimation of the temperature transient and their uncertainties by the signal deconvolution.*

Keywords: dynamic systems, systems identification, temperature measurement, uncertainties.

1. Introduction

The dynamic temperature measurement refers to all experiments in which thermal transients occur and were measured by a sensor. Transients can be generated due to temperature variations in the medium, in the sensor or in the own tested material. The dynamic errors are caused by the measurement system inertia (measurement system incapacity to follow the true temperature variation signal), feedback effects and the system relative sensitivity in frequency and in level of signal. The minimization of measurement dynamic uncertainties can be implemented when the dynamic properties of the sensor are known. This process is called signal deconvolution. Thus, the true transient of temperature can be recovered by the elimination of the measurement system influence.

The characterization and knowledge of the dynamic uncertainties is the key piece to define the levels of confiability of a dynamic measurement result. Therefore, its use is not restricted to the temperature measurement, being also applied to any other type of physical phenomena in which transients are observed during the phenomenon measurement.

This work has for objective a presentation of a methodology to determine the dynamic properties of temperature sensors in fast transient measurements. First, a transfer function is determined, and a dynamic correction is estimated with the objective to attenuate the effect introduced by the measurement system during the test process. The transfer function of a non-contact thermometer was determined based on identification system techniques. The Least Square (LS) method and Instrumental Variables (IV) estimators were used. The knowledge of the dynamics of a measurement system allowed a better estimate of true temperature in real time and their uncertainties. This methodology has been used by the Centro de Desenvolvimento de Tecnologia Nuclear - CDTN, organ of the Comissão Nacional de Energia Nuclear – CNEN, to minimize the dynamic uncertainties of an IR thermometer of the Laboratory for thermophysics properties determination by Flash Laser Method.

2. Methodology for System Identification

The Figure (1) presents, schematically, the experimental apparatus of CDTN Laboratory used to determine thermophysics properties of materials. The assembly bench has basically a CO_2 LASER, one sample holder located in the interior of a small tubular oven, a non-contact IR temperature measurement system and a data acquisition system.

The signal deconvolution recovers the true temperature transient occurring in the sample. This transient is directly related to the themophysics properties of the sample.

The system identification analyzes the transitory response observed in the system output when test signals are applied on the system input. Countless techniques that use different test signals and the most common signals are the step, the pulse and the ramp and they are widely studied in the modern control theory.

The test signal in the system input was applied by a heated surface at constant temperature that was read by the IR detector only when a shutter, positioned between the detector and the heated surface, was abruptly removed. The time for shutter removal is 0.1s. A ramp with 0.1s of slope time was considered as the input signal, where the minimum and maximum temperature levels were defined by the temperature differences between the shutter surface and the heated surface,

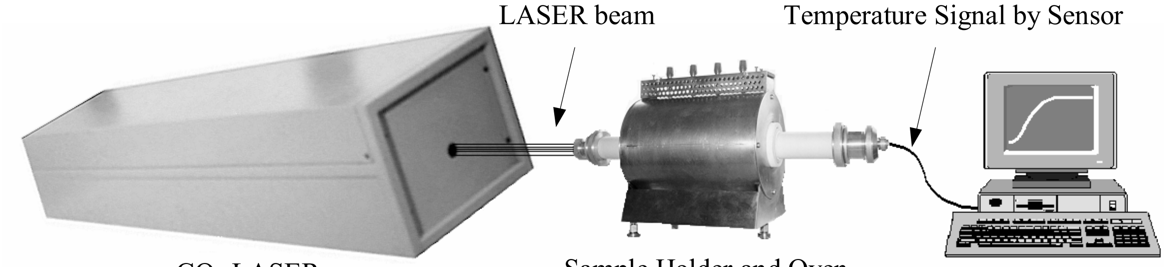

Figure 1. Schema of thermophysics properties determination bench.

The application of the input signal is the most critical part for system identification methods. Ideal steps are difficult to be obtained and they request appropriate equipment. In some cases, other types of more appropriate signals like ramps, pulses, PRBS signals or any well known signal can be used.

After the application of a temperature step on input and reading the output signal of measurement temperature system, the process of system identification that will generate a transfer function for the system can start. The process analyzes the output signal according with the type of input signal and several techniques are proposed in the literature (Michalski et al., 1991; Ogata, 1998; Aguirre, 2000; Kim, 2001). All techniques have as objective a description of the system output in function of the model variables. This analysis can be accomplished in the frequency domain, adapting a transfer function G(s) in the form showed in Eq. (1).

$$G(s) = \frac{k.e^{t_d s}}{\prod_{1}^{n} (1+\tau_n s)} \tag{1}$$

where k is the signal level in steady state region, t_d is the dead time of the system, τ represents the of the transfer function poles and n indicates the order of the analyzed system.

The transfer function in the frequency domain (s), can be transposed to the time domain (t) through the Anti-Laplace Transform.

The system transfer function (Eq. 1) can be represented by discreet form on the time. In agreement with Aguirre (2000) the discreet representations are especially appropriate to systems identification when algorithms are used to estimate the system parameters. The Equation (2) presents a widespread form of discreet representation:

$$A(q)y(k) = \frac{B(q)}{F(q)}u(k) + \frac{C(q)}{D(q)}u(k), \tag{2}$$

where $y(k)$ it is the system output, $u(k)$ it represents an external input and n(k) is the white noise. Considering q^{-1} a delay operator, so that $y(k)q^{-1}=y(k-1)$ and $A(q)$, $B(q)$, $C(q)$, $D(q)$ and $F(q)$ are the polynomials defined as:

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + \ldots + a_{n_y} q^{-n_y}; \\ B(q) &= b_1 q^{-1} + \ldots + b_{n_u} q^{-n_u}; \\ C(q) &= 1 + c_1 q^{-1} + \ldots + c_{n_\xi} q^{-n_\xi}; \\ D(q) &= 1 + d_1 q^{-1} + \ldots + d_{n_d} q^{-n_d}; \\ F(q) &= 1 + f_1 q^{-1} + \ldots + f_{n_f} q^{-n_f}. \end{aligned} \tag{3}$$

The application of system identification techniques for sensor parameter estimation has allows a dynamic calibration of the system output signal. Digital data compensation can be implemented. This digital compensation uses the inverse transfer function to determine the true value of the measurement (Dénos and Sieverding, 1997; Paniagua and Dénos, 2002).

4. System Identification and Parameters Estimate Methodology

The data window used to estimate the system parameters must represent all characteristics of the system when excited by a test signal. The characteristics of the signal applied as a test signal to this temperature measurement system are:

Temperature = 39.6 ºC for time = 0 seconds;

Ramp of Temperature;

Temperature = 93.1 ºC for time > 0.1 seconds.

Due to the lack of a reference temperature sensor for determination of the true input signal applied to the system, an estimate of this signal was made based in practice and experience.

Considering as hypothesis, that the system is linear, the test signal parameters can be the following temperature landings:

Temperature = 0 ºC for time = 0 seconds;

Ramp of Temperature;

Temperature = 53.5 ºC for time > 0.1 seconds.

Based on this model same conclusions can be made. Firstly, the system identification at this level of temperature variation (53.5 ºC) can be used to describe the system characteristics for different input levels. Besides, it is capable to describe the system characteristics when excited by any other signal.

A validation procedure for any system excitation conditions needs to consider the model a good model. In this phase some problems of system identification can become evident, as, for instance, the choice of the test signals and the system linearity.

If one considers this thinking and recognizes the practical limitations pertinent to each system identification process (in this case a single data window and a single test signal), an identification process was proposed using a Least Square (LS) Estimator. To compare the results, other system identification process using Instrumental Variable (IV) was applied to the system.

5. Results

5.1. Dead Time Estimation

The dead time estimation for the analyzed system could be made using the cross correlation function (CCF) between the input and the output of the system. However, the data window used has a low noise level that allow an easy dead time estimation that is given by the instant that the system begins to answer the signal applied on the input.

The window of data shown in the graph of the Fig. 2 presents the system output to the temperature input signal mentioned previously. This figure shows a typical supercritical system, the value of dead time is around 0.05 seconds.

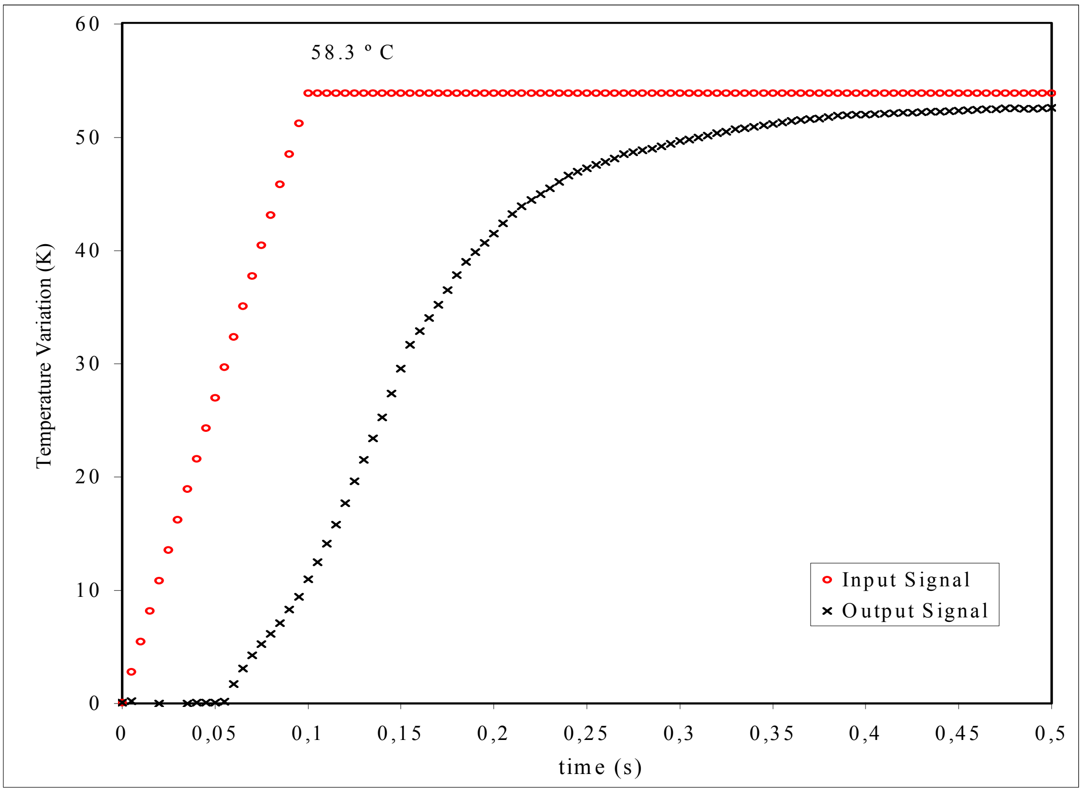

Figure 2. System output to an input in ramp.

5.2. The System Identification using the Least Square Estimator

The identification process using Least Square Estimation (LSE) was initially chosen due to its simple implementation and noise robustness. This last characteristic is not observed by identification that uses simply-output signals convolution.

Initially, a 10th order model was proposed, where 10 regressive outputs and 10 regressive inputs signals were considered. In the sequence, models of 20th, 5th, 2nd and 1st order were obtained. The validation of the model is based on the output signal deconvolution that should tend to the true input signal. The best result of these simulations is presented in the Fig. 3 and Fig 4.

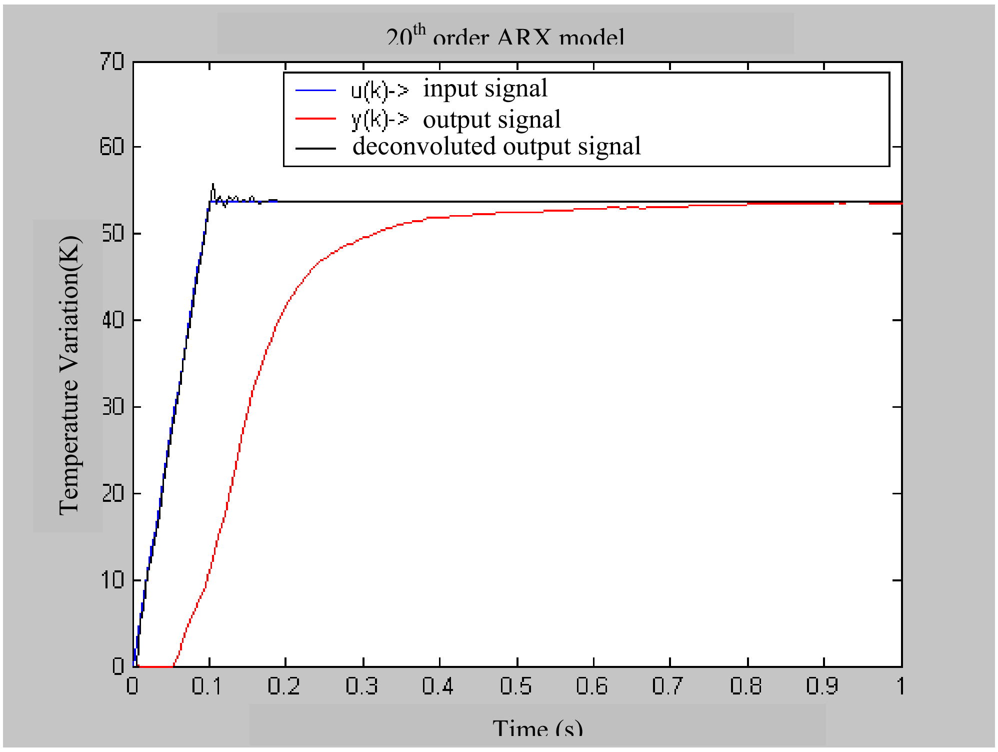

Figure 3. Recuperation of the input signal by output signal deconvolution.

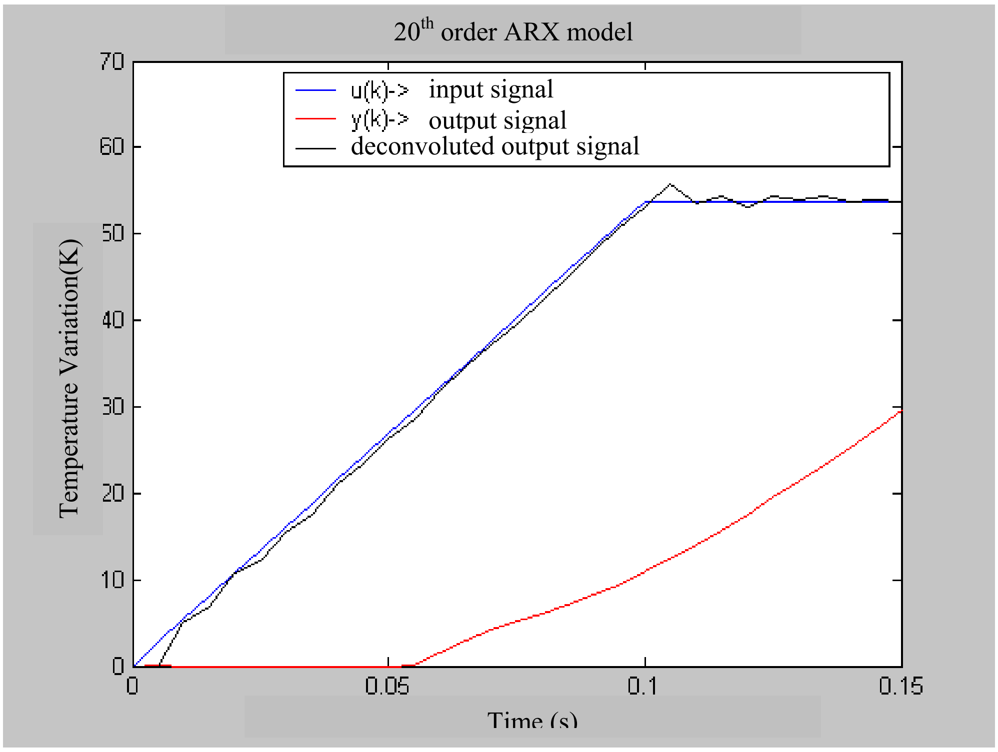

Figure 4. Zoom on Input, Output and deconvoluted Output Signals.

Among the analyzed models, the smaller least square deviation between the input-output signals after deconvolution was presented for the 20^{th} order model. Using this choice criterion, the system identification using 20 regressive inputs and 20 regressive outputs signals was the best model for the IR temperature measurement system presented in this work.

For the LSE models presented an excellent adaptation was observed to make dynamic corrections of experimental data. These corrections were based on the deconvolution of the signal supplied for the temperature measurement system that was previously identified. From the elimination of the influence of the measurement system, a dynamic uncertainties minimization of the measurement process was possible, and the true temperature transient occurred on the samples were recovered.

5.3. Validation Process

By definition, the residues of those model types tend to be a noise estimation and, so that, the LSE doesn't present polarization in the parameters determination, the error on the regression equation should be a white noise. Therefore, the residues should present white noise characteristics. By this way, the residues autocorrelation functions were calculated by the models of order 20^{th}, 10^{th}, 5^{th}, 2^{nd} and 1^{st} based on LSE to evaluate the random characteristic of the residues. All residues presented a random characteristic as showed in the Fig. 5. All of the mentioned models presented quite similar autocorrelation functions, so this analysis could not chose the best one among them. The residues analysis allowed obtaining a guarantee of correct parameter estimation for the models, eliminating the occurrence of estimation errors.

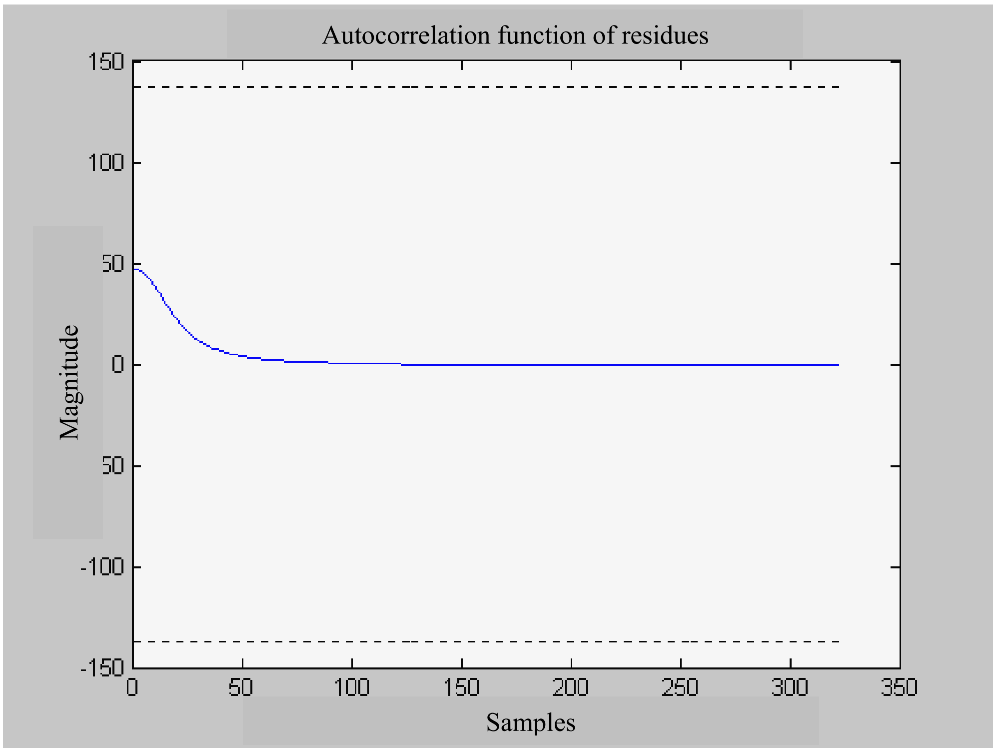

Figure 5. Autocorrelation function of residues for 20^{th} order models.

An implementation of an algorithm for evaluation the ERR index that represents the error reduction rate was obtained for inclusion of each model regression term. This criterion for model structure choice allows the individual importance quantification of each regressive term. The Table I shows the order of classification of each regressive term.

The construction of models with regressors with a larger degree of importance optimizes the structure of the model and it reduces the computational efforts. The comparison of those optimized models with non-optimized models shown previously finds limitations during the signal deconvolution process. That happens because the deconvolution demands an equivalence among the output-input regressive terms on the system transfer function.

5.4. The System Identification using the Instrumental Variables

The Instrumental Variables Estimators (IVE) method is indicated for situations where the LSE do not get satisfactory results because they do not simulated the noise perfectly and they demand that the vector of residues is always orthogonal to regressive terms.

Models were developed using IVE with 20^{th}, 10^{th}, 5^{th}, 2^{nd} and 1^{st} order to identify the proposed temperature measurement system.

After the system identification by IVE models, some difficulties were observed during the signal deconvolution process. The Matlab Program presented singularity problems in matrix for the accuracy demanded during the matrix inversion on the signal deconvolution. By this way, the IVE and LSE models performances comparison were not possible.

Table I – Importance level classification of each regression term of a model with 20 regressive inputs and 20 regressive outputs.

Regressive term	*Importance Level*
y(k-1)	1
y(k-2)	3
y(k-3)	33
y(k-4)	4
y(k-5)	36
y(k-6)	5
y(k-7)	8
y(k-8)	38
y(k-9)	24
y(k-10)	28
y(k-11)	16
y(k-12)	40
y(k-13)	15
y(k-14)	21
y(k-15)	39
y(k-16)	27
y(k-17)	19
y(k-18)	20
y(k-19)	22
y(k-20)	14
u(k-1)	12
u(k-2)	23
u(k-3)	34
u(k-4)	26
u(k-5)	11
u(k-6)	37
u(k-7)	32
u(k-8)	2
u(k-9)	7
u(k-10)	31
u(k-11)	10
u(k-12)	9
u(k-13)	18
u(k-14)	6
u(k-15)	35
u(k-16)	13
u(k-17)	30
u(k-18)	17
u(k-19)	29
u(k-20)	25

Importance order	*Regressive term*
1	y(k-1)
2	u(k-8)
3	y(k-2)
4	y(k-4)
5	y(k-6)
6	u(k-14)
7	u(k-9)
8	y(k-7)
9	u(k-12)
10	u(k-11)
11	u(k-5)
12	u(k-1)
13	u(k-16)
14	y(k-20)
15	y(k-13)
16	y(k-11)
17	u(k-18)
18	u(k-13)
19	y(k-17)
20	y(k-18)
21	y(k-14)
22	y(k-19)
23	u(k-2)
24	y(k-9)
25	u(k-20)
26	u(k-4)
27	y(k-16)
28	y(k-10)
29	u(k-19)
30	u(k-17)
31	u(k-10)
32	u(k-7)
33	y(k-3)
34	u(k-3)
35	u(k-15)
36	y(k-5)
37	u(k-6)
38	y(k-8)
39	y(k-15)
40	y(k-12)

6. Conclusions

By considerations and hypotheses assumed on this IR temperature measurement system identification, this system was consider a linear system, used just a test signal and consider that the system was satisfactorily excited in level of signal and in frequency.

The main problem of this identification is the inexistence of a temperature reference sensor, capable to determine the true input signal applied on the system. So, an estimate of this signal was made based on practical experience.

The models based on IVE were sufficiently effective to estimate the parameter of the system. However, the validation process must make a comparison of IVE and LSE models by the signal deconvolution. For IVE models some limiting problems were observed on deconvolution process. By this way, systems identification by IVE was inadequate for dynamic corrections of transient data.

The based models in LSE showed excellent performance to be applied for dynamic corrections on transient data. This correction is based on signal deconvolution process for the temperature measurement system previously identified. By eliminating the influence of the measurement system, a dynamic uncertainties minimization of the measurement process was possible, and the true unsteady temperature occurred on the samples was recovered.

The residue analysis allowed obtaining a guarantee of correct parameter estimation for the models, eliminating the occurrence of estimation errors.

An implementation of an algorithm for evaluation ERR index, that represents the error reduction rate, was obtained for inclusion of each model regression term. This criterion for model structure choice allows the quantification of the individual contribution of each regressive term. The Table I shows the order of classification of each regressive term

The signal deconvoluction technique offered restrictions on the application for some estimator types and some model's structures. The estimators must be of LSE (excluding the IVE) and the model's structure must present for each regressive input an equivalent regressive output (excluding models optimized by the ERR index that usually presents a non equivalent input and output regressive terms).

The characterization and knowledge of the dynamic uncertainties are the key pieces to define the confiability levels of a dynamic measurement result. Therefore, its use is not restricted to the temperature measurement, being also applied to any other type of physical phenomena where transients are observed during the phenomenon measurement.

This work demonstrated the application viability of system identification methodology to determine the dynamic properties of temperature sensors in fast transient measurements, determining its transfer function, and estimate a dynamic correction with the objective to attenuate the effect introduced by the measurement system during the test process. The transfer function of a non-contact thermometer was determined based on systems identification techniques and LSE and IVE were used. The knowledge of the dynamics of a measurement system allowed a better estimate of true temperature in real time and their uncertainties. The Centro de Desenvolvimento de Tecnologia Nuclear - CDTN, organ of the Comissão Nacional de Energia Nuclear – CNEN, used these results in this paper to minimize the dynamic uncertainties of a IR thermometer of the laboratory of thermophysics properties determination by the Flash Laser Method.

7. References

AGUIRRE, L.A., **Introdução à Identificação de Sistemas**, Editora UFMG, 2000.

DÉNOS, R.; SIEVERDING, C. H. Assessment of the cold-wire resistance thermometer for high-speed turbomachinery applications, J. Turbomach 119:140-148, 1997.

GROSSI, P. A. **Modelagem físico-matemática de sistemas de determinação de propriedades termofísicas com aplicação ao método flash laser**. 2003. 107 p. Dissertação (Mestrado em Engenharia Mecânica) - Escola de Engenharia, Universidade Federal de Minas Gerais, Belo Horizonte, 2003.

KIM, S. J. An inverse filtering technique for the recursive digital filter model, Department of Information & Communication Engineering, Tongmyong University Technology, Busan, Korea, 608-711, ISIE, Pusan, p. 193-1940, 2001

OGATA, K.; SEVERO, B. Engenharia de controle moderno. In:_____. **Modelagem matemática de sistemas dinâmicas**. 3. ed. Rio de Janeiro: Prentice-Hall, Cap. 2 a 4, p. 10-174, 1998.

MICHALSKI, L.; ECKERSDORF, K.; MCGHEE, J., **Temperature measurement .** New York: J. Willey, p 152-349, 1991.

PANIAGUA, G.; DÉNOS, R. Digital compensation of pressure sensors in the time domain. Experiments in Fluids, v 32, p 417-424, 2002.

8. Responsibility notice

The authors Pablo Andrade Grossi, Ricardo Alberto Neto Ferreira and Roberto Márcio de Andrade are the only responsible for the printed material included in this paper.