ID: 32

A Review of Soft Sensor Methods for Mach number Measurement at LAPAN Supersonic Wind Tunnel

Jefri Abner Hamonangan[1], Sinung Tirtha Pinindriya[1]
[1]Institution/affiliationAeronautics Technology Center, LAPAN
Jl. Raya LAPAN-Rumpin, Desa Sukamulya, Kecamatan Rumpin – Bogor[2,3]Institution/affiliation
Phone: (021) 75790383
e-mail: jefri.abner@lapan.go.id, sinung.tirtha@lapan.go.id

Abstrak – *Wind tunnel is used to provide air flow to an object so that the aerodynamics characteristic of the object can be determined. The given air flow will be varying according to the object working condition. LAPAN Supersonic Wind Tunnel can operate at the speed of 1 – 3.5 Mach. The value of 1 – 3.5 Mach is determined from calculating the measurement of static pressure and stagnation pressure. Sometimes problem occurs when one of the sensor was unavailable to use, this situation can delay the ongoing test in the wind tunnel. The purpose of this paper is to review the soft sensor method to be applied as a backup for the physical sensor.*

Keyword: *Wind Tunnel, Supersonic, Soft Sensor, Pressure Sensor.*

1. Introduction

Wind tunnel is a tool / facility used by researcher to measure or monitor the behavior an object in an air flow. The operation of a wind tunnel is based on testing a reduced-scale model of an aerodynamic object [1]. In wind tunnel testing, air speed, force and moment measurement of the test object is the a few variable researchers need to know.

There are a few type of wind tunnel based on their speed regime [2]:

- Subsonic tunnel (incompressible)	$0 < Ma < 0.25$
- Subsonic tunnel (compressible)	$0.25 < Ma < 0.8$
- Transonic tunnel	$0.8 < Ma < 1.2$
- Supersonic tunnel	$1.2 < Ma < 5$
- Hypersonic tunnel	$5 < Ma$

Ma or Mach is a ratio of velocity at a point in fluid to velocity of sound. Blowdown Supersonic wind tunnels are designed to produce supersonic air speeds for aerodynamic analysis and testing on scaled models under well controlled test conditions [3].

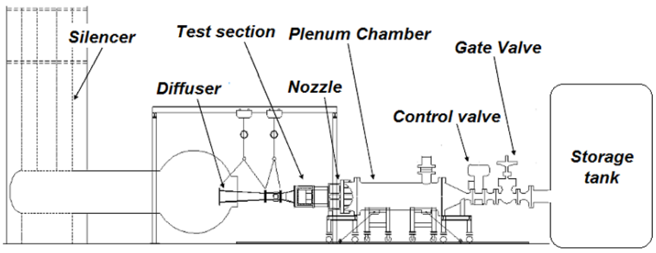

Figure 1. Schematic diagram of a supersonic blowdown wind tunnel

Before starting a wind tunnel test we have to set a few parameters to gain a certain speed, those parameters are pressure of the storage tank and the sliding block. The parameter setting was achieve by calibrating the wind speed to the storage tank pressure and the sliding block setting. But due the open loop tunnel condition, the outside condition (wind, temperature, etc.) can still have a small influence to air speed, so we still need to know the exact speed measurement from the sensors. To measure the air speed in supersonic tunnel we are using 2 pressure sensor, static pressure sensor and total pressure sensor.

For pressure sensor calibration, the data acquisition collects the pressure sensor output in (voltage) as pressure given with the pressure gauge calibrator, and the calibration data have a linear trend [4].

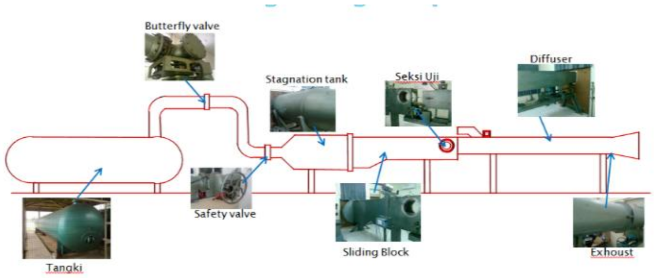

Figure 2. LAPAN Supersonic wind tunnel

In order to measure an air speed, we use the Bernoulli's compressible equation:

$$\frac{P_0}{P} = \left[1 + \frac{\gamma - 1}{2} M^2\right]^{\frac{\gamma}{\gamma - 1}} \quad \text{......................... (1)}$$

Where P_0 is stagnation/total pressure, P is static pressure, γ is ratio of specific gas heat (1.4 for air) and M is Mach number.
From eq 1 we can get:

$$M = \sqrt{\frac{2}{\gamma - 1}\left[\left(\frac{P_0}{P}\right)^{\gamma/(\gamma - 1)} - 1\right]} \quad \text{............................. (2)}$$

Problem occurs when one of the sensors become malfunction, so we can't determine the exact speed measurement. If we can get a replacement sensor the problem is solve, but some time we can't get the replacement or repair the sensor immediately.

2. Soft Sensor

In the last two decades, soft sensors have been increasingly applied in process industry as an alternative to traditional hardware instruments. Soft sensors are inferential estimators, drawing conclusions from process observations when hardware sensors are unavailable or unsuitable; they have an important auxiliary role in sensor validation when performance declines through senescence or fault accumulation [5].

Applications range from oil industry [6], chemical processes [7], metallurgical industry [8]. Typically, they are predictive models based on large amount of data available. In general, one can broadly classify soft sensors in two types, namely, the model driven (white-box models) and data-driven models (black-box models). First-principle models are dependent on a prior mechanical knowledge and thus often unavailable since industrial process are too complicated to analyze, making the mechanical knowledge rather hard-won. The data driven models rely on data modelling techniques and are trained on data collected during the operation of the process [9].

ISBN: 978-602-60581-2-6

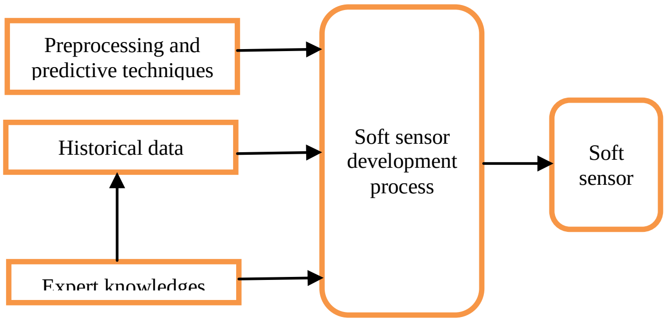

Figure 3. Soft sensor development process

Preprocessing and predictive techniques: The statistical and machine learning techniques for the data processing and for the actual soft sensor.

Historical data: The historical data for the training and parameterization of the preprocessing and the predictive methods.

Expert knowledge: The role of expert knowledge is needed when a case like distinguishing between two different drift discussed or determine a validation of data.

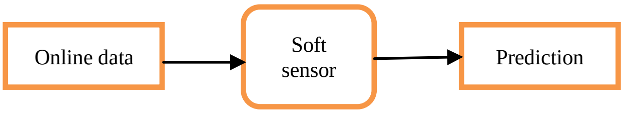

Figure 4. Soft sensor operation

A wide variety of statistical interference techniques and machine learning techniques have been employed in data - driven soft sensors, among which representative examples are principal component system regression (PCR) that incorporates principal component analysis (PCA) with a regression model, partial least square (PLS) regression, support vector machine (SVM) [18], and artificial neural network (ANN) [9]. According to a recent review paper on a recent data based soft sensor, the regression method (PCR) is the most widely used.

3. Soft Sensor Data

2.1. Historical Data

The historical data consist of a number of an input variables, for example, hardware sensor measurement and, one or more target variables. Some time there can be a relevant delay between collecting data measurement, this is cause by the fact that the target variables may have to be obtained in a time consuming manner (e.g. manual evaluation of quality measurement in a laboratory. Nevertheless, for the historical data, it can be assumed that the delays are compensated by entering the target values at the time point of taking the sample for the historical data [10].

2.2. Online / real-time data.

When the soft sensor system finished the model is applied in a real system application and needs to deal with a real data stream. Compare to historical data, online / real time data have a slightly different characteristic.

2.3. Data collection and preprocessing

There are some problems with data collections and preprocessing for soft sensor modelling such as, sampling time, missing data, outliers, working conditions accuracy and so on [11] [19].

2.4. Sampling time

In the majority of problems, the acquisition frequency of easy-to-measure variables is much higher than the acquisition frequency of hard-to-measure variables. In such cases, there is the necessity to synchronize the variables. This problem is usually referred to in the literature as

ISBN: 978-602-60581-2-6

multi rate character, or multiple rate phenomenon [12]. There are two approaches to this problem.

a) Down sample of the easy-to-measure data samples. With this approach in accordance to the slow sampling rate of the hard to measure variables, we exclude the samples of the easy to measure data samples that do not have a corresponding hard to measure (target) value [13].
b) In order to estimate the hard-to-measure variables, low sampling rate variables, a finite impulse response (FIR) model is estimated and applied on the samples.

2.5. Missing data

The problem of missing data occurs when no value is stored for variable in an observation. A possible cause of missing data is related to the transmission of the data between the sensors and the database, errors in the database, problems in accessing the database, etc. [8]. There are two different approach for dealing with missing values (1) single imputation where the missing values are replaced in a single step (using, e.g., mean/median values) and (2) multiple imputation, which are iterative techniques where the several imputations steps are performed.

2.6. Outliers

Outliers are observation values that deviate significantly from the typical, meaningful range of values. Outliers can be caused, for example, by sensor malfunction, communication, errors or sensor degradation [11]. If we're using PLS algorithm, outliers detection and handling plays a critical role in soft sensor development because PLS algorithm are sensitive to outliers in data set [14]. In [14], a multivariate method for online outlier detection was offered. In addition, they also proposed a novel Bayesian approach to differentiate the outliers that represent a process change from those erroneous readings.

4. Data Driven Techniques For Soft Sensor Development

In the data driven techniques there are 3 most common methods for the development of soft sensor, the PCA method, PLS and ANN [13].

4.1 Principal Component Analysis

The PCA algorithm reduces the number of variables by building linear combinations of them. This is done in such a way that these combinations cover the highest possible variance in the input space and are additionally orthogonal to each other. In the context of the process industry data this is a very useful feature because the data there are often co-linear. In this way, the collinearity can be handle and the dimensionality of the input space can be decreased at the same time. The PCA process was able to identify frequency ranges where the inline and vertical cross-axis forces are correlated or uncorrelated to each other [16].

4.2 Partial Least Squares

This algorithm, instead of focusing on the covering of the input space variance, pays attention to the covariance matrix that brings together the input and the output data space. The algorithm decomposes the input and output space simultaneously while keeping the orthogonality constraint. In this way it is assured that the model focuses on the relation between the input and output variables. The two methods differ also in the type of data matrices that are analyzed. Typically, data matrices analyzed by PLSC have a complex and specific structure whereas the data matrices analyzed by PLSR tend to be simple matrices. PLSC is also very versatile and has been adapted to several different situations such as multi-block analysis. PLSR, being an iterative process, requires long computation time which can be prohibitive for some applications with very large data sets [17].

ISBN: 978-602-60581-2-6

4.3 Artificial Neural Networks

The original intention of ANNs was to build computational models motivated by the operation of biological neurons, which are the basic information processing units in nervous systems. The task of both the biological and the artificial neuron is to collect information at the inputs, to process this information and to output it. There is a large variety of computational intelligence models which are more or less biologically plausible and can be summarized under the term artificial neural network. In case of soft sensor, the most commonly applied type of ANN is the MLP's (Multilayer Perceptron) [9]. An MLP is a feed forward ANN that maps sets of input data onto a set of appropriate outputs. It consists of one input layer, one output layer and at least one hidden layer.

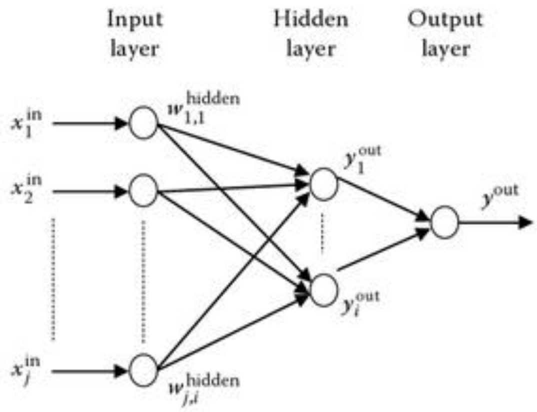

Figure 5. MLP Structure

The role of the input layer is to collect input data and provide it to the hidden layer for further processing. The number of input layer is equivalent to the dimensionality of the input data. The role of hidden units is to collect the signals at their input, that is, the output of preceding layer; multiply them by the connection weights; build a sum of them; and process the using the transfer function g hidden.

$x_i^{hidden}=g^{hidden}\left(\sum_j w_{(j,i)}^{hidden} x_j^{in}\right)$

Where:

x_i^{hidden} = Is the output of the i the hidden unit
$w_{(j,i)}$ = Is the weight between the j the input unit and i is the hidden unit
$g^{hidden}(\ )$ = Is the transfer function of the output neuron
x_j^{in} = Is the j th variable of the input sample

5. Soft Sensor Application

The application of soft sensor can be found across many fields. A few applications of soft sensor are, Online prediction, process monitoring and process fault detection also as a hardware sensor backup [9].

5.1 Online Prediction

Soft sensor for online prediction is use because the prediction of online values cannot be measure online by automated measurements. This may be for technological reason (e.g., there is no available instruments to do the measurements), for economical reason (e.g. the necessary instrument is too expensive). Soft sensor can, in such scenario provide useful information about the values interest and in the case when the soft sensor fulfills given standards, it can also have incorporated in to automated control loop process. Online prediction based on semi-analytic performance prediction techniques as used in physical layer abstraction method [20].

ISBN: 978-602-60581-2-6

5.2 Process monitoring and process fault detection.

Commonly process monitoring technique are based on multivariate statistical techniques like PCA. These measures have, on the one hand, providing information about the contribution of the particular features to a possible violation of the monitoring statistics.

5.3 Hardware sensor backup

Soft sensor can also act as a sensor backup with a tendency of failure or with a requirement of a periodic maintenance. In such situation, to prevent disturbance or delay to the system, soft sensor can be development to replace the unavailability.

6. Conclusion

There is no doubt that soft sensor will have an important role in a process industry and instrumentation. Up until now, soft sensor has been implemented as a backup or as a replacement for the unavailability of physical sensor. From this review, the soft sensor method commonly used as a hardware backup is PCA and PLS. The PCA algorithm reduces the number of variables by building linear combinations of them. In this case (soft sensor for Mach number) only have a few variable, so we think the PLS method is the right method to use. But, this method still must be proven through a series of wind tunnel test.

Contributorship Statements

All authors contributed equally to this work. All authors discussed the result and implications and commented on manuscript at all stages.

References

[1] B. Ilić, M. Milosavljević, J. Isaković, and M. Miloš, "Stagnation Pressure Transient Control in a Supersonic Blowdown Wind Tunnel Test Facility," Materials Today: Proceedings, vol. 3, pp. 987-992, // 2016.

[2] E. Krause, Fluid Mechanics: With Problems and Solutions, and an Aerodynamics Laboratory: Springer, 2005.

[3] A. N. Shahrbabaki, M. Bazazzadeh, A. Shahriari, and M. D. Manshadi, "Intelligent Controller Design for a Blowdown Supersonic Wind Tunnel," International Journal of Control and Automation, vol. 7, 2014.

[4] Jefri Abner H., Prawito, P., Agus Aribowo, A Labview Based Optimization of Supersonic Wind Tunnel Instrumentation Systems, Indonesian Journal of Electrical Engineering and Informatics, Vol. 8 No.2, pp. 353-363, 2020.

[5] L. Fortuna, S. Graziani, A. Rizzo, and M. G. Xibilia, Soft Sensors for Monitoring and Control of Industrial Processes: Springer London, 2007.

[6] B. O. S. Teixeira, W. S. Castro, A. F. Teixeira, and L. A. Aguirre, "Data-driven soft sensor of downhole pressure for a gas-lift oil well," Control Engineering Practice, vol. 22, pp. 34-43, 1// 2014

[7] S. Shokri, M. A. Marvast, M. T. Sadeghi, and S. Narasimhan, "Combination of data rectification techniques and soft sensor model for robust prediction of sulfur content in HDS process," Journal of the Taiwan Institute of Chemical Engineers, vol. 58, pp. 117-126, 1// 2016

[8] Y. G. Li, W. H. Gui, C. H. Yang, and Y. F. Xie, "Soft sensor and expert control for blending and digestion process in alumina metallurgical industry," Journal of Process Control, vol. 23, pp. 1012-1021, 8// 2013.

[9] J. G. Webster and H. Eren, Measurement, Instrumentation, and Sensors Handbook, Second Edition: Electromagnetic, Optical, Radiation, Chemical, and Biomedical Measurement: Taylor & Francis, 2014.

[10] C. Shang, F. Yang, D. Huang, and W. Lyu, "Data-driven soft sensor development based on

deep learning technique," Journal of Process Control, vol. 24, pp. 223-233, 3// 2014.
[11] F. A. A. Souza, R. Araújo, and J. Mendes, "Review of soft sensor methods for regression applications," Chemometrics and Intelligent Laboratory Systems, vol. 152, pp. 69-79, 3/15/ 2016.
[12] Y. Wu and X. Luo, "A novel calibration approach of soft sensor based on multirate data fusion technology," Journal of Process Control, vol. 20, pp. 1252-1260, 12// 2010.
[13] P. Kadlec and B. Gabrys, "Local learning-based adaptive soft sensor for catalyst activation prediction," AIChE Journal, vol. 57, pp. 1288-1301, 2011.
[14] H. J. Galicia, Q. P. He, and J. Wang, "Adaptive Outlier Detection and Classification for Online Soft Sensor Update," IFAC Proceedings Volumes, vol. 45, pp. 402-407, // 2012.
[15] P. Kadlec, B. Gabrys, and S. Strandt, "Data-driven Soft Sensors in the process industry," Computers & Chemical Engineering, vol. 33, pp. 795-814, 4/21/ 2009.
[16] Ya Huang, Neil Ferguson, Principal component analysis of the cross-axis apparent mass nonlinearity during whole-body vibration, Mechanical systems and signal processing, 2020.
[17] Anjali Krishnan, L. J. Williams, Anthony R. McIntosh, Herve Abdi, Partial Least Squares Methods: Partial Least Squares Correlation and Partial Least Square Regression, Journal Neuroimage, 2010.
[18] Alberto Munoz, Javier M. Moguerza, Gabriel Martos, Support Vector Machines, Wiley Statsref: Statistics Reference Online, 2019.
[19] Uma K., M. Hanumanthapa, Data Collection Methods and Data Pre-processing Techniques for Healthcare Data Using Data Mining, International Journal of Scientific & Engineering Research, Vol. 8 Issue 6, 2017.
[20] Serdar Sahin, Antonio M. Cipriano, et.al, Iterative Decision Feedback Equalization Using Online Prediction, IEEE Access, 2019.