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SURFACE RESPONSE-BASED PERFORMANCE ASSESSMENT OF A VIRTUAL-FLOWMETER BASED TRANSDUCER FOR HELIUM MONITORING

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Abstract - The assessment of the metrological performance of a virtual flowmeter-based transducer for helium under cryogenic conditions is proposed. At this aim, first a model of the transducer, mainly based on a virtual flowmeter exploiting Sereg-Schlumberger method and a valve model exploiting finite-element approach, is presented. The transducer and valve models are validated experimentally on a case study for helium monitoring in cryogenic systems at the European Organization for Nuclear Research (CERN). Then, a fully simulated approach is performed in order to assess the transducer performance. In particular, the analysis effort is optimized by systematically exploring operating conditions by means of 3d-CCRD strategy.

Keywords: virtual flowmeter, uncertainty analysis, response surface, design of experiments

1. INTRODUCTION

In smart transducer based on *virtual (or soft) sensors*, model simulation plays a key role during project assessment and enhancement [1]. Several indexes of metrological performance have to be evaluated systematically, at varying operating conditions, influence parameters, and uncertainty sources, as well as, moreover, over the input range as a whole [2]. Different strategies have been proposed depending on the level of a-priori knowledge of the process [3]. In particular, solutions based on artificial neural networks [4], [5], Bayesian method [6], Principal component analysis (PCA) [7], have been widely explored.
Once the model is defined, simulations are run at varying the model parameters, i.e. operating conditions, design and setting parameters, as well as input range. This is carried out usually by following an intuitive approach: the investigation space is explored by either or a purely random approach, or by an one-factor-at-time strategy. This can bring to misleading results, because only a reduced portion of the investigation space is explored, and not the most significant one for describing the performance landscape effectively. Moreover, often the relationship among performance and model parameters is not appreciably linear, and, in this way, the performance covariance, i.e. the parameters joined effect (interaction), is not revealed. Finally, the more comprehensive Monte-Carlo method turns out to be burdensome from a computational point of view.
Statistical experiment design optimizes test burden by allowing a systematic exploration of a multidimensional parameter space with a high degree of resource exploitation [8],[9]. In this paper, a metrological performance analysis, based on a statistical experiment design, is proposed for tuning the simulation effort to the complexity and accuracy of the model of a virtual flowmeter-based transducer. In Section II, the model of the transducer is illustrated. In Sections III and IV, a case study of a virtual flow meter-based transducer [10] for helium monitoring in cryogenic operations at European Organization for Nuclear Research (CERN) and some preliminary results are shown.

2. MODEL OF THE FLOWMETER-BASED TRANSDUCER

The mass flow $\dot{m}$ through a valve is indirectly measured by the virtual flow meter-based transducer for cryogenic helium. An a-priori knowledge about the valve and the actual helium behaviors (the pressure and the temperature at the input and the output of the valve) are combined with an a-posteriori modeling, in order to assess the mass flow. In Fig.1[10], the transducer with the corresponding three models (actual helium, valve, and virtual flow-meter) integrated in its structure are highlighted. In particular, the helium pressure and temperature (at the inlet and at the outlet of the valve) are measured by means of appropriate sensors.

In order to perform the uncertainty characterization, the model of each transducer component has been realized and successively validated through experimental tests.

2.1. Valve and transducer model

The uncertainty analysis was performed on a simulated valve. In particular, a cryogenic valve 3D CAD model was used as reference to perform a CFD (Computational Fluid Dynamics) simulation. The model was divided in two parts: the body and the valve plug (Fig. 2).

The ANSYS® Fluent software included in ANSYS®Workbench™ platform was used to run the CFD simulations. The fluid domain, corresponding to

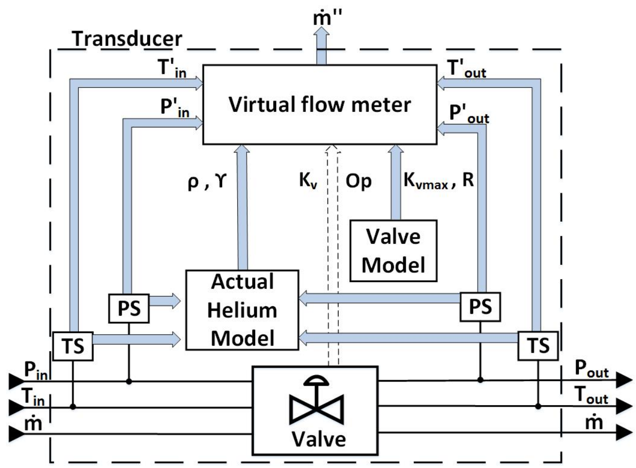

Figure 1. Architecture of the virtual flow meter-based transducer (pressure -PS- and temperature -TS- sensors)

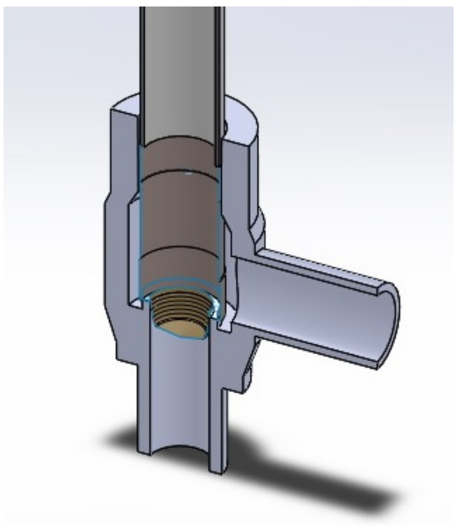

Figure 2. Cryogenic valve 3D CAD model (valve plug -*grey*- and body -*light grey*-)

the valve volume, was meshed. An optimum number of elements and nodes, in order to create a grid independent system, was found after several tests.

Both helium and flowmeter models have been realized in MATLAB© environment. As regard the virtual flowmeter, the Sereg-Schlumberger model has been taken into account. Two different formulations are described according to the gaseous or liquid phases of the helium.

- Gasified helium Sereg-Schlumberger

$$p_v = 1.25; \qquad p_c = p_{in} \cdot (\frac{2}{\gamma+1})^{\frac{\gamma}{\gamma-1}} \tag{1}$$

$$p_{sc} = (0.96 - 0.28 \cdot \sqrt{\frac{p_v}{p_c}}) \cdot p_v \tag{2}$$

$$K_m = \frac{p_{in} - p_c}{p_{in} - p_{sc}} \tag{3}$$

$$X_c = 0.6 \cdot \gamma \cdot K_m; \qquad X = \frac{p_{in} - p_{out}}{p_{in}} \tag{4}$$

$$Y(p_{in}, p_{out}) = \begin{cases} \frac{2}{3} & \text{if } X \leq X_c \\ 1 - \frac{X}{3X_c} & \text{otherwise} \end{cases} \tag{5}$$

$$\dot{m}(p,T) = 23.6 \cdot K_v \cdot Y(p_{in}, p_{out}) \cdot \sqrt{X \cdot \rho \cdot p_{in}} \tag{6}$$

- Liquefied helium Sereg-Schlumberger

$$\dot{m}(p,T) = 23.3 \cdot K_v \cdot \sqrt{\rho \cdot (p_{in} - p_{out})} \tag{7}$$

where K_v is in both the cases the valve coefficient describing the valve characteristics.

The knowledge of valve parameters, i.e. the valve coefficient (K_v) and the valve opening (Op), together with the valve model and the helium thermo-physical properties, namely density ρ and heat capacity ratio γ, are needed. At this aim, a Look Up Table (LUT) reporting the helium characteristics in dependence of specific temperature and pressure has been realized taking advantage of the software package HePak by Cryodata. A MATLAB script enters in the LUT with the values of pressure and temperature given by the transducers and performs a linear interpolation in order to provide the desired helium density and heat capacity.

2.2. Experimental Results of Model Validation

A validation test on the simulated system was performed. Some measurements were carried out at CERN on the test station for superconducting magnets in the SM18[11] laboratory. SM18 is a test facility where all the LHC superconductive components were tested before final installation in the tunnel. In particular, the measurements were carried out through the cryogenics supervisory system of the test station for superconducting magnets in vertical position, called the 'Long Station'.

In the following, the simulated system validation is illustrated.

In the simulated system, as inputs, the helium mass flow, the fluid temperature (at the inlet and the outlet of the valve) and the valve outlet pressure were chosen. As results, the ANSYS simulation output was the inlet valve pressure. Such a pressure was compared with the pressure measured at the inlet of a chosen Long Station valve. In particular an hot-gas line was chosen and the measurements, performed by means of a transducer supplied by WIKA[12], were assumed as a reference for comparing simulated and measured data. For this reason, the quality of the simulation system has been assessed with respect to the measured pressure. In particular, the performance is compared by assessing the percentage difference vs measured data.

A set of 21 measurements were performed at valve inlet with a valve opening range between 50 and 80 %.

The observed mean percentage error is equal to 0.15%, and for this reason, the use of a simulated valve for the uncertainty analysis can be assumed as acceptable. The transducer presented in Fig.1 was then validated. The Long station cryostat, installed in SM18 facility and already chosen for the valve model validation, was also used to validate the transducer model.

The estimated mass flow was compared with the measured one at valve inlet. In the hot-gas line, an actual flow-meter transducer by Brooks [13] is installed, and it was assumed as a reference in all the tests.

The characteristics of the installed valve are: an equal percentage valve, a maximum flow coefficient K_{vmax} of 5.8 m^3/h, and a rangeability of 1:50. The temperature at the valve inlet and outlet is considered as constant, and for this reason, only the inlet temperature was measured. Finally, both the valve inlet and outlet pressures were measured by means of WIKA transducers. The flow rate was changed by increasing the temperature and opening the valve, at constant pressure, inside the cryostat.

In Fig.3, the percentage error of the estimated mass flow with respect to the measured one is presented.

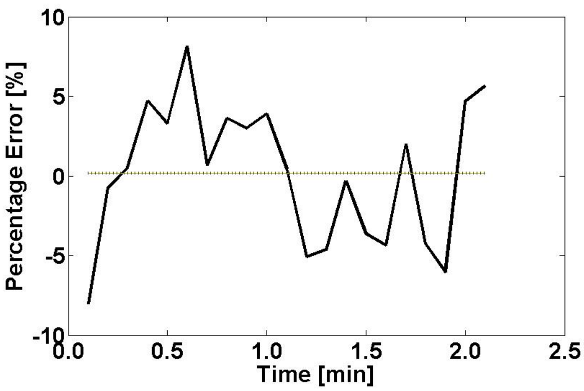

Figure 3. Percentage error measured mass flow vs estimated mass flow

A mean percentage error of 0.17 % was observed.

3. PROPOSED PERFORMANCE ASSESSMENT

The virtual flowmeter has to be installed on the cryogenic implants for helium monitoring at CERN. A fully experimental characterization cannot be performed. The paper proposal, therefore, is based on a performance assessment based on a simulated approach capable of determining the flowmeter metrological performance over different working conditions.

With reference to the flowmeter architecture shown in Fig.1, pressure p_{in}, temperature T_{in} and nominal mass flow $\dot{m}$ are the input parameters for a valve model which determines the output pressure p_{out} and temperature T_{out}, corresponding to a defined valve aperture l value. The valve behavior is, moreover, characterized by its coefficient K_v. Input and output values of pressure and temperature are measured by means a set of four sensors (PS and TS for pressure and temperature, respectively, in Fig.1).

The measured values of pressure and temperature are the input quantities both of the Helium model and the flow meter model blocks. The former block is aimed at simulating the thermo-physical behavior of the helium when expanding through the valve, thus estimating its density ρ and the ratio γ between the heat capacity at constant pressure and volume. ρ and γ along with the estimated value of K_v are the other inputs of the block implementing the Sereg-Schlumberger model equations, in order to estimate the desired mass flow. The difference between the estimated and the reference mass flows, expressed as percentage of the reference mass flow, provides the error e. It is evaluated in different input configurations and processed in order to compute the following metrological performance parameters:

$$\bar{e} = \frac{1}{N}\sum_{k=1}^{N} e_k \tag{8}$$

$$\sigma_e = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(e_k - \bar{e})^2} \tag{9}$$

where N is the number of input configurations, and e_k is the observed error in the $\mathrm{k^{th}}$ input configuration. In other words, $\bar{e}$ is the overall mean error, σ_e is the associated standard deviation.

The main steps for the assessment of performance characteristics related to the virtual flow meter are described in the following. In particular, a statistical experiment design has been exploited for efficiently sampling the input space domain assuring the reduction of the experimental burden.

Pressure and temperature at valve input along with the reference mass flow have been adopted as input parameters. In order to systematically and efficiently explore the input space, the values of the input parameters are varied in the different simulation configurations (described later) according to the experimental plan shown in Fig.4 (referred to as 3D Central Composite Rotatable Design, 3D-CCRD).

3.1. Parameters domain discretization and exploration

With regard to the considered application, the domain of interest has been sampled through two different and nested approaches according to the parameters typology. As stated above, the input parameters subspace have been discretized by means of 3D-CCRD strategy (Fig.4). Originally proposed for surface response techniques, 3D-CCRD turned out to be an efficient approach to explore large multidimensional domains to point out most of the desired information.

In particular, the domain points have been generated according to the discrete values of the input parameters reported in Tab.1.

Each point of the adopted experimental plan corresponds to a specific combination of input parameters

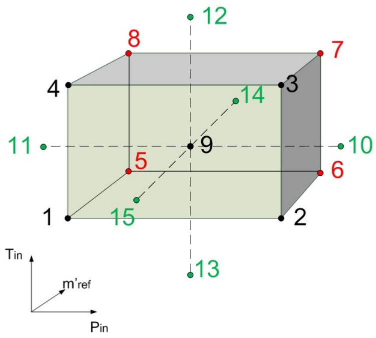

Figure 4. Experimental plan adopted to map the input parameters domain.

Table 1. Values of the input parameters in the 3D-CCRD.

Pressure [kPa]	Temperature [K]	Ref. mass flow [g/s]
100	100.0	0.00
595	166.4	2.98
1000	211.5	5.00
1595	277.9	7.98
2000	323.0	10.00

values; as an example, the point referred to as 3 in Fig.4 determines the test configuration characterized by 1000 kPa, 211.5 ^{o}C and 5 g/s.

For the sake of clarity, the 15 input points are listed in Tab.2..

Table 2. Values of the input parameters in the 3D-CCRD.

Input Points	Pressure [bar]	Temperature [K]	Ref. mass flow [g/s]
0	5.95	166.4	2.98
1	15.95	166.4	2.98
2	15.95	277.9	2.98
3	5.95	277.9	2.98
4	5.95	166.4	7.98
5	15.95	166.4	7.98
6	15.95	277.9	7.98
7	5.95	277.9	7.98
8	10.00	211.5	5.00
9	20.00	211.5	5.00
10	1.00	211.5	5.00
11	10.00	323.0	5.00
12	10.00	100.0	5.00
13	10.00	211.5	10.00
14	10.00	211.5	0.00

4. TEST PROCEDURE AND RESULTS

The following steps highlight the proposed test procedure:

a) A specific configuration of input parameters is set by selecting a row of Tab.2;

b) Once determined the test configuration, the mass flow, m_r measured by the virtual flow meter is determined;

c) The difference, e_r between measured and reference mass flow is evaluated;

d) Steps from a) to c) are repeated with r=1,..,15, until all the rows of the CCRD have been considered; a set of 15 values of e_r is achieved;

e) The performance factors, $\bar{e}$ and σ_e, are estimated correspondingly.

The reference and estimated mass flow, evaluated in the 15 input configurations, are shown in Fig.5 .

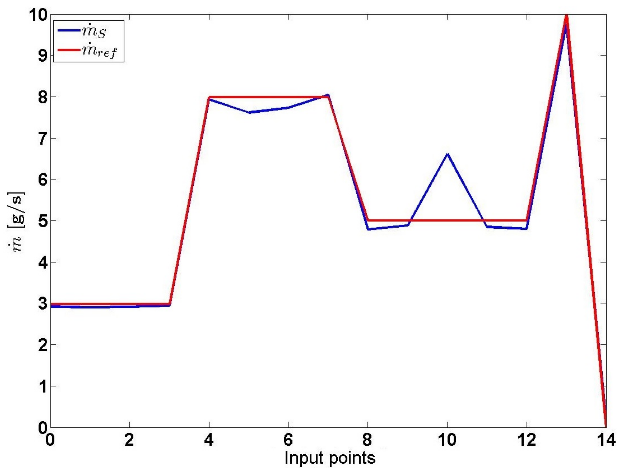

Figure 5. Reference mass flow $\dot{m}_{ref}$ vs estimated mass flow $\dot{m}_S$.

As regard the performance parameters, an overall mean error $\bar{e}$ of 0.9%, and the associated standard deviation σ_e of 9.7% have been observed.

A satisfying agreement between the reference and estimated mass flow is experienced in the whole investigated domain but the for the point 10, where simulation issues, due to the very low pressure value, occurred.

5. CONCLUSIONS

The performance assessment of a virtual flow meter has been presented in the paper. The VFM is composed by actual pressure and temperature transducers and a software module mandated to estimate the desired mass flow; in particular, a case study involving the measurement of helium mass flow in cryogenic environment at CERN has been carried out.

To reduce the experimental burden associated the performance assessment, the attention has been focused on two specific problems: (i) carry out the assessment procedure without requiring to turn off the helium circuit at CERN, and (ii) efficiently investigate the domain of the input parameters. The former problem has been faced by means a fully simulated approach, in which also the cryogenic valve (after a suitable experimental validation) has been included in the simulation model. The latter has been overcome thanks to the adoption of a suitable statistical technique, that made possible to limit the number of input points (equal to 15) to be measured. As performance factors, the mean value $\bar{e}$ and the associated standard deviation σ_e of the differences between nominal and estimated mass flow has been considered; values of $\bar{e}$ and σ_e as low as 0.9% and 9.7% have been experienced.

Ongoing activities are currently focused on the uncertainty analysis of the VFM; at this aim, the combined use of design of experiments and analysis of variance will be exploited to assess the significance of the effect of some relevant configuration and noise parameters on the considered performance factors.

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