Development of a soft sensor for indirect temperature measurement in a coffee machine

G. Cosoli, P. Chiariotti, M. Martarelli, S. Foglia, M. Parrini, E.P. Tomasini

Abstract—**Sometimes in control processes it would be necessary to know variables at locations that are barely accessible. In such cases, soft sensors (also known as "virtual sensors") could really help. In fact, they are powerful instruments for the indirect measure of quantities that would not be measurable, if not with the installation of physical sensors that could perturbate the normal working conditions of the system under test. In this paper, the authors describe an approach to indirectly measure temperature values in a brew group of a professional coffee machine. A Finite Element (FE) model simulating both the fluid dynamics and the thermal distribution on the group was developed and validated by dedicated experimental tests. The FE model was then exploited to feed an autoregressive exogenous model (ARX model) linking the temperature in the boiler (i.e. a quantity ordinarily assessed in the coffee machine) and the one near the water output, where otherwise a hardware sensor would compromise the correct coffee brewing process and the safety/quality of the brewed coffee. The obtained data-driven soft sensor can help to improve the control unit architecture of the coffee machine.**

Index Terms—**Autoregressive exogenous model, Data-driven models, Numerical simulation, Soft sensor, System identification, Temperature sensors**

I. Introduction

The main objective of a soft (or virtual) sensor is to estimate unavailable quantities based on other available measurements. In the last three decades, soft sensors have gained more and more popularity in many industrial applications, since they have become very efficient and powerful tools, able to substitute hardware (i.e. physical) sensors when the targeted monitoring variable is not easily accessible or is measurable only expensively or with significant delays with respect to the timing requested [1]–[3]. Therefore, soft sensors represent a valuable alternative to traditional means for the acquisition of critical variables and, consequently, for process monitoring in general [4].

They were born in the field of process control, but nowadays their application has widely broadened in different areas: biomedical engineering [5]–[7], automotive [8], industrial applications [9]–[11], structural health monitoring [12]–[14], building energy efficiency and thermal comfort [15], smartphone applications [16] and even agriculture [17]–[19].

Virtual sensors base their functioning on the estimation of an analytical model depending on the data collected by means of physical sensors, or, alternatively, provided by numerical models (e.g. Finite Element Models); the second option can accelerate the training phase of the analytical model in absence of experimental data. This is a fundamental aspect, for example in industrial applications of neural networks [20]. The model representing the system that receives and processes the input data can be obtained with different system identification techniques. Among others, Neural Networks (very efficient in combining, as inputs, quantities from different sensors for estimating variables not directly measurable [21]), genetic algorithms (making it possible to estimate fast and accurate models useful also in the field of virtual sensing [22]), transfer functions, multi-state-dependent parameter models, polynomial models, represent valid options for the purpose. The accuracy of the model is fundamental in order to obtain reliable output from the soft sensor.

In this paper, the authors want to describe the experimental and numerical studies which have allowed them to develop a "soft sensor" able to indirectly measure the temperature value of water used for coffee brewing in a commercial coffee machine produced by Nuova Simonelli. The target point is close to the hydraulic circuit outlet, scarcely accessible with physical sensors in a non-intrusive way. Even tough temperature is an extremely important parameter to obtain a perfect coffee, commercial and professional coffee machines do not have many temperature measuring devices integrated in their architecture, because the presence of physical sensors can easily compromise the correct functioning of the machine, e.g. by modifying the normal fluid dynamics of the system, and alter the flavor/safety of the coffee itself (because of releasing issues). At present, the control of temperature is made indirectly by means of a sensor positioned on a metal part of the coffee machine, that entails a heat transmission delay between metal

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and water. Indeed, inserting a temperature gauge (e.g. a thermocouple) in correspondence of the flow output would modify the flow conditions themselves, which is evidently undesirable, as well could cause unwanted release of particles (e.g. increasing the content of heavy metals in coffee). On the other hand, knowing the temperature of the water exiting the hydraulic circuit of the brew group would make it possible to verify that it is in the optimal temperature range for the coffee brewing according to the producers' requirements, without the necessity to have hardware sensors installed in the water circuit. In general, the accuracy of temperature regulation needed for a coffee machine is generally equal to ±1°C.

The authors' idea was to develop a virtual sensor starting from temperature measurements ordinarily made by means of the coffee machine integrated sensors in correspondence of the boiler. A FE model is necessary to produce temperature data in different points of the brew group, which are scarcely accessible in operational conditions. In this way, after having validated the numerical model itself (by means of measurements made with temperature gauges specifically installed on the brew group that are not present in commercial machines), it is possible to generate data for developing the analytical model constituting the soft sensor.

At first, the coffee machine group head (sometimes referred to as "brew group" or "brew head" or simply "group") has been experimentally characterized in terms of temperature distribution in space and time. Then, a numerical model has been realized and validated by means of experimental data thus collected. Thanks to the numerical results, it has been possible to obtain temperature distributions also in points commonly not accessible/accessible with difficulty, so that an analytical model has been derived according to system identification theory by means of a linear ARX (Auto-regressive with eXogenous input) model. This represents an innovative indirect method for the temperature measurement on the brew group, in order to improve the machine control ability and to maximize its efficiency thanks to the soft-sensing abilities.

Such a model could be integrated in the control unit of the coffee machine, so improving its performance and allowing a deeper control of the coffee brewing process itself, without the need of adding physical sensors to the machine hardware.

II. Materials and Methods

In order to realize an analytical model able to predict the temperature in the points of interest, the model itself has to be trained by means of data (for this reason, we often talk about "data-driven models"). There are two possibilities: to use experimental or numerical data. The second choice is preferable in case of points scarcely accessible or when hardware sensors could affect the normal mode of operation of the system under test.

TABLE I
Accuracy of Thermocouples Type T, Class I, according to the IEC 60 584-2:1995.

Thermocouple Type T	Class I (°C)
Temperature	$-40 \leq T \leq 125$
Tolerance	± 0.5
Temperature	$125 \leq T \leq 350$
Tolerance	± 0.004*|T|

"T" stands for "temperature".

A. Experimental Characterization

To measure the temperature distribution in the brew group of the coffee machine, thermocouples of Type T, Class I were used. Their accuracy values, according to the IEC 60584 [23] are reported in Table I.

Both water and metal temperature values were acquired, according to the sensor positioning reported in Table II.

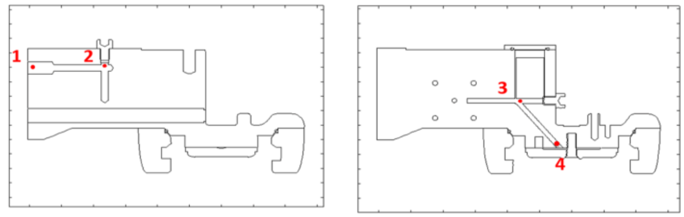

Fig. 1. Thermocouples positioning in the water circuit: Point 1 is near the water entry, Point 2 close to the top cap (on the picture on the left), Point 3 is near the front cap and Point 4 inside the portafilter.

Temperature signals were acquired by means of a DAQ system (34980A multifunction switch/measure unit, Agilent [24]).

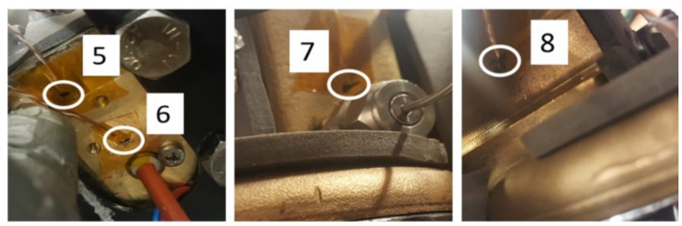

Fig. 2. Thermocouples positioning on the brew group metal surface: two on the back side (labelled as "5" and "6", on the left of the picture), one on the right side (labelled as "7", on the centre of the picture) and one on the left side labelled as "8", on the right of the picture.

TABLE II
Thermocouple Sensors Positioning.

Sensor	Location	Notes
3 thermocouples in the hydraulic circuit	Near the water entry, close to the top and the front caps (because of the easy access to these locations)	Labels 1, 2 and 3 in Fig. 1
1 thermocouple on metal	Integrated in the portafilter (which, however, is just outside the water circuit)	Label 4 in Fig. 1
1 thermoresistance PT100	On the top of the brew group	Supplied with the coffee machine
1 thermocouple	Immersed in the boiler	-
5 thermocouples	On the brew group metal surface: 2 on the back side (near the water input point and close to the cartridge heater), on the right and on the left sides	Fastened by means of specific high temperature tape; labels "5" and "6" in Fig. 2 (left) for the back side, "7" and "8" (centre and right, respectively) for right and left sides

Moreover, power supplied by the cartridge heater was measured by means of a Power Analyzer (Precision Power Analyzer WT3000, Yokogawa [25]). The sampling frequency was equal to 2 Hz for temperature measurement, to 20 Hz for power measurement.

Finally, also the logical signal of the static relay controlling the power supply of the cartridge heater was acquired by means of another DAQ (NI6008, National Instruments [26]).

B. Numerical Characterization

The numerical model of the brew group was realized in COMSOL Multiphysics [27]. The geometry was imported in .stl format as provided by Nuova Simonelli; it includes the group head, the group ring seat, the solenoid valve and the hydraulic circuit, as described in Fig. 3 and Fig. 4.

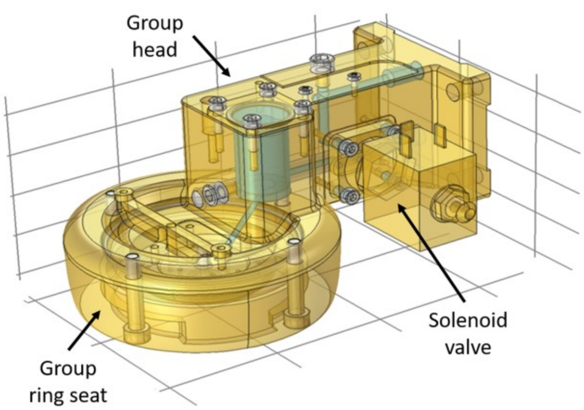

Fig. 3. Geometry of the numerical FEM model; it consists of the brew group itself (the "group head"), the group ring side (to which the portafilter can be attached), the hydraulic circuit and the solenoid valve (which allows - or not - the water flow).

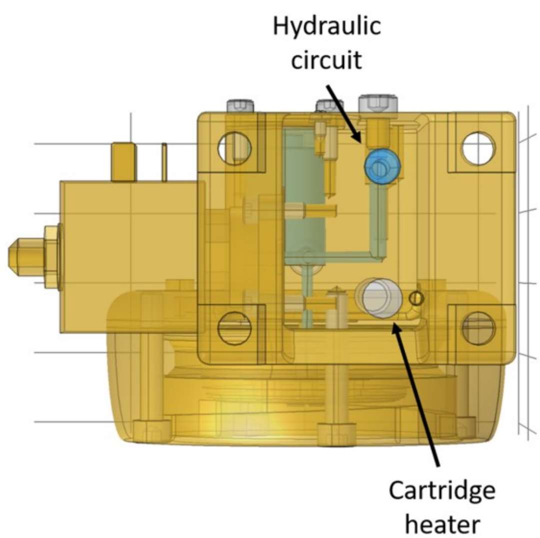

Fig. 4. Geometry of the model - back view; it is possible to note the water input in the hydraulic circuit, as well as the cartridge heater.

The materials used for the model domains are reported in Table III.

Both thermal and fluid dynamics aspects of the brewing phenomenon were simulated, thanks to interface "Conjugate Heat Transfer", including the "Laminar Flow" interface (the flow inside the hydraulic circuit of the brew group can be considered laminar, given the pipe diameter, the flow velocity and the water properties). This interface solves the continuity (1) and momentum (2) equations (i.e. the Navier-Stokes equation, which represents the conservation of momentum) [28]:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho u) = 0 \tag{1}$$

$$\rho \frac{\partial u}{\partial t} + \rho u \cdot \nabla u = -\nabla p + \nabla \cdot \tau + F \tag{2}$$

where:
- ρ is the density (kg/m^3);
- u is the flow velocity (m/s);
- p is the pressure (Pa);
- F is the body force vector [N/m^3];
- τ is the viscous stress tensor (Pa), which is defined in Equation (3), where μ [Pa*s] is the dynamic viscosity, I is the identity matrix and the apex ^{T} stands for "transposed" [28]:

$$\tau = \mu(\nabla u + (\nabla u)^T) - \frac{2}{3}\mu(\nabla \cdot u)I \tag{3}$$

In addition, also the heat equation (4) [28] is solved:

$$\rho C_p \left(\frac{\partial T}{\partial t} + u \cdot \nabla T\right) + \nabla \cdot (q + q_r) = \alpha_p T \left(\frac{\partial p}{\partial t} + u \cdot \nabla p\right) + \tau : \nabla u + Q \tag{4}$$

where:
- C_p is the specific heat capacity at constant pressure (J/(kg·K));
- T is the absolute temperature (K);
- q is the heat flux by conduction (W/m^2);
- q_r is the heat flux by radiation (W/m^2);
- α_p is the coefficient of thermal expansion (1/K);
- Q contains heat sources other than viscous heating (W/m^3).

With regard to the fluid dynamics part, the inputs to the model were the input velocity and the outlet condition (i.e. atmospheric pressure) on the hydraulic circuit; the input velocity was derived from the measured values of flow rate and pipe section. On the other side, i.e. for the thermal section, the inputs to the model were the temperature of the input water, the initial temperature values of water and metal domains and the heating power for the cartridge heater. These values were derived from experimental measurements, as described in the previous section.

The results from this kind of simulation allow to achieve a

TABLE III
MODEL MATERIALS AND THEIR THERMAL PROPERTIES: DENSITY (kg/m3), THERMAL CONDUCTIVITY [W/(m*K)] AND SPECIFIC HEAT (J/(kg*K)).

Material	Location	ρ (kg/m^3)	k (W/(m·K))	C_p (J/(kg·K))
Water	Hydraulic circuit	Already provided in COMSOL Multiphysics materials database depending on temperature and pressure		
Brass OT57	Brew group	8400	120	375
Steel AISI 304	Cartridge heater, screws	8000	16.2	500

mapping of temperature, which is very difficult to obtain by means of physical sensors [29].

C. *ARX Model*

System Identification Toolbox™ in MATLAB® [30] environment was used for a grey-box system identification, starting from input-output data. In particular, the system dynamics was represented by means of a linear ARX model, which is a polynomial model, estimated using time domain data.

Input data could be both experimental and numerical ones. We exploited numerical data because the target point is barely accessible and we do not want to alter the normal operating conditions of the machine. The ARX approach (already used in literature for temperature modelling [31], [32]) was thus used on numerically generated data (from the FE model described in the previous section) to obtain a relationship between the output temperature (i.e. temperature at Point 3) and the setpoint temperature (i.e. the one set in the boiler). This approach was chosen both for its low computational cost and for its better accuracy with respect to different polynomial models, as it is reported in Table IV.

Equation (5) characterizes the simplified model [33]:

$$A(z)y(t) = B(z)u(t) + e(t) \tag{5}$$

where:

- $A(z) = a_0 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3} + a_4 z^{-4}$;
- $B(z) = b_1 z^{-1}$;
- $y(t)$ = temperature on Point 3 (i.e. data obtained from simulation);
- $u(t)$ = input temperature (i.e. boiler setpoint).

In these equations, z^{-1} is the backward shift operator that compactly represents time difference equations, as described in Equation (6):

$$z^{-1}u(t) = u(t-1) \tag{6}$$

This polynomial model was then validated by experimentally measuring the temperature on the point of interest (i.e. Point 3).

Six different temperature setpoints was considered for the boiler, starting from the value most commonly used in practice (T_b) and considering lower temperatures (in a range of 10°C, with a 2°C-step). Simulations with these different temperatures were run for generating data targeted to the training of the ARX model in correspondence of different inputs (i.e. different boiler setpoint values).

TABLE IV
DIFFERENT POLYNOMIAL MODELS AND THEIR ACCURACY

Model	Accuracy
ARX (Autoregressive exogenous model)	93.62
BJ (Box-Jenkins polynomial model)	92.65
AMX (Autoregressive–moving-average model)	82.63
OE (Output-Error polynomial model)	76.89

III. RESULTS

In this section, the results related to experimental measurements on the coffee machine brew group, the numerical results from the FE model and the ARX model obtained from the system identification procedure are discussed. Data are provided in terms of relative temperature values. Absolute temperature values cannot be exposed for confidentiality issues. However, the whole approach still holds.

A. *Experimental Characterization*

The parameters of interest extracted for the simulation are the following ones:

1) Temperature of the input water;
2) Initial temperature of the metal (obtained from the temperature value measured by the coffee machine integrated thermoresistance);
3) Velocity of the input flow (derived by flow rate and section);
4) Heating power (mean value measured during the coffee brewing operation).

The comparison point between experimental and numerical results is Point 3, which is the point of greatest concern. This is the point in which sensor mounting accuracy is the highest. Indeed, Point 4 suffered of mounting uncertainty: it should have been mounted inside the water circuit but it turn out to be external. On the contrary, Point 4 on the FE model was kept inside the water domain. This choice was adopted on purpose, to guarantee the presence of a terminal control point on the circuit.

The parameters that were evaluated for the model validation are the following ones:

1) Lowest temperature;
2) Highest temperature;
3) Heating time in correspondence of Point 3 (up to the desired temperature, labelled as "T_d").

An example of the measurements made is reported in Fig. 5 and in Fig. 6, with regard to temperature (in water) and power measurements, respectively. It is possible to observe that the target temperature is reached on point 3 after approximately 2 s after the start of brewing operation. Indeed, the initial decrease is due to the cooling effect taking place when water flows in the hydraulic circuitry.

The temperature values measured on the metal surface resulted to be not very useful for the simulation, since in the FE model we are interested on the temperature in the canal surface, which is higher than the superficial one. The same for the temperature measured in the boiler, since it is lower than that measured in Point 1 (maybe because of the cooling in the tube connecting the boiler and the hydraulic circuit of the brew group).

With regard to the logical signal measured on the relay controlling the cartridge heater, it was noted that reproducing this trend in simulation, we did not obtain a sufficient heating of water: probably, in real conditions, the thermal inertia of the group makes the cartridge not to cool down rapidly when the relay is OFF. To evaluate the magnitude of the controlling effect on the heater switching on, experimental measurements

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were carried out in two different conditions:
1) cartridge heater always supplied by the power grid during the coffee brewing;
2) cartridge heater supplied under the control unit action.

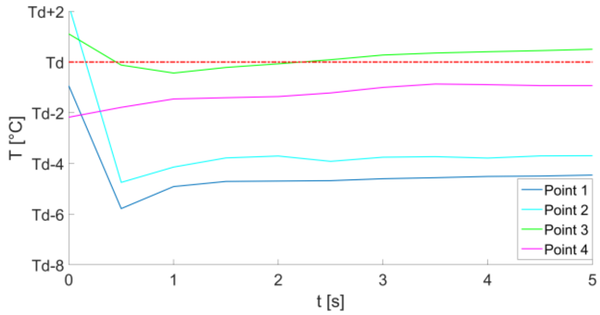

Fig. 5. Example of temperature measurements in water circuit; T_d indicates the desired value of temperature for output water. Being Point 4 not comparable between experimental and numerical conditions (since in the first case it is outside the hydraulic circuit, while in the FEM model it is inside the water domain), the point of greatest concern is Point 3.

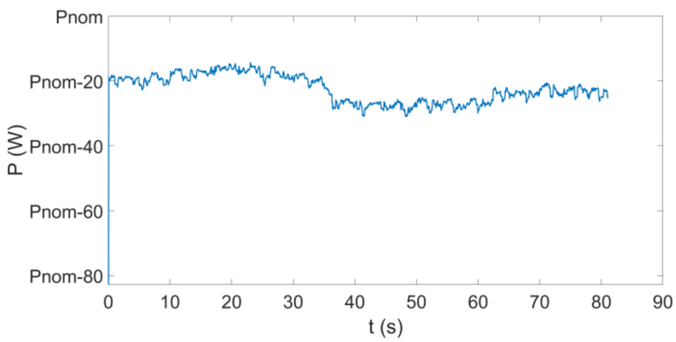

Fig. 6. Example of power measurement during coffee brew (P_{nom} indicates the nominal value of the power supplied by the cartridge heater); in this test, the cartridge heater was powered in a continuous way during the brewing (without the action of the control unit).

In particular, a comparison was made between a measurement carried out in the former case and a curve averaged on 5 measurements made under the control unit action. The results with control unit acting and with continuous cartridge heater supply are reported in Fig. 7 and Fig. 8, respectively.

The results show similar trends, so that in simulation, for sake of simplicity, we considered a continuous power source of the cartridge heater (i.e. cartridge heater always switched on during the coffee brewing phase).

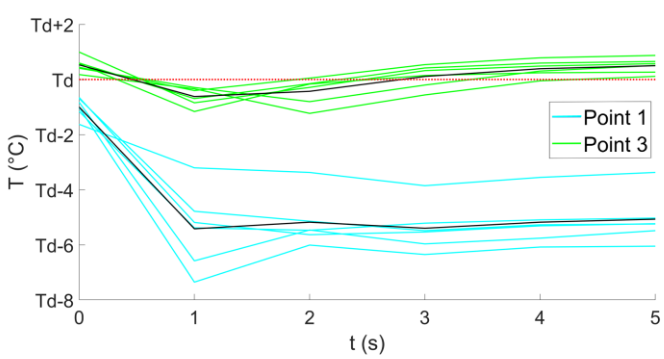

Fig. 7. Temperature measurements with cartridge heater supplied under the action of control unit; the curve averaged on 5 measurements is drawn in black.

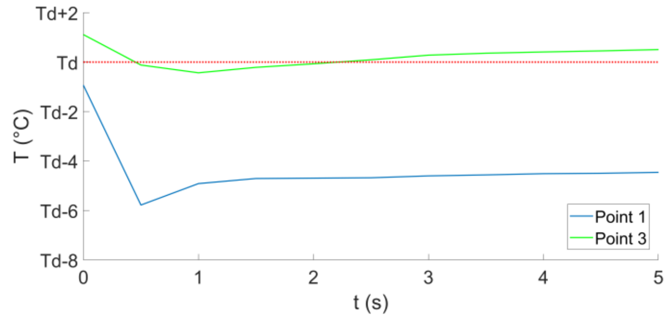

Fig. 8. Temperature measurements with continuous power source of the cartridge heater.

B. *Numerical Characterization*

The initial conditions for the FE model were set as follows:
1) Initial temperature of water: the highest temperature measured by the thermocouples immersed in water (Points 1-3);
2) Initial temperature of metal: it is obtained by means of parametric studies starting from the measurement carried out by the thermoresistance integrated in the machine;
3) Temperature of the input water: lowest temperature measured for the input water (i.e. Point 1).

The model obtained was experimentally validated by comparing the results on Point 3, which is the one closest to the hydraulic circuit outlet, since, as previously said, Point 4 is not comparable between experimental and numerical setups.

The results obtained from the FE model validation are good, especially if we consider the temperature measured on Point 3, which is the most interesting one. The comparison between experimental and numerical results can be observed in Fig. 9 in terms of deviations in correspondence of Point 3, which is the one of greatest interest.

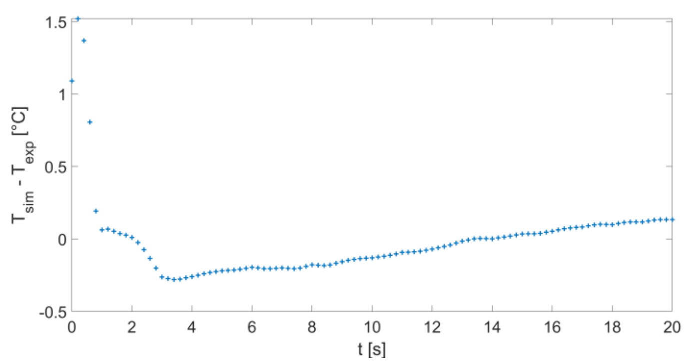

Fig. 9. Model validation – deviations between simulated (i.e. data from FE model) and experimental temperature values in the point of interest (i.e. Point 3).

With regard to Point 3 (i.e. the point of major concern), the deviations between simulated (T_{sim}) and experimental (T_{exp}) data at the maximum and minimum temperature are 0.1°C and 0°C, respectively. The intercept value with the horizontal line representing the desired temperature for water (T_d) is equal to 1.95 s, both in simulated and experimental data.

It is worth to note how, slightly varying the position of thermocouple junction in Point 2 (as described in Fig. 10), the effect on temperature is significant, as it can be noted in Fig.

11.

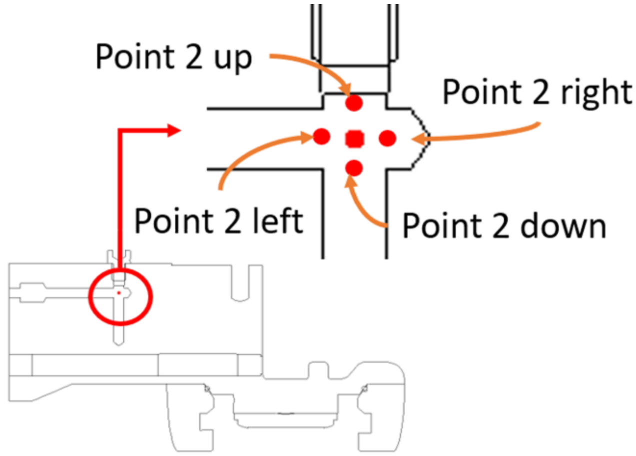

Fig. 10. Different positioning of thermocouple junction in Point 2; thanks to numerical simulation, the authors investigated the effect of a slight change of the thermocouple junction position around the nominal location (i.e. the perfectly centered one).

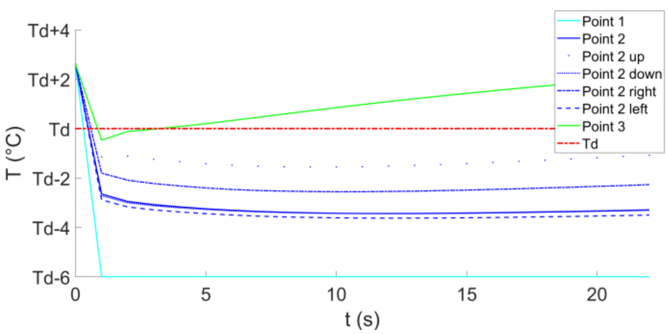

Fig. 11. Effect of different positions of thermocouple junction in Point 2 on temperature measurement; results on Point 2 with the different positioning of the thermocouple junction are reported in blue.

In particular:

1) Temperature in Point 2, up: approximately equal to 2°C hotter than temperature in Point 2;

2) Temperature in Point 2, down: approximately equal to Temperature in Point 2;

3) Temperature in Point 2, right: approximately equal to 1°C hotter than temperature in Point 2;

4) Temperature in Point 2, left: approximately equal to 0,2°C colder than temperature in Point 2.

C. *ARX Model*

The numerical results used to feed the ARX model are reported in Fig. 12.

The results of ARX model identification, reported in terms of polynomial coefficients given for the different input values analyzed are reported in Table V.

The validation of the model with experimental data was made for the typical temperature set point value of the boiler, i.e. T_b. It resulted that, in the working conditions of the coffee machine, the model accuracy is equal to 93.62%; the comparison between the model output and the experimental data in these conditions is reported in Fig. 13. It is possible to notice that ARX model output fits experimental data very well. Also FE method provides a similar trend and the minimum temperature is coincident in the three curves.

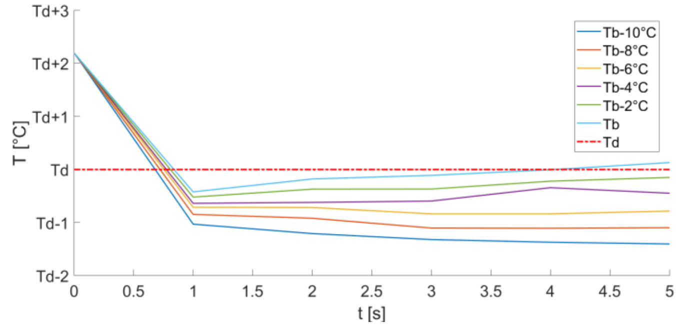

Fig. 12. Numerical results obtained with different boiler setpoint values (T_b is the commonly used value); these are the data feeding the ARX model for the system identification.

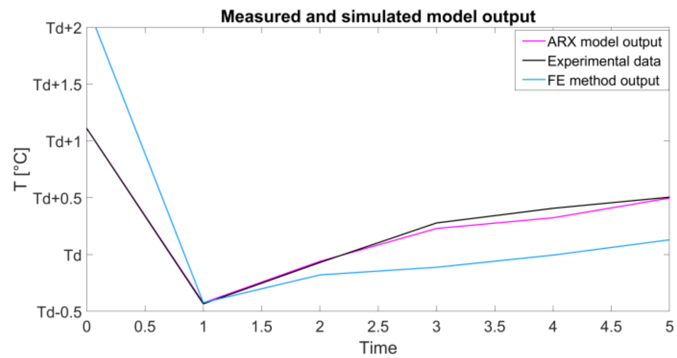

Fig. 13. Model validation for boiler setpoint = T_b. The accuracy in this conditions is approximately equal to 93.62%.

With regard to the uncertainty of the virtual sensor, Monte Carlo analysis was carried out in order to evaluate the system uncertainty. The computed ARX model was run for 10^7 times giving as input a Gaussian distribution of the boiler temperature (considering a standard deviation of 1°C), centered on its setpoint, and evaluating its output in correspondence of the time instant on which the output temperature reaches the target value T_d. the distributions of input and output temperature are reported in Fig. 14. The standard deviation obtained was equal to 0.07, which turns out in an extended uncertainty of 0.14°C if considering a coverage factor k=2. Considering the time needed to reach the target temperature, the Monte Carlo simulation provides a distribution with a mean value of 2.18 s and a standard deviation of 0.37 s.

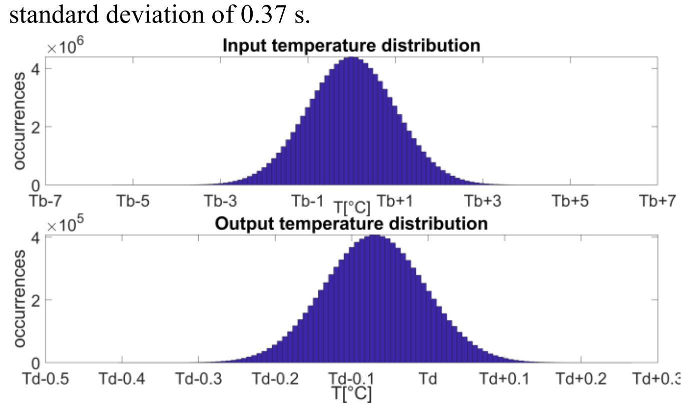

Fig. 14. Input (top) and output (bottom) temperature distributions of Monte Carlo simulation; T_b is the typical value for the temperature setpoint in the coffee machine boiler, while T_d is the desired temperature in Point 3.

TABLE V
ARX MODEL COEFFICIENTS FOR DIFFERENT INPUT TEMPERATURE VALUES - T_B IS THE TYPICAL TEMPERATURE SET IN THE BOILER

T_{input} (°C)	Coefficients					
	a_0	a_1	a_2	a_3	a_4	b_1
T_b-10	1	-0.971	-0.342	0.364	-0.003	0.059
T_b-8	1	-1.785	-0.800	0.035	-0.043	0.009
T_b-6	1	-0.626	-0.481	0.100	0.038	0.036
T_b-4	1	-0.372	-0.259	-0.338	-0.058	-0.028
T_b-2	1	-1.039	-0.094	0.164	-0.016	0.018
T_b	1	-0.725	-0.440	0.172	0.026	0.038

a_i (i = 1, 2, 3, 4) and b_1 are the ARX model coefficients according to Equation (5). T_b is the typical value for the temperature setpoint in the coffee machine boiler.

IV. DISCUSSION AND CONCLUSIONS

In this paper, the authors present the experimental and numerical studies that brought to the development of a soft sensor enabling temperature measurement in the brew group of a professional coffee machine in correspondence of a point close to the water exit. This location is barely accessible in a coffee machine (both professional and for home use); moreover, the presence of a physical sensor (e.g. a thermocouple junction) would compromise the normal flow conditions as well as alter the safety/flavor of the coffee brewed. A numerical FE model, which was validated by means of experimental data (acquired with temperature sensors installed in the group specifically for this objective), was exploited to generate data for feeding an ARX model constituting the core of the virtual sensor developed. In this way, it is possible to indirectly measure the temperature value on a point otherwise not accessible. This information can be useful for better tuning the brewing machine temperature range to the one required by the specific type of coffee. In correspondence of the normal operation conditions of the coffee machine, the accuracy of the ARX model is approximately equal to 93.62%, with an associated expanded uncertainty equal to 0.14°C (k=2) if an input temperature standard deviation of 1°C is considered; this is fundamental for the soft sensor functioning, since it allows the operator to obtain reliable data. Knowing the temperature of water at the outlet of the hydraulic circuit is of key importance for ensuring that the brewing operation does not alter the flavor of coffee. Moreover, such a single input-single output model could be easily integrated in the control unit of the coffee machine, thus guaranteeing a better control of the whole brewing process as well as benefits in terms of energy efficiency. Indeed, the whole approach is general enough to be repeated for obtaining temperature data also in different points with respect to the one considered in this paper, in case they would be of concern.

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REFERENCES

[1] L. Fortuna, S. Graziani, A. Rizzo, and M. G. Xibilia, "Soft Sensors for Monitoring and Control of Industrial Processes," Springer Science & Business Media, 2007.
[2] P. Albertos and G. C. Goodwin, "Virtual sensors for control applications," *Annu. Rev. Control*, vol. 26, no. 1, pp. 101–112, Jan. 2002.
[3] Y. Dote and S. J. Ovaska, "Industrial applications of soft computing: a review," *Proc. IEEE*, vol. 89, no. 9, pp. 1243–1265, Sep. 2001.
[4] P. Kadlec, B. Gabrys, and S. Strandt, "Data-driven Soft Sensors in the process industry," *Comput. Chem. Eng.*, vol. 33, no. 4, pp. 795–814, Apr. 2009.
[5] K. de O. A. de Moura and A. Balbinot, "Virtual Sensor of Surface Electromyography in a New Extensive Fault-Tolerant Classification System," *Sensors*, vol. 18, no. 5, May 2018.
[6] K. Liu, Y. Inoue, and K. Shibata, "Physical sensor difference-based method and virtual sensor difference-based method for visual and quantitative estimation of lower limb 3D gait posture using accelerometers and magnetometers," *Comput. Methods Biomech. Biomed. Engin.*, vol. 15, no. 2, pp. 203–210, 2012.
[7] N. Raveendranathan *et al.*, "From Modeling to Implementation of Virtual Sensors in Body Sensor Networks," *IEEE Sens. J.*, vol. 12, no. 3, pp. 583–593, Mar. 2012.
[8] Q. Ahmed, A. I. Bhatti, and M. Iqbal, "Virtual Sensors for Automotive Engine Sensors Fault Diagnosis in Second-Order Sliding Modes," *IEEE Sens. J.*, vol. 11, no. 9, pp. 1832–1840, Sep. 2011.
[9] B. Bidar, F. Shahraki, J. Sadeghi, and M. M. Khalilipour, "Soft Sensor Modeling Based on Multi-State-Dependent Parameter Models and Application for Quality Monitoring in Industrial Sulfur Recovery Process," *IEEE Sens. J.*, vol. 18, no. 11, pp. 4583–4591, Jun. 2018.
[10] X. Yuan, Z. Ge, Z. Song, Y. Wang, C. Yang, and H. Zhang, "Soft Sensor Modeling of Nonlinear Industrial Processes Based on Weighted Probabilistic Projection Regression," *IEEE Trans. Instrum. Meas.*, vol. 66, no. 4, pp. 837–845, Apr. 2017.
[11] L. Simoni et al., "On the use of a temperature based friction model for a virtual force sensor in industrial robot manipulators," presented at the IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, 2018, pp. 1–6.
[12] F. Heidtmann and D. Soffker, "Virtual Sensors for Diagnosis and Prognosis Purposes in the Context of Elastic Mechanical Structures," *IEEE Sens. J.*, vol. 9, no. 11, pp. 1577–1588, Nov. 2009.
[13] J. Kullaa, "Development of virtual sensors to increase the sensitivity to damage," *Procedia Eng.*, vol. 199, pp. 1937–1942, Jan. 2017.
[14] T. Schumacher and A. Shariati, "Monitoring of structures and mechanical systems using virtual visual sensors for video analysis: Fundamental concept and proof of feasibility," *Sens. Switz.*, vol. 13, no. 12, pp. 16551–16564, 2013.
[15] J. Ploennigs, A. Ahmed, B. Hensel, P. Stack, and K. Menzel, "Virtual sensors for estimation of energy consumption and thermal comfort in buildings with underfloor heating," *Adv. Eng. Inform.*, vol. 25, no. 4, pp. 688–698, Oct. 2011.
[16] C. Crema, A. Depari, A. Flammini, E. Sisinni, A. Vezzoli, and P. Bellagente, "Virtual Respiratory Rate Sensors: An Example of A Smartphone-Based Integrated and Multiparametric mHealth Gateway," *IEEE Trans. Instrum. Meas.*, vol. 66, no. 9, pp. 2456–2463, Sep. 2017.
[17] J. A. Sánchez-Molina, F. Rodríguez, J. L. Guzmán, and J. A. Ramírez-Arias, "Water content virtual sensor for tomatoes in coconut coir substrate for irrigation control design," *Agric. Water Manag.*, vol. 151, pp. 114–125, Mar. 2015.
[18] C. H. Guzmán *et al.*, "Implementation of virtual sensors for monitoring temperature in greenhouses using CFD and control," *Sens. Switz.*, vol. 19, no. 1, 2019.
[19] J. . Sánchez, F. Rodríguez, J. L. Guzmán, and M. R. Arahal, "Virtual sensors for designing irrigation controllers in greenhouses," *Sens. Switz.*, vol. 12, no. 11, pp. 15244–15266, 2012.
[20] P. Castellini and G. M. Revel, "An Experimental Technique for Structural Diagnostic Based on Laser Vibrometry and Neural Networks," *Shock and Vibration*, vol. 7, no. 6, pp.381-397, 2000.
[21] G. R. C. Possetti *et al.*, "Optical-Ultrasonic Heterogeneous Sensor Based on Soft-Computing Models," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 9, pp. 2338–2346, Sep. 2015.
[22] E. Copertaro, P. Chiariotti, A. A. E. Donoso, N. Paone, B. Peters, and G. M. Revel, "XDEM for Tuning Lumped Models of Thermochemical

Processes Involving Materials in the Powder State," *Eng. J.*, vol. 20, no. 5, pp. 187–201, Nov. 2016.
[23] Thermocouples - Part 1: EMF specifications and tolerances, IEC 60584-1:2013, 2013.
[24] 34980A Multifunction Switch/Measure Unit, Keysight (formerly Agilent's Electronic Measurement)'.
[25] WT3000 - High accuracy. Yokogawa Test & Measurement Corporation, www.tmi.yokogawa.com.
[26] USB-6008, National Instruments, www.ni.com.
[27] *COMSOL Multiphysics*® v. 5.2, COMSOL AB, Stockholm, Sweden, www.comsol.com.
[28] P. A. Nikrityuk, "Computational Thermo-Fluid Dynamics: In Materials Science and Engineering," John Wiley & Sons, 2011.
[29] H. P. Ho, K. C. Lo, and S. Y. Wu, "A scanning thermocouple probe for temperature mapping", *IEEE Trans. Instrum. Meas.*, vol. 50, no. 5, pp. 1167–1170, Oct. 2001.
[30] MATLAB R2018b, MATLAB - MathWorks, www.mathworks.com.
[31] G. J. Ríos-Moreno, M. Trejo-Perea, R. Castañeda-Miranda, V. M. Hernández-Guzmán, and G. Herrera-Ruiz, "Modelling temperature in intelligent buildings by means of autoregressive models", *Autom. Constr.*, vol. 16, no. 5, pp. 713–722, Aug. 2007.
[32] T. Loussouarn, D. Maillet, B. Remy, V. Schick, and D. Dan, "Indirect measurement of temperature inside a furnace, ARX model identification," *J. Phys. Conf. Ser.*, vol. 1047, no. 1, p. 012006, 2018.
[33] H. Garnier and L. Wang, "Identification of Continuous-time Models from Sampled Data," Springer Science & Business Media, 2008.

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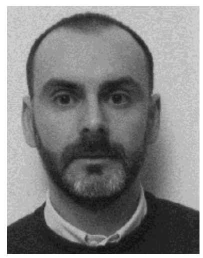

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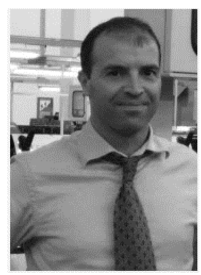

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