**Please describe how the manuscript meets the journal criteria (e.g., novelty, need for rapid publication, topical scope).**

The manuscript describes the realization for the first time of a dual sensor based on luminescence sensing which uses one single luminophore and one single optical channel can measure two distinct and cross-interfering parameters: oxygen concentration and temperature. This is realized thanks to neural network. The manuscript describes how the setup, the data collection and the performance evaluation need to be redefined for this new generation of sensors.

The field of machine learning is subject of a large amount of research and tha authors think that is essential to published this results in such a new field as quickly as possible.

The importance and potential of this approach is enormous, since it is not limited to the two parameters measured here. It can be applied to any multiple luminescence sensor, independently of the chemistry of the luminophore itself. It shows that when interferences and cross-sensitivities are present, the proposed approach greatly outperforms the classical approach of analytical modelling of the sensor characteristics and of implementing non-linear fitting algorithms. The great research

Luminescence (fluorescence, phosphorescence) is a technique which is enormously important for both fundamental and applied research.

**Please describe and argue the technical point(s) where the editor might have made incorrect or incomplete assessment. Your response should be concise and related to the content of your manuscript only.**

The first reviewer poses the question about the difference between the manuscript and a previously published work and comments that the parameters for the neural network are previously described and “This largely undermined the contributions of this manuscript.”

The criticism is not founded. Our previous work of reference 26 is a purely theoretical study on multi-dimensional regression problems to demonstrate that they can be solved using multi-tasking neural network architectures and which architectures are most appropriate for this type of problems. As example synthetic data were generated using the classical Stern-Vollmer equation which is a well-known and best accepted analytical model for this type of sensors.

The manuscript submitted to Optica uses the architecture, which was previously found to work best. It is typical of scientific work to start from previous findings, without redoing the same work again. Similarly, for the excitation of the luminophore we use the wavelength which is known to work best with this type of luminophore.

However, the work which we would like to publish is not which architecture work best for a theoretical type of problem. We build a real physical optical sensor, we characterized and used for the acquisition of data needed for the training and we demonstrate a sensor performance which would not be possible with a standard approach. Secondly, the paper submitted here for publication does much more. It defines how the data acquisition should be carried out, which is essential to a sensor based on machine learning.

Furthermore, it introduces a new metric, the Error Limited Accuracy, which bridges the gap between two fields: physics and computer sciences. We strongly believe this metric is necessary for the characterization and, thus, the spreading of a new generation of sensors into applications.

The experimental result per se (Figs. 4 to 6) are new, unpublished and, to the best of the authors’ knowledge, of unprecedented detail and quality as compared to any previous publications of this type of sensor since span thoroughly in a four-dimensional space (oxygen concentration, temperature, modulation frequency and phase shift).

In conclusion, this work demonstrates that a new generation of sensor which are based on the proposed approach is not only possible but would work better than the conventional ones. This work thus represents a paradigm shift. This is the reason why we strongly think the work is of great relevance for the public of Optica and for the optical community in general and should be published on Optica.

**Please provide a detailed response to the review report(s), if applicable. Make sure that all points are addressed in a clear and concise manner. You may enter the response in the text box below or upload a file.**

**Reply to Reviewer 1**

**Reply to reviewer 2**

The authors thank the reviewer for the positive feedback and constructive comments.

Please fin below the reply to each point.

1. In section C.1, the authors described two types of input that were used to train the network. Please explain why the phase shifts of the first input (theta\_s) are divided by 90.

2. Is there any particular reason why the mini-batch of 32 samples was used?

3. Are the results in the Sensor Performance Section from the training data set or the testing data set (new data that never been seen by the model)? If it is from the testing data set, could the authors describe its data collection?

4. To generate the model, it requires 65 hours of training data collection and an additional 5 hours for training the model. Could the authors discuss whether this process should be repeated every time a new sensor is manufactured? Or is there any way to translate the generated model into a new sensor?

This is a very appropriate and interesting questions. In machine learning it is possible to use transfer learning to adjust an almost completely trained network with a much-reduced amount of data. The authors are working in this direction and will investigate the extent of new data needed in the future.