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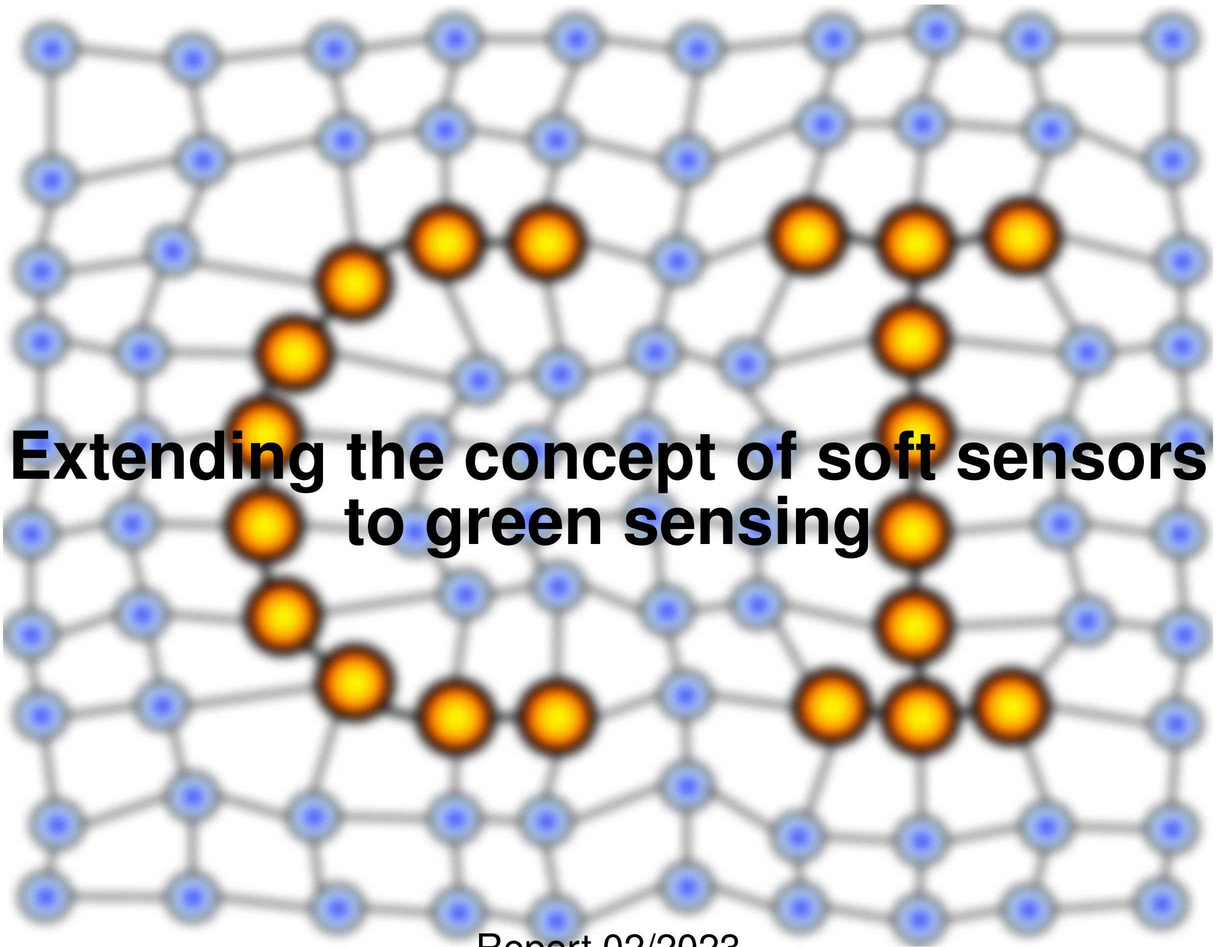

Extending the concept of soft sensors to green sensing

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Abstract

There are many innovative technical developments that are denoted ”green”, ranging for example from very generic green power to more specific green AI. In the context of soft sensors, this paper describes its extension to *green sensing*, taking into account and implementing various aspects of efficiency and sustainability in addition to more traditional performance criteria, such as precision, robustness, and interoperability.

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1 Introduction

Diverse and in many cases complex sensors are now an integral part of many applications of the industrial internet of things (IIoT). In addition to evaluations and derived formalized measures of the pure performance of technical solutions, considerations of their sustainability are increasingly becoming the focus of attention. In the context of soft sensors, this has not yet been done comprehensively and consistently, although some of its modules already address corresponding sustainability aspects selectively, such as green AI. This paper introduces a comprehensive concept of green sensing and, with the help of some examples, provides essential levers and evaluation mechanisms for the transition of general soft sensor approaches to green sensing, particularly in the context of the industrial internet of things.

2 Concept of soft sensors

Smart sensors have become an indispensable part of the disruptive transformation of our global civic societies in all three sectors of society, such as civil [15, 17], government [7, 12], and business [9, 8]. The concept of soft sensors [8], also referred to as virtual sensors, is often used when complex measured variables are to be determined that are not directly accessible by a physical measurement principle, such as temperature or pressure. Among many others, a prominent example is chemometrics [4] where multivariate statistical calibration models are utilized to derive one or more measured variables from often high-dimensional raw data points, e.g., spectral signatures. Aggregated data from various sources are also frequently used, which need not necessarily all be sensors, but may be derived from state models, for example, or include a-priori expert knowledge that is not explicitly given. Since the relation between raw data and measured variables is typically not available in a mathematically closed form, data-driven approaches, such as machine learning-based calibration models are widely utilized [1].

This development has enabled numerous industrial internet of things applications [3] representing a significant force driving the transformation to Industry 4.0. The modular architecture of IIoT systems comprises four layers in a hierarchical structure of increasing abstractness, from the device layer containing physical components, such as hardware sensors, to the network layer connecting several devices and providing aggregated input to the next higher service layer, where software-embedded algorithms run to model data and derive relevant information. These three layers are matched by the concept of soft sensors, which in turn are key to many IIoT applications. For completeness, the fourth level is the content layer providing the user interface, which will not be considered here.

3 Concept of green sensing

The initial design of the soft sensor framework is focused on sheer functionality and effectiveness to facilitate as many and diverse applications as possible. Efficiency and sustainability, on the other hand, are hardly ever considered. And this is even though some key modules, taken on their own, do now have sustainability considerations. For

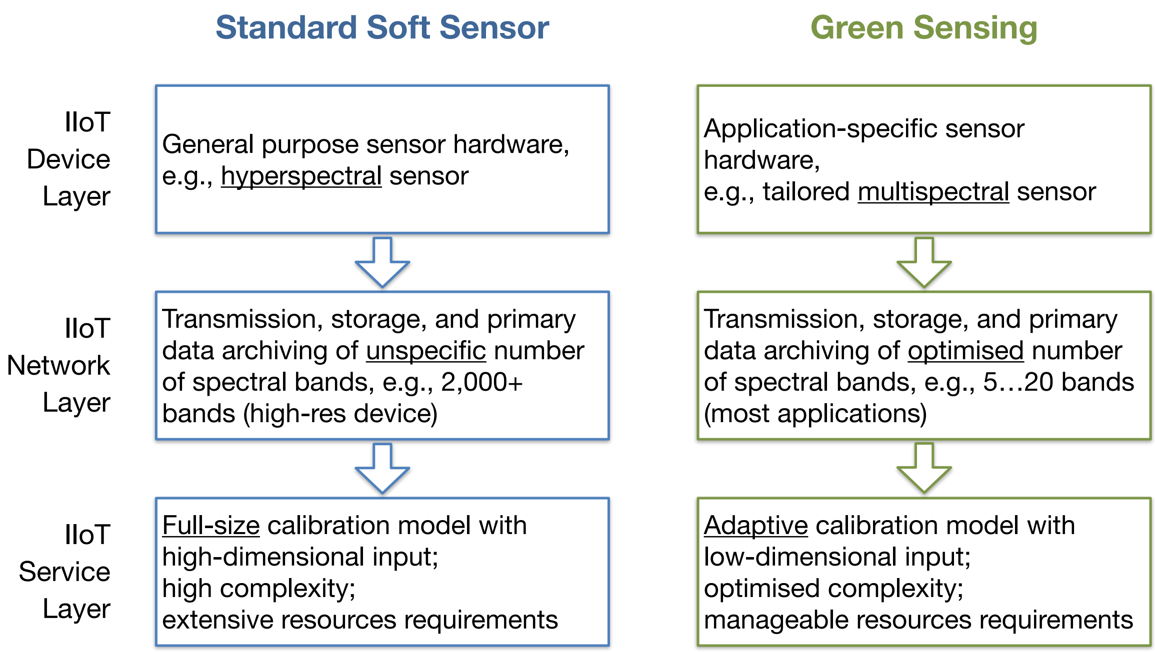

Figure 1: Comparison of a standard soft sensor (left panel) with the concept of green sensing (right panel). By means of spectroscopy as selected use case, the figure shows the most significant differences between standard soft sensors and green sensing on all three relevant layers of IIoT. The actual device benefits from fewer spectral bands, which goes hand in hand with less resource (semiconductors, memory, etc.) and energy consumption in the production of the hardware. Both the network and service layers also benefit from fewer spectral bands, as less data needs to be transmitted, processed, and stored, which in turn saves energy during operation on the one hand and raw materials for fewer or smaller hardware components on the other. In particular, the service layer can use widely available processor hardware (e.g., optimized graphics cards) due to optimized complexity, e.g., by moving from floating point 64 to floating point 16 data types.

example, key algorithms of IIoT applications are increasingly running on blockchain technologies, whose initial poor eco-balance has gradually moved into the focus of specific further developments [2]. As noted above, machine learning plays a central role as a pillar of artificial intelligence (AI), and this has been evaluated for some time under the term green AI with regard to sustainability [13].

However, a complete consideration of the efficiency of soft sensors as a whole in terms of their sustainable design and use is more than desirable in light of their expected enormous potential for our society and economy. Consequently, concepts developed under these considerations should be called green sensing although this term has been used occasionally in a different context [6, 16]. Given the wide range of soft sensors, green sensing will have ample facets. Since chemometrics is a particularly relevant application for soft sensors, it will be applied here as a first use case (Figure 1). The setup considered here specifically assumes a spectrometer as the hardware sensor and machine learning as the basis for the calibration model [14]. Starting on the device layer, the transition from general-purpose hyperspectral to tailored multispectral sensor hardware builds the foundation for green sensing in this context. The network layer benefits from a significantly reduced number of spectral bands in terms of spectral raw data transmission, buffering, and potentially archiving. In order not to lose precision, robustness (e.g., against noise), and interoperability of the measurement, an adaptive calibration model with respectively low-dimensional input and optimized complexity substitutes the typical full-size model which leads to moderate requirements of resources for developing, validating, and operating the corresponding data processing unit on the service layer.

The green sensing approach presented here, including the selected use case (Figure 1), serves as a formalized basis for a variety of other applications of the concept of soft sensors from the perspective of efficiency and sustainability. Especially applications with high-dimensional and / or numerous aggregated data, whose intrinsic data dimension is however often unrecognized significantly lower, benefit from this approach as expected. In addition to the considerations of data dimensionality prominently presented here, the concept of green sensing also includes considerations of the density and dynamics of the sampling points. Here, the sampling theorem [5, 11] is the measure for the optimization.

Another important aspect in the context of green sensing is the utilization of physics-informed machine learning [10], e.g., physics-informed neural networks, in soft sensors to overcome the traditional data-driven black-box character of machine learning-based calibration models not just for the sake of sheer performance and potentially better interpretability, but also against the background of efficiency and sustainability. This has positive implications in the environmental footprint of both the training and the recall phase and thus downstream as well for the entire IIoT application implemented with it.

4 Discussion

All aspects mentioned in Sect. 3 together lead to ecologically sustainable and economically even more viable technical solutions for the benefit of global society. This justifies the introduction and usage of such a generic term as green sensing. This is done following similar technical terms, such as green AI or even more general green power.

However, as with all these theoretical concepts, viewed from a scientific perspective, a quantitative definition or at least a threshold whether or not something is green, appears rather impractical. In this respect, retreating to the position that the above-mentioned principles have been, at least partially, taken into account and implemented during soft sensor development is also a sensible approach here, leading to clear added value with regard to efficiency and sustainability. As a subset of soft sensors, green sensing denotes innovative technical approaches with an extended focus on the ecological impact of the underlying application.

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6 Author contributions

The author contributions were as following: Conceptualization – US, AM, AB; Methodology – US, PM, AB; Writing – original draft by US; Writing – review & editing by US, AM, PM, AB.

References

[1] A. Backhaus and U. Seiffert. Classification in high-dimensional spectral data: Accuracy vs. interpretability vs. model size. *Neurocomputing*, 131:15–22, 2014.

[2] A. Bada, A. Damianou, C. Angelopoulos, and V. Katos. Towards a green blockchain: A review of consensus mechanisms and their energy consumption. In *Proc. DCOSS*, pages 503–511, 2021.

[3] H. Boyes, B. Hallaq, J. Cunningham, and T. Watson. The industrial internet of things (IIoT): An analysis framework. *Computers in Industry*, 101:1–12, 2018.

[4] S. Deming, D. Massart, Y. Michotte, L. Kaufman, and B. Vandeginste. *Chemometrics: A textbook*. Elsevier Science, 1988.

[5] T. Gray. Applied electronics: A first course in electronics, electron tubes, and associated circuits. *Physics Today*, 7(11):17–18, 1954.

[6] V. Gupta, S. Tripathi, and S. De. Green sensing and communication: A step towards sustainable IoT systems. *Journal of the Indian Institute of Science*, 100:383–398, 2020.

[7] D. Hall and S. Aungst. The use of soft sensors and I-space for improved combat ID. In *Human Factors Issues in Combat Identification*, pages 161–170, 2017.

[8] Y. Jiang, S. Yin, J. Dong, and O. Kaynak. A review on soft sensors for monitoring, control, and optimization of industrial processes. *IEEE Sensors Journal*, 21(23):12868–12881, 2021.

[9] P. Kadlec, B. Gabrys, and S. Strandt. Data-driven soft sensors in the process industry. *Computers & Chemical Engineering*, 33(5):795–814, 2009.

[10] G. Karniadakis, I. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, and L. Yang. Physics-informed machine learning. *Nat Rev Phys*, 3:422–440, 2021.

[11] H. Lüke. The origins of the sampling theorem. *IEEE Communications Magazine*, 37(4):106–108, 1999.

[12] Y. Ma, S. Liu, G. Xue, and D. Gong. Soft sensor with deep learning for functional region detection in urban environments. *Sensors*, 20:3348, 2020.

[13] R. Schwartz, J. Dodge, N. Smith, and O. Etzioni. Green AI. *Communications of the ACM*, 63:54–63, 2020.

[14] T. Villmann, E. Merényi, and U. Seiffert. Machine learning approaches and pattern recognition for spectral data. In *Proc. ESANN*, pages 433–444, 2008.

[15] F. Wen, T. He, H. Liu, H. Chen, T. Zhang, and C. Lee. Advances in chemical sensing technology for enabling the next-generation self-sustainable integrated wearable system in the IoT era. *Nano Energy*, 78:105155, 2020.

[16] F. Xiao, J. Chen, X. Xie, L. Gui, L. Sun, and R. Wang. SEARE: A system for exercise activity recognition and quality evaluation based on green sensing. *IEEE Transactions on Emerging Topics in Computing*, 8:752–761, 2018.

[17] S. Xu, A. Jayaraman, and J. Rogers. Skin sensors are the future of health care. *Nature*, 571:319–321, 2019.

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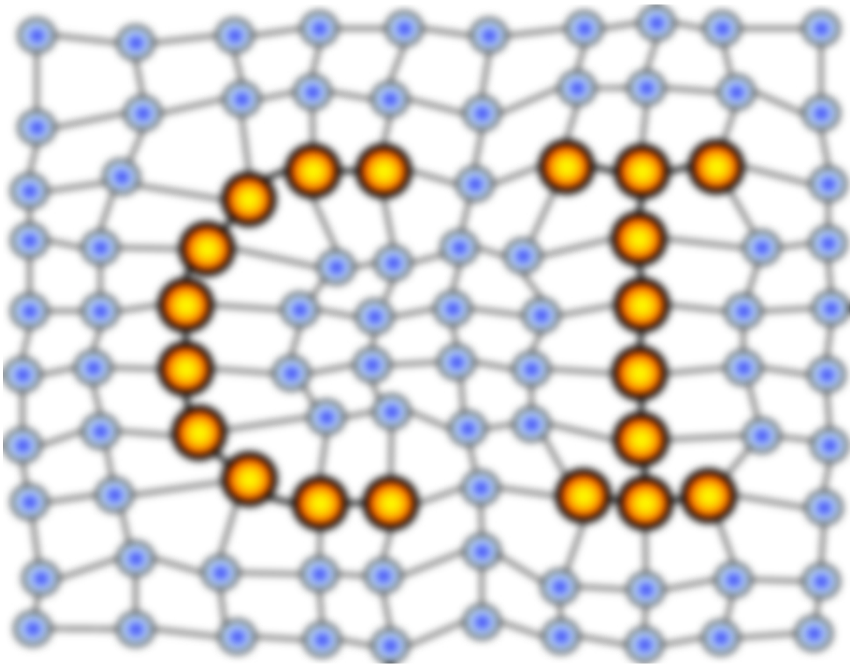

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