



HAL
open science

Performance of a Multiparametric Water Quality Sensor in a Small-Scale Water Distribution Network

Balakumara Vignesh Muppudathi, Stéphane Laporte, Yan Ulanowski,
Senthilmurugan Subbiah, Bérengère Lebental

► **To cite this version:**

Balakumara Vignesh Muppudathi, Stéphane Laporte, Yan Ulanowski, Senthilmurugan Subbiah, Bérengère Lebental. Performance of a Multiparametric Water Quality Sensor in a Small-Scale Water Distribution Network. 2023 IEEE SENSORS, Oct 2023, Vienne, Austria. pp.1-4, 10.1109/SENSORS56945.2023.10324917. hal-04433257

HAL Id: hal-04433257

<https://univ-eiffel.hal.science/hal-04433257v1>

Submitted on 30 Jul 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial - NoDerivatives 4.0
International License

Performance of a Multiparametric Water Quality Sensor in a Small-scale Water Distribution Network

Balakumara Vignesh Muppudathi^{1,2}, Stephane Laporte¹, Yan Ulanowski¹, Senthilmurugan Subbiah², and Berengere Lebental¹

1: COSYS, IMSE, Universite Gustave Eiffel, France

2: Department of Chemical Engineering, Indian Institute of Technology Guwahati, India

berengere.lebental@univ-eiffel.fr

Abstract— Ensuring access to good quality water is crucial for sustainable development, particularly in developing nations. However, the lack of affordable and reliable solutions for monitoring water quality remains a significant challenge that the LOTUS sensor meets: it is a compact and versatile multiparametric sensor designed for real-time monitoring of chlorine, pH, temperature, and conductivity in potable water. The proposed solution features a cylinder-like structure, measuring 21 cm long and 3.5 cm in diameter. It integrates temperature sensors, conductivity sensors, and a 2 x 10 sensor array of multi-walled carbon nanotube (CNT) chemistors. The CNTs, arranged in random networks between interdigitated electrodes, can remain non-functionalized or be functionalized with a dedicated polymer to modulate their sensitivity. Six LOTUS sensors were tested in a 44m-long water loop under a flow rate of 0.3m/s and pressure of 1 bar to evaluate the system performance. To manage the high noise levels caused by strong electromagnetic interferences in the facility, particularly under flowing water conditions, a strong effort was put into data denoising techniques. After extensive denoising and calibration model optimization, temperature, conductivity, chlorine, and pH estimation were achieved with mean absolute error (MAE) as low as 0.34°C, 73.2 $\mu\text{S}/\text{cm}$, 0.13 mg/L and 0.12 pH unit in flowing water (achieved on different sensors due to dataset limitations). Notably, the dataset also demonstrates the role of CNT functionalization in chemical sensing, with the selected polymer modulating the sensitivity to pH by 50%.

Keywords—Multiparametric; Carbon nanotube; water quality monitoring; multisensor;

I. INTRODUCTION

UNICEF labels “Water scarcity” as a risk multiplier impacting socio-economic and geopolitical issues while adversely affecting human survivability [1]. While the main drivers of water scarcity are climate changes, urbanization, and population growth, deteriorating water quality and lack of integrated water management further degrades the situation. The 2022 UN Sustainable Development Goals report highlights that the lack of water monitoring is more prevalent in countries with lower GDP [2], [3], as they lack sufficient infrastructure to support the required monitoring. In this article, we present the results of a validation campaign in a scale 1 water loop of a low-cost, real-time multiparametric water quality sensor that can be directly installed in water distribution

pipelines and does not require any complex or expensive infrastructure.

This sensor was developed as part of the EU-Indo Horizon 2020 project LOTUS (<https://www.lotus-india.eu/>), which focuses on providing affordable sensing solutions for monitoring water quality and decision-support tools to improve water management and distribution.

II. THE LOTUS SENSOR

Current water quality monitoring technologies can be generally classified into online or offline analysis. The latter consists of laboratory analysis based on samples collected in the distribution network, which is expensive in time and resources and is not real-time. The alternative, online monitoring, has extensively demonstrated its advantages to optimize water quality but is available for only a limited set of parameters at a reasonable cost (<1,000 €), typically pH, chlorine, conductivity, and temperature [4]–[7]. Even considering the available parameters so far, the cost of monitoring several parameters together (which is needed by water operators) quickly adds up to numbers that even mature economies cannot always afford (> 5,000 € range) in sufficient numbers. The LOTUS project targets precisely to offer a multiparameter sensor at the cost and size of a typical monoparameter sensor. This is achieved by co-integrating on a 1cm² silicon chip, physical sensors (based on MEMS technology), and chemical sensors based on functionalized Carbon nanotube sensor arrays, as is detailed in Fig. 1[8].

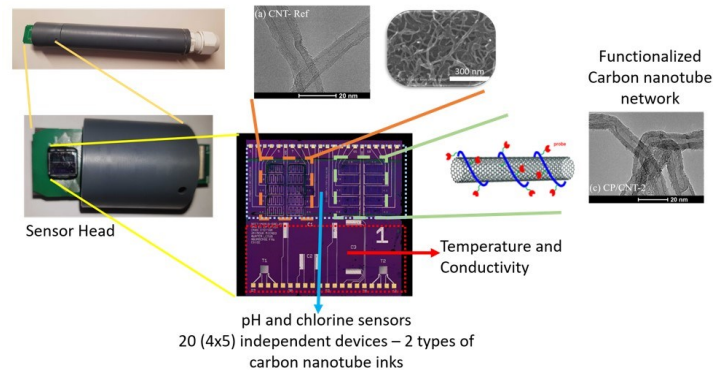


Fig. 1. LOTUS sensor - chip: overview

Each LOTUS sensor chip contains, more specifically, 2 temperature sensors (T1 and T2), 3 conductivity sensors (C1 to C3), and a 2x10 array of chemistors targeting pH and chlorine [8]. The chemistors consist of multi-walled carbon nanotubes ink-jet printed between interdigitated electrodes. Ten of the chemistors use functionalized CNTs (labeled 1.F – 1.I and 2.F – 2.I), and the other 10 non-functionalized CNTs (labeled 1.A – 1.E and 2.A – 2.E). The functional polymer is a polyfluorene carrying urea moieties. The multiplicity of sensing devices within the chip provides redundancy to the measurements and enables performance improvement via data fusion.

III. DEPLOYMENT IN SENSE-CITY WATER LOOP

To anticipate the performance of LOTUS sensors in field conditions, six different LOTUS sensors were deployed for an extended period of time in a scale 1, 44 m-long water loop in Sense-city facility (<https://sense-city.ifsttar.fr/>) located at Université Gustave Eiffel, France. At any given time, 2 units of the LOTUS sensor can be installed in the loop and tested under flow (Fig. 2). While some of the sensors were deployed for several weeks, and one even for over a year, the exposure to flow was during shorter periods of time only (due to operating constraints of the facility). The flow rate was ~ 0.3 m/s and ~ 1 bar when under flow. The temperature, conductivity, chlorine, and pH ranged from 15°C and 20°C, 870 μ S/cm to 1270 μ S/cm, 0 to 5 mg/L, and pH 7 to 8.5 over the course of the different experiments.



Fig. 2. Sensor installation in the Sense-city pipe

IV. DATA PROCESSING

A total of 20 GB of data was collected and sorted out. Fig. 3 shows an 800h-long example of collected data, comparing the signal of one of the chemistors with the data of the reference sensors in the water loop measuring pH, chlorine, flow rate, and temperature. Sense-City is outfitted with multiple power equipment, making it an electromagnetically-noisy environment. This contaminates the sensor response with several artefacts, as illustrated in Fig. 4. A series of algorithms compatible with real-time sensor operation were applied to reduce the impact of these artefacts on the sensor response. An example of such data post-processing is shown in Fig. 5. Among the six sensors, one of the sensors, labeled here S1, was selected for further analysis of temperature, chlorine, and pH performances, as its dataset could be consistently denoised and

contained sufficient variations for all the target parameters except conductivity. The conductivity performance was assessed on another sensor, S2.

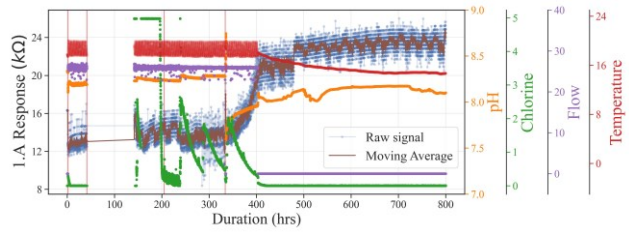


Fig. 3 Response from sensing device 1.A of LOTUS sensor "chip 141" from Sense-city. The reference chlorine sensor only operates under flow, so it features 0mg/L when the flow is OFF irrespective of the actual chlorine level.

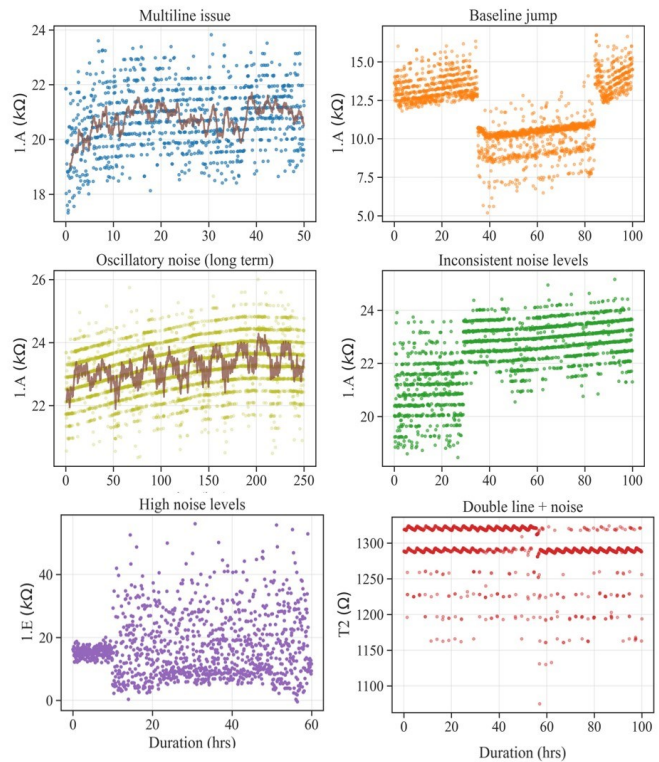


Fig. 4 Artefacts in a sensor response during testing in Sense-city

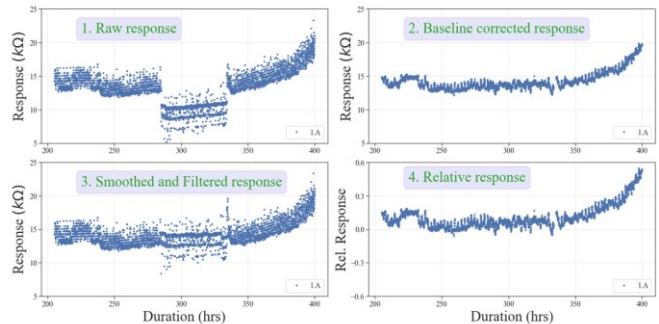


Fig. 5 . Processing the raw response to get the relative response, which is used in the model development and estimation

To assess sensing performances, relevant dataset was randomly divided into 70:30. The calibration model for the target parameters were estimated over the 70% of the data and tested over the remaining 30%. Several data splits (10 to 20) were studied, and the mean value of the MAE over the splits is indicated here. However, it was not possible to apply a real-life calibration approach, where calibration is done on the first acquired data and then applied to the following data, as the dataset did not provide sufficient data.

V. SENSING PERFORMANCES

A. Temperature and Conductivity

For temperature and conductivity, models could be built with and without flow to assess the effect on performances. The calibration model for the temperature sensor is linear as expected from the device physics: $T_{pred} = a_0 + a_1 T_i$, where T_{pred} is the predicted temperature, T_i refers to the T1, T2 sensor outputs, and a_0 and a_1 are the coefficient of the calibration models (identified on the training datasets).

For the conductivity sensors, the calibration model is linear in both temperature T_{pred} and conductivity C_{pred} : $C_i = b_0 + b_1 T_{ref} + b_2 C_{ref}$. It is worth mentioning that the device physics predicts a model inversely proportional to conductivity over the full range of water conductivity (from deionized water to seawater). However, the range of conductivity considered here being small in comparison, a linear model is suitable. The average MAE of the selected sensors are listed in Table 1. While the MAE with and without flow are acceptable for water quality monitoring applications, one observes that the presence of flow increases the MAE by a factor 2 to 3.

TABLE 1. TEMPERATURE AND CONDUCTIVITY SENSOR PERFORMANCE

Parameter	Flow	Sensor	MAE	Range
Temperature	On	S1	T1: 0.43 T2: 0.34	17°C – 20°C
	Off	S1	T1: 0.09 T2: 0.09	14°C – 18°C
Conductivity	On	S2	C1: 204 C2: 73 C3: 128	750 – 1270
	Off	S2	C1: 31 C2: 154 C3: 657	750 – 1220

B. Chlorine and pH estimation

In water, chlorine is present as HClO (active chlorine) and ClO⁻. The active chlorine concentration (C_{HClO}) can be estimated from the total chlorine concentration (C_{Cl}) added, pH, and temperature (T) of the sample[8] by the formulae:

$$C_{HClO} = C_{Cl} (1 + 0.98 \times 10^{\text{pH} - \text{pKa}(T)})^{-1} \quad (1)$$

$$\text{pKa}(T) = 7.5 - 0.01 (T - 30) \quad (2)$$

Unlike the physical sensors, the calibration model was not known before the experiment. Moreover, some devices may have different responses due to device variability. Fig. 6 illustrates the method used for model identification: the correlation coefficient R^2 is evaluated for a panel of models and compared between different models and devices.

The following models were found to have the best performances:

- $S_i = \alpha C_{HClO} + \beta \text{pH} + \epsilon$,
- $S_i = \alpha C_{HClO} + \beta \text{pH} + \gamma C_{ClO^-} + \epsilon$ and
- $S_i = \alpha C_{HClO} + \beta \text{pH} + \xi \text{Temperature} + \epsilon$

where S_i is the sensor response, and α , β , γ , ξ are the coefficients and ϵ is the residuals. As they had very similar performances, the model with the least parameters was retained to avoid overlearning: $S_i = \alpha C_{HClO} + \beta \text{pH} + \epsilon$. A set of 5 chemistors (with higher R^2) 1.A, 1.B, 1.C, 1.D, and 1.H was selected via exhaustive search, and the model was inverted. The MAE for the chlorine and pH estimation were 0.13 mg/L and 0.12 units, respectively. Fig. 7 shows the prediction as a function of time. Because of the high noise level, small jumps in chlorine and pH remain hard to track. Interestingly, the functionalized chemistors were found to have an average sensitivity of 0.81 %/pH unit and the non-functionalized with 0.41 %/pH unit to pH, which shows the role of functionalization.

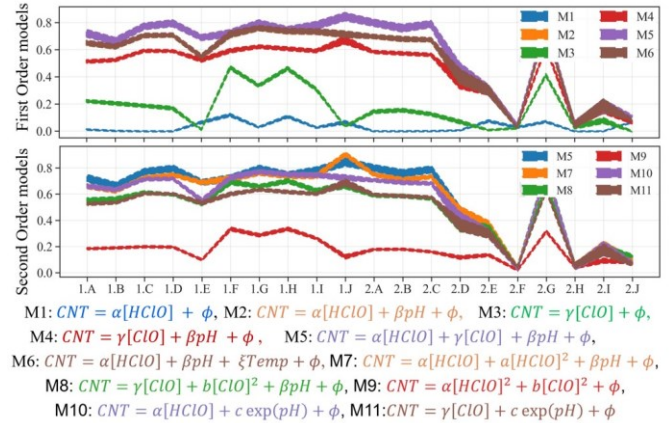


Fig. 6. Correlation coefficient of Models on cHClO and pH for each chemistor

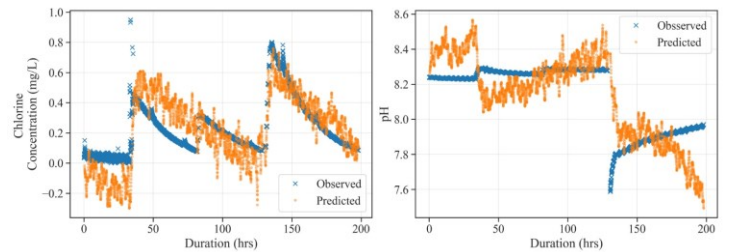


Fig. 7. Time series prediction of active chlorine and pH from the selected chemistor

VI. CONCLUSION AND FUTURE WORK

The Sense-City deployment allows us to anticipate the future real-life performances of LOTUS multiparameter water quality sensors. Despite high noise levels and several artefacts, suitable calibration models for all the sensing devices in the sensor were developed, and the MAE values are compatible with the requirements of real-time applications. To make this technology more suitable for deployment, intense effort is presently ongoing to reduce its noise level.

REFERENCES

- [1] UNICEF, Water and Environment team, “Programmatic Approaches to Water Scarcity,” UNICEF, Mar. 2021. Accessed: Jun. 12, 2023. [Online]. Available: <https://www.unicef.org/media/95341/file/UNICEF%20guidance%20note%20programmatic%20approaches%20to%20water%20scarcity.pdf>
- [2] United Nations, “Sustainable Development Goals Report,” United Nations, 2022. [Online]. Available: <https://unstats.un.org/sdgs/report/2022/The-Sustainable-Development-Goals-Report-2022.pdf>
- [3] United Nations Environment Programme, “Progress on ambient water quality. Tracking SDG 6 series: global indicator 6.3.2 updates and acceleration needs,” Nairobi, 2021. Accessed: Jun. 13, 2023. [Online]. Available: https://www.unwater.org/sites/default/files/app/uploads/2021/09/SDG6_Indicator_Report_632_Progress-on-Ambient-Water-Quality_2021_EN.pdf
- [4] P. Cousin *et al.*, “Improving Water Quality and Security with Advanced Sensors and Indirect Water Sensing Methods,” in *Instrumentation and Measurement Technologies for Water Cycle Management*, A. Di Mauro, A. Scozzari, and F. Soldovieri, Eds., in Springer Water. Cham: Springer International Publishing, 2022, pp. 251–277. doi: 10.1007/978-3-031-08262-7_11.
- [5] I. Yaroshenko *et al.*, “Real-Time Water Quality Monitoring with Chemical Sensors,” *Sensors*, vol. 20, no. 12, Art. no. 12, Jan. 2020, doi: 10.3390/s20123432.
- [6] P. Kruse, “Review on water quality sensors,” *J. Phys. Appl. Phys.*, vol. 51, no. 20, p. 203002, May 2018, doi: 10.1088/1361-6463/aabb93.
- [7] J. Hall *et al.*, “On-Line water quality parameters as indicators of distribution system contamination,” *J. AWWA*, vol. 99, no. 1, pp. 66–77, 2007, doi: 10.1002/j.1551-8833.2007.tb07847.x.
- [8] G. Perrin and B. Lebental, “Uncertainty-Based Calibration Method for Environmental Sensors—Application to Chlorine and pH Monitoring With Carbon Nanotube Sensor Array,” *IEEE Sens. J.*, vol. 23, no. 5, pp. 5146–5155, Mar. 2023, doi: 10.1109/JSEN.2023.3238900.