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INVERSE MEASUREMENT METHODS FOR DETECTING BUBBLES IN A FLUIDIZED BED REACTOR – TOWARDS THE DEVELOPMENT AN INTELLIGENT TEMPERATURE SENSOR

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ABSTRACT

Temperature is the most common physical variable that needs to be measured for the efficient and safe operation of industrial processes. Some of these applications present particularly severe measurement conditions, such as in fluidized bed coal combustion in which temperatures exceed 1000 ºC and the medium is highly abrasive and corrosive. Under these conditions protecting devices must be adopted to preserve the integrity of transmitters in contact with such a harsh medium. The objective of this work is to contribute in the development of an intelligent temperature sensor capable of autonomously compensating these side effects and of reconstructing the actual process temperature through numerical solution of the inverse measurement problem. Considering a thermocouple exchanging heat through convection and conduction a linear differential equation can be written relating the indicated and the process temperatures. A discrete version of this equation, obtained by the finite differences method, allows to explicit the indicated in terms of the process temperature or the process in terms of the indicated temperature. Although the approach is feasible in mathematical terms, solving the inverse problem implies that experimental errors and noise embedded in the indicated temperature will be tremendously amplified to the point of completely corrupting the reconstructed process temperature. A regularizing technique, based on the adjustment of a polynomial curve on the last few indicated temperature points, is proposed to overcome this problem. Numerical and experimental results show that this technique allows the reconstruction of the process temperature under realistic experimental conditions at relatively high noise and error levels.

NOMENCLATURE

a_i – polynomial coefficients
A (m^2) – area
A_i – coefficient of the first line in G^{-1}
B_i – coefficient of the second line in G^{-1}
C – specific heat
G – Gram's matrix
G^{-1} – inverse of Gram's matrix
h – convection coefficient
M (kg) – mass
t – time
T_{ind} – indicated temperature
$\vec{T}_{ind}$ – indicated temperature vector
T_{proc} – instantaneous process temperature
W – weight
$\vec{w}$ – weight vector
x_i – unknown
$\vec{x}$ – unknown vector
Δt – timestep
τ – time constant
τ_{avg} – average time constant
M – number of points
N – polynomial order

INTRODUCTION

Gas bubbling fluidized beds are used in the industry for a variety of purposes, such as the catalytic cracking of hydrocarbons and the combustion of coals. A gas bubbling fluidized bed may be regarded as a mixture comprised of two phases, a bubble phase and a particulate or emulsion phase. Bubbles are dispersed within the continuous emulsion phase and are formed as the fluidizing gas is injected at the bottom of the bed. They move upwards dragging wakes of particulate and may coalesce into larger bubbles, split and recoalesce. These intricate and interdependent phenomena result in an extremely complex gas-solid flow dynamics, characterized by high reaction and heat transfer rates. A complete understanding of such phenomena is of crucial importance, not only for the correct design of fluidized bed reactors, but also for their efficient and safe operation.

The properties and evolution of bubbles in gas fluidized beds are investigated using either intrusive or non-intrusive measuring techniques. Measurements through capacitive and electroresistive external probes, optical and X ray observations through photography and filming, with or without the use of gas tracers, are among the most common non-intrusive methods. These methods, even though not disturbing the process, are either limited to small beds or allow observations only near to the confining walls. Intrusive techniques are based on phase detection probes for measuring local physical properties. The majority of commonly used probes are thermal, capacitive, optical, differential pressure, and electroresistive. Regardless of disturbing the process to some extent, intrusive probes are applicable to beds of any size and constitute the most adequate choice in large scale industrials systems.

The main problem involved in probing gas-solid flows in fluidized bed reactors concerns the extremely harsh experimental environment in which the probe is immersed: temperatures exceeding 1000 ºC, material deterioration due to friction with the fluidized particulate, chemical corrosion, presence of electrostatic charges, etc. Thermal probes are an interesting option to work in such conditions because of its low cost and intrinsic robustness. The measurement principle is based on the temperature difference between the reacting emulsion phase (burning coal particles for instance) and the gas bubbles phase constituted of the exceeding injected gas. The signals delivered by such thermal probes tend to concentrate on characteristic levels and can be used to extract residence times, pierced lengths, bubble diameters, etc.

There is, however, significant limitations concerning the possibility of obtaining some of these physical description parameters. For instance, previous works account for the problem of determining a bubble diameters histogram from the corresponding measured pierced lengths histogram, which implies in solving an extremely ill-conditioned integral equation. The consequence of this is that negligible experimental errors may be amplified to the point of completely corrupting the reconstructed histogram. Also, any distortion on the measured signals, even at favorable signal to noise ratios, may seriously compromise the significance of the results. Since experimental errors and measurement distortions are unavoidable, special signal processing techniques must be applied to manage such problems in order to obtain acceptable results [1].

This work is focused on the problem of developing a numerical signal processing technique capable of reconstructing the original process temperature signal from its distorted measured signal obtained from the probe. In the case of thermal probes employed in fluidized bed reactors, such distortions are caused mainly by non-linear effects and delays due to insulation of the temperature sensor (a sheathed thermocouple for instance). The proposed method is based on deconvolving the measured signal through an inverse numerical model of the transduction equation to obtain the process signal. This approach is suitable for on-line implementation and allows the development of an intelligent micro-processed thermal sensor that autonomously corrects distortion effects.

Numerical and experimental tests were carried out aiming at validating the proposed method. Different regularization techniques, based on data smoothing, were numerically tested in order to determine the best tradeoff between computational effort and the ability to handle higher measurement noise levels. The optimized reconstruction algorithm was tested with signals obtained from a sheathed thermocouple immersed sequentially in cold and hot water to reproduce the effect of gas bubbles in a reacting emulsion. Results show that the true process temperature can be readily reconstructed with some increase in the original noise levels.

FORMULATION OF THE PROBLEM AND RECONSTRUCTION ALGORITHM

Consider a sheathed thermal probe immersed in a reacting two-phase flow as indicated in the following figure. The local instantaneous temperature of the flow and the corresponding indicated temperature will be respectively denoted by T_{proc} and T_{ind}. They differ because of the thermal resistance associated with heat convection on the external surface of the sensor and due to thermal accumulation by the material of the sheath.

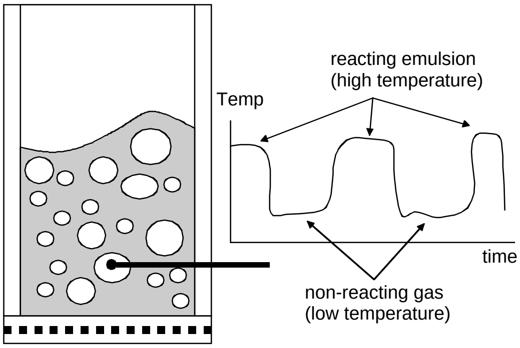

Figure 1 – Use of a temperature sensor to detect phases in a reacting gas-solid flow

Convection is characterized by the convection coefficient h (kW/m^2/K) and by the external surface A (m^2), while thermal accumulation is described by the sheath's mass M (kg) and specific heat C (kJ/kg/K). Thus, neglecting radiation effects and heat conduction through the sensor's cable, the governing equation can be written as follows:

$$MC\frac{dT_{ind}}{dt} - hA(T_{proc} - T_{ind}) = \tau\frac{dT_{ind}}{dt} - (T_{proc} - T_{ind}) = 0 \quad ...(1)$$

where $\tau = MC/(hA)$ is the probe's time constant. This equation expresses the transduction relation between the input or process variable and the output or indicated variable. Solving the so-called direct problem, i.e. calculating the output (T_{ind}) from the known input (T_{proc}), can be done in a very straightforward manner. However, solving the corresponding inverse problem is certainly a difficult task because of its intrinsic ill-conditioned nature. In other words the calculus of T_{proc} from T_{ind} is strongly affected by the presence of experimental errors in the measurements of T_{ind}. This effect has already been studied and some solution techniques have been proposed such as J.V. Beck's function specification method [7] and D. Murio's mollification method [8]. However, the numerical instructions associated with such methods are excessively long for their implementation in a few Kbytes in dedicated microcontroller.

A convenient approach to this constraint is based on a finite difference version of equation (1), that is:

$$\frac{\tau}{\Delta t}\left(T_{ind,n} - T_{ind,n-1}\right) - \left(T_{proc,n} - T_{ind,n}\right) = 0 \qquad (2)$$

in which Δt denotes an adequate time discretization step, and the second indices n or n-1 that the variable refers to the times $t = n\Delta t$ or $t = (n-1)\Delta t$ respectively. Thus the direct and inverse problems are expressed by:

$$T_{ind,n} = \frac{1}{\tau + \Delta t}\left(\Delta t\, T_{proc,n} + \tau\, T_{ind,n-1}\right) \qquad (3)$$

$$T_{proc,n} = T_{ind,n} + \frac{\tau}{\Delta t}\left(T_{ind,n} - T_{ind,n-1}\right) \qquad (4)$$

A numerical experiment is effective to demonstrate the corresponding sensitivities to the presence of noise. Consider a process whose temperature originally varies according to a square wave from 90 to 100 ^{o}C, a thermal probe with a time constant of $\tau = 1s$ and a time step of $\Delta t = 0.01s$. The direct problem is solved (equation (3)) with random noise (< 0.02 ^{o}C) added to T_{proc} and the resulting T_{ind} is shown in Figure 2 (top). The inverse problem (equation (4)) is solved with the same noise signal added to T_{ind} and the calculated T_{proc} is shown in Figure 2 (bottom). It can be seen that the inverse problem shows to be extremely sensitive, even for very small errors of less than 0.02 ^{o}C over an average temperature signal of 95 ^{o}C.

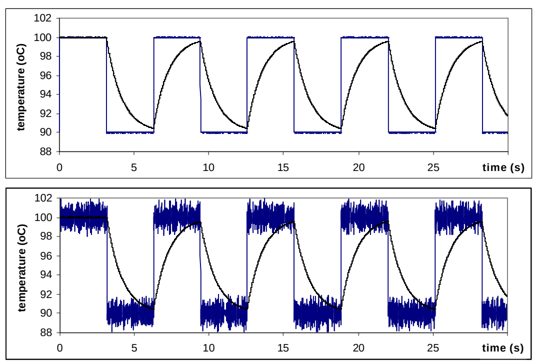

Figure 2 – direct and inverse problems (equations (3) on top and (4) on bottom respectively) solved with random noise (< 0.02 ^{o}C) added to the input temperature (blue trace represents T_{proc} and black trace denotes T_{ind})

These problems has been the object of study of several researches in the past and, as a result of their efforts, several a posteriori methods are available to reconstruct the process temperature in realistic conditions. Tikhonov's method proposed in 1983 [2] is certainly a classic choice and is based on the introduction of regularizing terms into the inversion process. The main disadvantage of Tikhonov's method is that to work properly these regularizing terms must be weighted by specific coefficients which must be determined previously and are situation-dependent [3]. Another interesting a posteriori approach is the Van-Cittert iterative deconvolution technique, based on forming successive approximations of the unknown systems impulse response using the convolution equation [4] [5]. This technique works remarkably well but is restricted to linear systems and is not suited for on-line processing. Adaptive filtering by wavelets [1] and redundant measurements [6] can also be employed in non-linear problems with good results but still restricted to a posteriori applications.

The on-line reconstruction of the process temperature (T_{proc}) must be based on a finite number simple operations performed on the last few acquired temperatures. This is so because of limitations in the present microcontroller technology which, although its astonishing developments in the last few years, are still far beneath the computational power necessary to solve such types of inverse problems by classical methods. For instance, a very widespread option is Microchip's model 18F252 which has a memory of 32 Kbytes for the instructions and 1.5 Kbytes for the data. The approach adopted in this work is based on a smoothing technique for the calculation of the derivative in equation (1). More precisely, this derivative performs like a high-pass filter and, consequently, low-frequency components present in the original indicated temperature the signal are attenuated, while high frequency components mainly contained in the noise signal are amplified. The smoothed derivative is determined by fitting a polynomial of order N to the last M+1 points, as indicated in Figure 3.

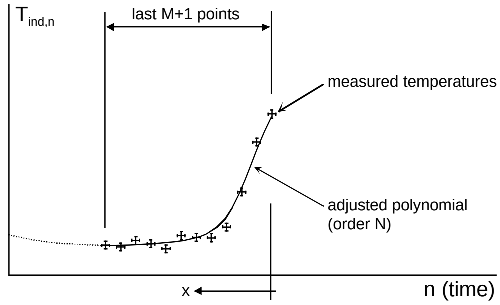

Figure 3 – T_{ind} and dT_{ind}/dt in (1) are estimated through an adjusted polynomial over the last M+1 temperature points

In mathematical terms this can be expressed as:

$$\vec{T}_{ind} = a_0\,\vec{x}_0 + a_1\,\vec{x}_1 + \ldots + a_N\,\vec{x}_N \qquad (5)$$

where

$$\vec{T}_{ind} = \begin{pmatrix} T_{ind,n} \\ T_{ind,n-1} \\ T_{ind,n-2} \\ \vdots \\ T_{ind,n-M} \end{pmatrix}, \quad \vec{x}_0 = \begin{pmatrix} 0^0 \\ 1^0 \\ 2^0 \\ \vdots \\ M^0 \end{pmatrix}, \quad \vec{x}_1 = \begin{pmatrix} 0^1 \\ 1^1 \\ 2^1 \\ \vdots \\ M^1 \end{pmatrix}, \ \ldots \ \vec{x}_N = \begin{pmatrix} 0^N \\ 1^N \\ 2^N \\ \vdots \\ M^N \end{pmatrix}$$

...(6)

and the coefficients (a_i) being determined according to some error minimization scheme. The weighted residual (or weighted least square) technique was adopted in this work. The main reason for this choice is the possibility of defining different weighting vectors $\vec{w} = (w_i)$ to emphasize different parts of the indicated temperature signal, producing different coefficients sets according to specific needs. This approach leads to the following equations:

$$\begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_N \end{pmatrix} = G^{-1} \begin{pmatrix} (\vec{T}_{ind}, \vec{x}_0) \\ (\vec{T}_{ind}, \vec{x}_1) \\ \vdots \\ (\vec{T}_{ind}, \vec{x}_N) \end{pmatrix} \tag{7}$$

where G is the associated Gram's matrix

$$G = \begin{bmatrix} (\vec{x}_0,\vec{x}_0) & (\vec{x}_0,\vec{x}_1) & \cdots & (\vec{x}_0,\vec{x}_N) \\ (\vec{x}_1,\vec{x}_0) & (\vec{x}_1,\vec{x}_1) & \cdots & (\vec{x}_1,\vec{x}_N) \\ \vdots & \vdots & \cdots & \vdots \\ (\vec{x}_N,\vec{x}_0) & (\vec{x}_N,\vec{x}_1) & \cdots & (\vec{x}_N,\vec{x}_N) \end{bmatrix} \tag{8}$$

which inner product is defined as

$$(\vec{x},\vec{y}) = \sum_{k=0}^{M} w_k\, x_k\, y_k \tag{9}$$

The main advantage of this approach is that the Gram's matrix in equation (7) can be previously inverted because it depends only on $\vec{w}$ and on the number of fitted temperature points (M+1). Furthermore, these operations need not to be fully implemented since only $T_{ind,n}$ and its first derivative are needed at x = 0 to replace in (1). According to (5) these values can be calculated as

$$T_{ind}(0) = \vec{T}_{ind}\Big|_{\vec{0}} = a_0 \text{ and } \frac{dT_{ind}}{dt}(0) = \frac{d\vec{T}_{ind}}{d\vec{x}_1}\Bigg|_{\vec{0}} = a_1$$

...(10)

from what equation (4) becomes

$$T_{proc,n} = a_{0,n} + \tau a_{1,n} \tag{11}$$

where the index n was introduced to stress the fact that a_0 and a_1 refers to $t = n\Delta t$ and must be recalculated for all time steps. Synthetically these operations can be summarized in the following steps

1. set M, N and $\vec{w}$
2. calculate G^{-1} in (7) and extract the first and second lines, i.e.

$$(A_0, A_1, \ldots, A_N) = (G^{-1})_{row=1} \tag{12.1}$$

and

$$(B_0, B_1, \ldots, B_N) = (G^{-1})_{row=2} \tag{12.2}$$

3. initiate the temporal loop with adequate values for $T_{ind,n}$, $T_{ind,n-1}$, ... $T_{ind,n-M}$
4. calculate a_0 and a_1 through the formulas

$$a_0 = (A_0, A_1, \ldots, A_N) \begin{pmatrix} (\vec{T}_{ind}, \vec{x}_0) \\ (\vec{T}_{ind}, \vec{x}_1) \\ \vdots \\ (\vec{T}_{ind}, \vec{x}_N) \end{pmatrix} \tag{13.1}$$

$$a_1 = (B_0, B_1, \ldots, B_N) \begin{pmatrix} (\vec{T}_{ind}, \vec{x}_0) \\ (\vec{T}_{ind}, \vec{x}_1) \\ \vdots \\ (\vec{T}_{ind}, \vec{x}_N) \end{pmatrix} \tag{13.2}$$

5. calculate $T_{proc,n}$ through equation (10)
6. make n = n+1, acquire a new indicated temperature and scroll values in $\vec{T}_{ind}$; that is

$$\begin{aligned} T_{ind,n-M} &= T_{ind,n-M+1} \\ T_{ind,n-M+1} &= T_{ind,n-M+2} \\ &\vdots \\ T_{ind,n-1} &= T_{ind,n} \\ T_{ind,n} &= T_{ind,new} \end{aligned} \tag{14}$$

7. iterate from step 4.

VALIDATION OF THE PROPOSED RECONSTRUCTION ALGORITHM

An experimental test was conceived to validate the proposed reconstruction algorithm under realistic conditions. The test consisted in immersing a sheathed thermocouple in hot (93.081 ^oC) and cold (-0.099 ^oC) water repeatedly to simulate a process in which the temperature varies according with a square wave. The thermocouple's time constant was previously determined in a series of step input tests and resulted in $\tau_{avg} = 13.04\,s$. An unsheathed thermocouple was used to obtain the instantaneous process temperature to be reconstructed from the indicated temperature.

A 24-bit data acquisition board (PXI-4351) was used to digitize the measured temperatures with a resolution of the maximum of 0.05 ^oC. The acquisition frequency was set at 30 Hz to avoid aliasing effects and to be sure to correctly capture the edges of the process signal. The reconstruction algorithm detailed in the preceding section was implemented in LabView on a PC platform (National Instruments PXI-8170 pentium III 850 MHz). After an initial time interval necessary for all transients vanish, the reconstruction is performed on-line at the same rate that the measurements are acquired. Figure 4 shows the instantaneous process temperature obtained from the unsheathed thermocouple, the indicated temperature given by the sheathed thermocouple and the corresponding reconstructed temperature.

Although some over and undershooting, it is clear from Figure 4 that the reconstructed temperature is considerably close to the true process temperature.

The performance of the reconstruction algorithm depends strongly on intrinsic parameters such as the polynomial order (N) in equation (5) and on the number of temperature points on which the polynomial is being adjusted (M+1). The weighting vector $\vec{w}$ also has a significant overall influence. To assess these influences we adopted $w_k = \exp(-k\Delta t)$, after which the following error quantifier can be defined:

$$e = \sqrt{\frac{\sum_0^M (T_{proc,n} - T_{true,n})^2}{M}} \tag{15}$$

where $T_{proc,n}$ are the reconstructed process temperature obtained from (11) and $T_{true,n}$ are the true process temperature given by the unsheathed thermocouple. The following table shows the evolution of this error.

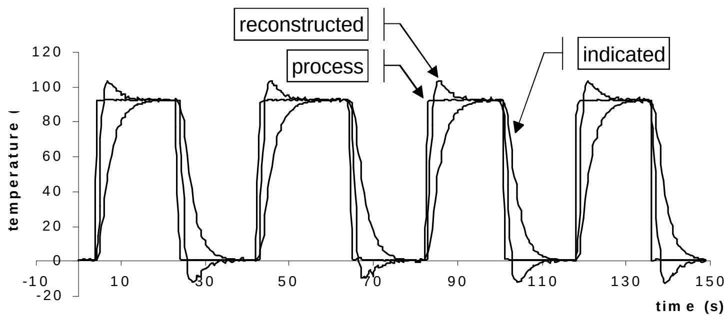

Figure 4 – experimental true process and indicated temperatures and the corresponding reconstructed process temperature (equation (11)).

Table 1 – averaged error between the true and the reconstructed process temperature according to equation (15) in ^oC. (weighting vector: e^{-t})

number of points (M+1)	polynomial order (N)								
	2	3	4	5	6	7	8	9	10
3	16.351								
4	16.385	17.346							
5	16.756	16.352	20.136						
6	17.135	16.102	17.899	25.541					
7	17.447	16.072	17.037	21.108	35.534				
8	17.680	16.123	16.606	19.319	26.978	53.659			
9	17.841	16.200	16.368	18.358	23.468	37.547	86.084		
10	17.946	16.276	16.232	17.769	21.572	30.815	56.347	143.809	
11	18.011	16.344	16.150	17.385	20.395	27.175	43.729	89.478	246.487
12	18.048	16.398	16.103	17.114	19.615	24.911	36.888	66.233	147.677
13	18.070	16.438	16.077	16.919	19.063	23.403	32.642	53.606	105.267
14	18.081	16.466	16.063	16.776	18.655	22.340	29.804	45.800	82.234
15	18.087	16.485	16.056	16.669	18.346	21.558	27.802	40.587	68.063
20	18.093	16.513	16.050	16.427	17.558	19.606	23.113	29.309	40.628
30	18.093	16.515	16.050	16.370	17.263	18.708	20.893	24.258	29.578
40	18.093	16.515	16.050	16.369	17.256	18.650	20.633	23.432	27.476
50	18.093	16.515	16.050	16.369	17.256	18.649	20.626	23.381	27.229

CONCLUSIONS

O procedure for reconstructing the true process temperature from measured indicate temperatures has been proposed in this work. The algorithm is based on inverting a discrete model of the transduction equation, followed by a regularization procedure since the inverse problem is intrinsically ill-conditioned. The regularization is achieved by fitting a polynomial over the last few measured indicated temperatures and by correcting the present temperature and estimating its temporal derivative through the coefficients of the polynomial. This procedure is suitable for on-line implementation due to the reduced number of mathematical operations associated. Numerical and experimental testes were carried out in order to validate the proposed procedure. Results show good agreement between the true process temperature, determined from an unsheathed thermocouple, and the reconstructed temperature obtained from equation (11). Future work should include a more extensive work on different weighting functions and additional procedures to minimize over and undershooting of the reconstructed signal.

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