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Methodology for sensor calibration in agro-industrial facilities

Alberto Barbaresi
Dep. of Agricultural and Food Sciences
University of Bologna
Bologna, Italy
alberto.babaresi@unibo.it

Mattia Ceccarelli
Dep. of Agricultural and Food Sciences
University of Bologna
Bologna, Italy
mattia.ceccarelli5@unibo.it

Miki Agrusti
Dep. of Agricultural and Food Sciences
University of Bologna
Bologna, Italy
miki.agrusti@unibo.it

Marco Bovo
Dep. of Agricultural and Food Sciences
University of Bologna
Bologna, Italy
marco.bovo@unibo.it

Enrica Santolini
Dep. of Agricultural and Food Sciences
University of Bologna
Bologna, Italy
enrica.santolini2@unibo.it

Patrizia Tassinari
Dep. of Agricultural and Food Sciences
University of Bologna
Bologna, Italy
patrizia.tassinari@unibo.it

Daniele Torreggiani
Dep. of Agricultural and Food Sciences
University of Bologna
Bologna, Italy
daniele.torreggiani@unibo.it

***Abstract*—The rising need of precision in several sectors, agriculture included, brings to the development of new monitoring systems customised for the specific application. These systems often take advantages of probes offered by the market, however, the integration between market probes and home-built systems, requires tests to validate the recorded measurements.**

This paper provides a methodology to perform a calibration procedure when the probes fail the validation test.

The results show the comparison of the measurements collected by investigated sensors and reference sensor coupled with the application of simple correlation methods can bring to an improvement of the sensor precision as far as to pass the validation test.

Index Terms*—*smart monitoring systems, aquaculture, agro-industrial facilities, validation test, calibration.

I. Introduction

In the recent years, several sectors, agriculture included, are asking to increase production and therefore precision [1]–[3].

The application of remote monitoring techniques to the agro-industrial and food processing facilities have proven to be a favourable approach to improve the sustainability, the quality of the hosted processes, the safety of products and personnel and the efficacy of control systems [4], [5].

Nevertheless, some issues reduce the development and diffusion of monitoring systems in particular in the agricultural sector. The latter in fact often involves several applications that require to measure and monitor different metrics, systems must be easy to understand, manage and use, moreover systems and sensors must be robust to resist to strongly aggressive environments. Moreover, nowadays, the market offers solutions that, for their specificity, are not economically affordable for the farms.

Recently, the industrial and scientific research is working for the development of monitoring systems that can fit the farm requirements but to an affordable price. Considering all these characteristics, in order to analyse the productions and measure the efficiency of control systems, several metrics must be monitored, collected and stored and should be remotely available in real time.

Since a monitoring system able to collect all the involved metrics usually is not available on the market, specific monitoring system must be developed and realised. Modern monitoring systems are currently used for different purposes in order to ensure welfare and safety of humans, plants and animals, and support the management of facilities and buildings [6]–[8].

Some of the main aspects in the definition of the most suitable system, concern the choice of the sensors, the validation of the acquired measurements and the calibration of the sensors.

A few works proposed methodologies to validate the measurements, [9]–[12] suggesting to compare the measurements recorded by the investigated sensor with a more accurate reference sensor and then calculate an indicator based on the difference between the two measurements [13].

The papers in the literature do not investigate the case of sensors that fail the validation test. One of the solution to this problem is to use a more precise, and often expensive, sensor.

However, according to the producers and the normal practice, some operations, such as a new calibration of the sensor, can be carried out to improve the measurement quality. The

SIMTAP project

present paper aims at investigating and assessing measure improvements of accuracy and reliability achieved by different models for the sensor calibration.

II. Materials and Methods

A. SIMTAP project and ISMaCS system

The aquaculture is one of the sector where the continuous monitoring is considered more and more necessary, in particular in IMTA (Integrated MultiTrophic Aquaculture) systems.

In this sector, the SIMTAP (Self-sufficient Integrated Multi-Trophic AquaPonic) project [14] aims at combining in-land aquaculture and hydroponic crops in a saltwater re-circulating loop to reduce the required fish feed inputs (e.g., fishmeal, fish oil, soybean, etc.) and the consumption of resources. In this project, four experimental sites have been implemented and, due to its multitrophic nature, SIMTAP requires that several metrics must be under control.

For each site, a specific Integrated Smart Monitoring and Control System (ISMaCS) is designed, built and installed. The ISMaCS is made by nodes that have a wireless communication to a gateway connected to the internet. While the hardware and software are specifically designed for this equipment, the ISMaCS uses probes available on the market. This integration requires specific calibration and validation tests since the one proposed by the producers can be insufficient.

Each node can host a few sensors to monitor metrics from indoor, outdoor and water environments and system energy consumption. One of the most important metric to monitor is the dissolved oxygen (DO) in the fish tanks. While some probes simply underwent to a validation test [9], the DO failed the validation test and needed a calibrations procedure as explained later.

B. Calibration procedure

The study was conducted with six sensors (Atlas Scientific Industrial Dissolved Oxygen Probe ENV-50-DO) and one sensor (OXY 70 Vio), used as a reference.
The aim of the study is to train a model able to apply a calibration for dissolved oxygen measurement (O_2) of the sensors, based on the measure of a reference sensor. Each sensor is submerged in water and is capable of measuring dissolved oxygen, temperature and conductivity. Data were acquired every 10 minutes for 4 days from 2021-03-17 to 2021-03-21.

After a data cleaning procedure (eliminating missing data, NaN values etc...), the dataset is divided in train set and test set, respectively composed by 80% and 20% of the data. Three calibration models have been trained and tested: the difference between them is in the number of the input features adopted.

The input features, i.e. dissolved oxygen (O_2), water temperature (T) and conductivity (C), are measured by the sensors. The target are the values of O_2 measured by the reference, therefore the task is classified as a regression problem. The test set will be used exclusively to evaluate and compare the different calibration models.

The evaluation of the calibration models has been carried out by using the Mean Absolute Error (MAE), the Identical Reference Value (*IRV*) and the Acceptance Reference Value *ARV* as defined in [15]. The three metrics have been computed before and after that each calibration model is applied. The models used to calibrate each sensor are Linear Regression (LR) models.

Given a target quantity y and a set of M input features $x = x_1, x_2, ...x_M$ (with both y and x variable in the time), the general definition of a linear model is:

$$y_i = \sum_{j=1}^{M} w^j x_i^j + w_0 \tag{1}$$

where: $w_0, w_1..., w_M$ are the *weights* of the model. In this case, the objective is to train the LR model in order to adjust the measurements of each sensor according to their relation with the reference instrument.

The *weights* of the model are computed using the *Ordinary Least Square* method (OLS) [16]. The method consist in finding the best set of weights $\bar{w} = w_0, w_1..., w_n$ which minimises a loss function $L(w)$ defined as the sum of squared differences between the reference and the sensor:

$$L(w) = \sum_{i=0}^{M} (y_i^{ref} - y_i(w))^2 = ||y^{ref} - y(w)||^2 \tag{2}$$

The first linear model takes into account only the values of dissolved oxygen measured by a sensor. Therefore, (1) will translate into:

$$O_2^{corr}{}_i = w_1 \cdot O_{2i} + w_0 \tag{3}$$

where: $O_2{}_i^{corr}$ is the i-th corrected measure for the corresponding value 0_{2i}.

The second linear model considers also the water temperature T, so that (1) becomes:

$$O_2^{corr}{}_i = w_2 \cdot T_i + w_1 \cdot O_{2i} + w_0 \tag{4}$$

In addition, in the third model is introduced the water conductivity C, therefore (1) can be rewritten as:

$$O_2^{corr}{}_i = w_3 \cdot C_i + w_2 \cdot T_i + w_1 \cdot O_{2i} + w_0 \tag{5}$$

C. Experimental campaign

To validate the ISMaCS measurements of the O_2 metric, an experimental campaign has been performed. The tests, aimed at acquiring data from different sensors and at comparing the data collected by the sensors of ISMaCS system with the data of the reference sensors, were planned and designed according to the specific metric monitored.

Thus, the expected range of values (i.e., min, max, average values) and the recording time step were properly selected.

TABLE I
SUMMARY OF RESULTS BEFORE AND AFTER CALIBRATION FOR EACH SENSOR AND MODEL

	Metric	Sensor 1	Sensor 2	Sensor 3	Sensor 4	Sensor 5	Sensor 6
No calibration	MAE	1.21	1.61	1.78	2.00	1.71	2.19
	ΔX	1.34	1.65	1.83	2.09	1.76	2.25
Model 1	MAE	0.19	0.13	0.19	0.13	0.14	0.14
	ΔX	0.29	0.17	0.30	0.20	0.25	0.27
Model 2	MAE	0.17	0.10	0.19	0.14	0.13	0.14
	ΔX	0.25	0.17	0.27	0.22	0.25	0.26
Model 3	MAE	0.18	0.11	0.23	0.15	0.14	0.17
	ΔX	0.27	0.18	0.3	0.26	0.26	0.32

D. IRV and ARV

The procedure reported in [15] describes the indices *IRV* and *ARV*. They can be introduced in order to evaluate the matching of two measurements.
As first, is to define ΔO_t as the difference between the oxygen value measured by the reference sensor and by the sensor to validate at time t:

$$\Delta O_t = O_t^{ref} - O_t^{sens} \tag{6}$$

Then, is to calculate the index ΔX as in the following:

$$\mu_s \geq 0 \Rightarrow \Delta X = \begin{cases} \mu_s + \sigma_s & \text{if } \mu_s - \sigma_s \leq 0 \\ 68^{th} \text{ perc of } \Delta O_t \text{ distr} & \text{if } \mu_s - \sigma_s > 0 \end{cases} \tag{7}$$

$$\mu_s < 0 \Rightarrow \Delta X = \begin{cases} |\mu_s| + \sigma_s & \text{if } \mu_s + \sigma_s \geq 0 \\ 68^{th} \text{ perc of } \Delta O_t \text{ distr} & \text{if } \mu_s + \sigma_s < 0 \end{cases} \tag{8}$$

where: μ_s and σ_s are mean and standard deviation of the distribution of ΔO_t, respectively.

Then, we assume that:

- if $\Delta X \leq IRV \Rightarrow$ reference and investigated sensors return identical measurements;
- if $IRV < \Delta X \leq ARV \Rightarrow$ measurements taken by the investigated sensor are suitable for the experiment;
- if $\Delta X > ARV \Rightarrow$ measurements taken by the investigated sensor are not suitable for the experiment.

In the present work the two parameters *IRV* and *ARV* have been set as in the following:

- $IRV = 0.5\ mg/l$
- $ARV = 1.0\ mg/l$

As second row in Table I shows, for the no calibration case, all the investigated sensors report a ΔX value bigger than *ARV* entailing the measurements collected by the six investigated sensors cannot be considered enough accurate for the purposes of the study, i.e. their use in the SIMTAP project.

E. MAE

The MAE is a measure of dissimilarity between two vectors. In this case is used to quantify the dissimilarity between the time series of each one of the six sensors with the reference sensor. MAE is defined in the following way [17]:

$$MAE = \frac{1}{N} \sum_{i=0}^{N} |y_i^{ref} - y_i| \tag{9}$$

where: N is the number of time-steps of the time series, ${y^{ref}}_i$ is the i-th value measured by the reference sensor and y_i is the i-th value measured by the sensor to investigate.

F. Model evaluation

As reported before, from the original data set, the 80% of data has been used as training and the 20% as test.
Each model were calibrated on the training set and saved in order to be used to predict test data. The goodness of prediction is then estimated by means of the MAE value of each calibration model.

III. RESULTS

The three models have been qualitatively and quantitatively evaluated in their ability to correct unseen sensors measurement, in order to obtain values closer to the reference sensor. As an example, in Fig. 1 is shown the the separation between train and test set for the time series of the first sensor (orange line), the time series of the data after the application of the calibration following the model 1 (green line) and the time series of the reference sensor (blue line).

It is clear that there is high difference between the measurements of the sensor 1 and the ones of the reference sensor. That seems to be mostly due to a systematic error. In this case, after the training has been performed, (3) for model 1 becomes:

$$O_2^{corr} = 0.57 \cdot O_2 + 8.48 \tag{10}$$

In the case of model 2, (4) becomes:

$$O_2^{corr} = 0.535 \cdot O_2 - 0.109 \cdot T + 8.47 \tag{11}$$

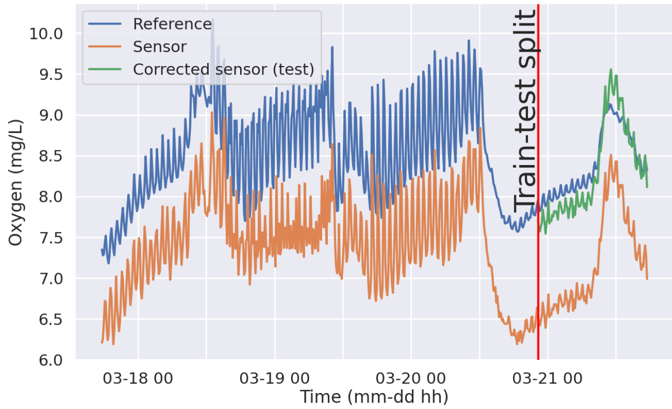

Fig. 1. Time series of oxygen measurements for the reference sensor (blue line) and the sensor 1 (orange line). The red vertical line separates the train set (left) from the test set (right). The green line is the measurements of the sensor 1 after the calibration following the model 1.

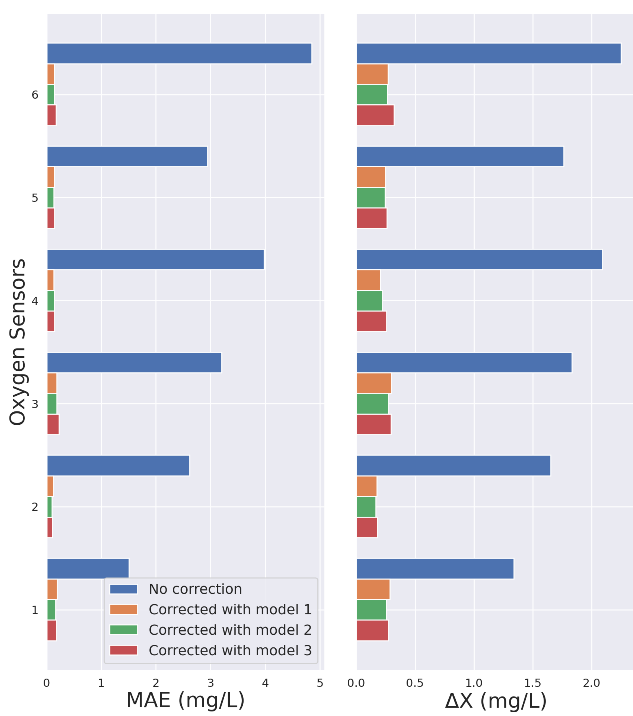

Fig. 2. MAE (left) and ΔX (right) computed for the six sensors for every calibration model for the test set. In blue the metrics computed with oxygen measurement without any correction of a calibration model, in orange the first model is used to calibrate the sensors, in green the results of the second model and in red those of the third model.

and for model 3, (5) becomes:

$$O_2^{corr} = 0.54 \cdot O_2 - 0.137 \cdot T + 0.0568 \cdot C + 8.47 \qquad (12)$$

All the models highlight a strong bias (intercept of the linear model) which may indicate a systematic error in the O_2 sensor measurements. Models 2 and 3 show an inverse dependency on temperature, while model 3 shows a relatively low dependency on the water conductivity.

In Fig. 2 is shown the comparison between *MAE* computed before any calibration (blue bars), and after each calibration (orange, green and red bar) for every sensor. The metrics are computed only in the test set, shown in the previous figure 1.

For every sensor, the calibration procedure has a clear benefit in terms of *MAE*, which is greatly reduced for every model with respect to the raw data. On the other hand, it seems that adding only the temperature as input - model 2 of (4) - has a very small effect on the quality of the output results. Moreover, adding the conductivity - model 3 of (5) - has a slight degrading effect on the scores for every sensor.

In Table I are collected all the scores in terms of ΔX and *MAE* for each sensor and for each model and before calibration.

The data confirm that sensor measurements benefit from a data level calibration, since every score, is reduced. In particular, the values of ΔX after calibration, are in range of acceptability, since the values are lower than *ARV*, and therefore, as described in section II-D, the results can be considered valid for the purpose of the study. Finally, the calibration procedure allowed to increase the precision of sensors bringing the reliability within the limits required by the specific research, avoiding to substitute the sensors with more precise - and therefore expensive - models.

IV. Conclusions

The rising need of precision in several sectors, agriculture included, brings to the development of new monitoring systems specifically built for the single experience. These systems often take advantages of probes offered by the market, however, the integration between market probes and home-built systems, requires tests to validate the recorded measurements. This paper investigates a methodology to perform a calibration procedure when the probes fail the validation test.

The results shows that the comparisons of measurements of six investigated sensors and reference sensor and the application of simple correlation methods, can drive to improve the sensor precision and to pass the validation test. All the tested methods proved to drastically increase the precision, accuracy and reliability with little differences among each other.

Under this light, the results confirms the importance of a calibration procedure, even tough cannot provide a general rank of method efficacy to apply to other experiments. For this reason, the Authors suggest to test all the methods in case of calibration and, considering the work was set in a specific period of the year, to repeat the calibration procedure periodically, to cover all the expected values monitored by the sensor. Moreover, the paper shows that the integration of different metrics can provide a considerable accuracy increment.

Finally, the calibration procedure can improve the reliability of the sensors, homogenise the measurements of different sensors, and in some cases, avoid to purchase more expensive sensors when probes fail the validation test making the monitoring systems more affordable for the agricultural sector improving the quality of the processes, the safety of products and personnel, the efficacy of control systems increasing the environmental sustainability of the farms.

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