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Analyzing the Performance of AI-Based Battery SoC Estimation: A Metrological Point of View

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Abstract—**Battery State of Charge (SoC) estimation systems play a crucial role in modern energy infrastructures challenges, including the integration of renewable energy, grid stability, and the electrification of transportation. The established technologies of Artificial Intelligence (AI) and Machine Learning (ML) have proven instrumental in achieving heightened accuracy and efficiency within battery state estimation frameworks. Highlighting a critical gap in current applications, the research underscores the need for a comprehensive treatment of measurement uncertainty in AI-driven battery state estimation. The proposed methodology introduces a novel approach that incorporates measurement uncertainty into the evaluation of the ML model, investigating how the SoC estimation system is influenced by the measurement accuracy, and contributing to a deeper understanding of uncertainties associated with AI systems. The investigation focuses on the application of data-driven ML techniques, particularly the Nonlinear AutoRegressive with eXogenous inputs (NARX) model for its proficiency in SoC estimation. The results provide valuable metrological insights into the ML model and a starting point toward reliable battery SoC estimation systems.**

Keywords—SoC, uncertainty, artificial intelligence, batteries, Monte Carlo

I. INTRODUCTION

Artificial Intelligence (AI) and Machine Learning (ML) technologies have become indispensable assets across a spectrum of research areas, each yielding profound benefits. In healthcare, these advanced technologies are revolutionizing diagnostics and treatment strategies [1]. By analysing extensive datasets derived from patient information, ML algorithms can predict diseases, identify patterns, and contribute significantly to drug discovery. This not only enhances the accuracy of medical diagnoses but also facilitates the development of personalized treatment plans. Environmental science has witnessed a transformative impact through AI applications. These technologies play a pivotal role in monitoring and analysing environmental changes, offering invaluable insights for predicting natural disasters and optimizing resource management. By processing complex climate data, AI assists scientists in understanding and addressing critical issues such as climate change and biodiversity loss [2]. In the financial sector, algorithms are deployed to great effect in detecting fraudulent activities, optimizing trading strategies [3], and enhancing risk management. Real-time data analysis empowers financial institutions to make informed decisions, contributing to overall financial stability. Manufacturing processes benefit from the integration of AI and ML, leading to cost reductions and increased efficiency [4]. Predictive maintenance models, powered by ML, identify potential equipment failures, minimizing downtime and optimizing resource utilization in manufacturing plants. In agriculture, AI optimizes crop management by monitoring soil conditions and predicting yields. By providing farmers with actionable insights, these technologies contribute to increased productivity and sustainability in the face of growing global food demands [5]. Finally, in the energy sector, AI and ML optimize production and consumption, increasing efficiency and reducing environmental impact. Smart grids, powered by these technologies, enable better management of power plants and facilitate the integration of renewable energy sources into the power grid, contributing to a more sustainable future [6].

The focus of this paper lies within the energy sector, with specific attention given to batteries and their State of Charge (SoC). As detailed in Section II, numerous studies in the literature have introduced analytical and AI methods for estimating the SoC or the State of Health (SoH) of batteries. Accurately determining the SoC is crucial for providing reliable information to end-users. This paper builds upon existing research by not only contributing to the accurate estimation of SoC but also by introducing an uncertainty evaluation that quantifies the reliability of these estimations. Recognizing that measurements without associated uncertainties lack meaningfulness [7,8], this paper takes a crucial step in elevating AI estimations to the status of measurements. The proposed methodology involves assessing these estimations against accuracy parameters comparing them to reference values obtained through accurate laboratory instrumentation. The paper employs a quasi-Monte Carlo method [9,10] during the testing phase of the ML algorithm, resulting in the derivation of distribution patterns and confidence intervals for the estimations. Consequently, the primary contribution of this paper is not only the enhancement of SoC estimation but, more significantly, the establishment of a rigorous process for uncertainty evaluation. The subsequent sections of this paper are organized as follows: Section II provides an overview of the SoC and batteries. Section III provides a brief introduction to AI, ML, and the adopted algorithm. The experimental activity is described in section IV. It includes the tests, the measurement setup, and the results. Finally, Section V summarizes the achievements and presents the conclusion of the work.

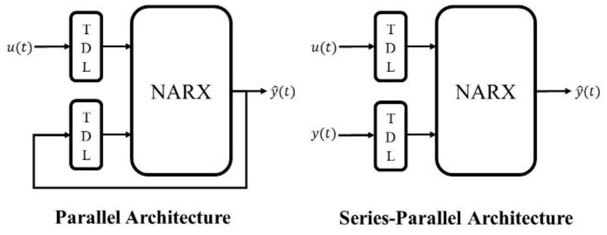

Fig. 1. Parallel and Series-Parallel NARX Architectures

II. Batteries and State of Charge

Battery energy storage systems (BESSs) are becoming essential elements of a sustainable power system. Their use is rapidly expanding in different applications, including the integration with renewable energy, grid stability, and the electrification of transportation [11]. Renewable energy sources are strongly intermittent, related to weather conditions and time of the day. To overcome this issue, BESS is used to store the excess energy during peak production periods and to release it during high demand, ensuring a smoother and more reliable power supply [12]. Moreover, BESS plays a crucial role in ensuring grid stability, mitigating the insufficient power supply during peak hours, providing peak shaving for the system, and providing backup power during outages and emergencies. Finally, the progress of vehicle electrification is intricately linked to advancements in battery energy storage technology [13]. Among the variety of battery chemical compositions, Lithium-ion is the most competitive and promising technology because of its advantages in terms of efficiency, extended life cycle, energy density, compact size and weight, fast charging, and low self-discharge rate [14,15]. Nevertheless, different factors can influence the correct performance and the health of Lithium-ion batteries, such as the number of charge and discharge cycles, the temperature at which the cells operate, the aging effects, and other environmental factors. Appropriate management and accurate monitoring of the battery parameters are therefore crucial. Among these, SoC, the level of charge of a battery relative to its capacity, represents one of the most important indicators of battery performance and life. SoC returns the percentage of the total charge that remains available for use, providing a vital metric for users and system controllers. Since SoC cannot be directly measured, the study of a proper estimation method is topical. Many algorithms have been proposed to predict SoC, and the most widely used are the open circuit voltage (OCV) measurement, the Coulomb Counting method, and model-based methods such as Kalman Filters (or a combination of such methods). Each one of these has its benefits and limitations depending on the application, type of battery, computation availability, and required precision. In the literature, numerous studies have also introduced analytical and AI methods for estimating the battery SoC [16-19]. For example, to accurately estimate the SoC of lithium-ion batteries, Wei et al. [16] proposed a novel machine-learning method to address the risk of gradient explosion and gradient descent using the dynamic nonlinear auto-regressive models with exogenous input neural network (NARX) with long short-term memories (LSTM). Similarly, Wang et al. [17] proposed a method based on a NARX regression neural network to get a better lithium-ion battery SoC estimation model. Nefraoui et al. [18] presented an effective battery SoC forecasting approach utilizing the NARX time's series optimized Levenberg-Marquardt training algorithm, and Bayesian-Regularization (BR). Finally, Feraco et al. [19] presented a method to estimate the SoC in Lithium-ion batteries of Hybrid Electric Vehicles (HEVs) with Artificial Neural Networks (ANNs). The performance of the investigated technique is demonstrated by estimating the SoC with a low estimation error for both the considered battery sizes. Coulomb counting is used to compute the reference value of the SoC during the real charge/discharge cycles. An analysis of the robustness of the proposed estimation method to offset errors on the measured input current is also performed.

III. SoC Estimation Model

In the accurate SoC estimating domain, data-driven ML techniques have garnered attention for their immense potential [20]. In the literature, several ML algorithms have been employed and discussed in terms of accuracy and efficiency [21]. Notably, among Recurrent Neural Networks (RNNs), the NARX model stands out for its capability of dynamic nonlinear modeling, memorizing past inputs, and handling exogenous inputs [19]. ANNs are defined as structures made of elementary units, called neurons. Neurons are organized in vertical structures, called layers. Mainly, three kinds of layers can be identified: the input, the hidden, and the output layer. Depending on how layers are connected and how information flows through the network, feedforward and recurrent ANNs are identified. The former are characterized by a unidirectional data flow, from the input layer to the output layer, while the latter are bidirectional networks. In fact, RNNs allow the output value from some layer to become the input of some previous layer. As an RNN, the NARX model shows the timing characteristics, being suitable for SoC estimation applications [17]. In particular, the values of the NARX output layer are fed into the input layer in the subsequent iteration. The number of considered previous values determines the network delay. For the implementation of the NARX model, two building approaches are available: parallel and series-parallel architecture, represented in Figure 1. The parallel architecture, also known as closed-loop implementation, involves using estimated values as input of the network. On the other hand, the series-parallel architecture, i.e., the open-loop implementation, feeds to the network the real output values. The timing characteristics are included in the model through the implementation of Time Delay Layers (TDLs).

In this work, the open-loop network architecture has been selected, as it represents a valid and manageable option for SoC estimation tasks [16]. The NARX network has been implemented using the Keras module of the TensorFlow library in Python language. Following the implementation of the network structure, the training and testing stages are needed to build the SoC estimation model. To this end, a dataset has been created based on laboratory experimental measurements of the battery discharge profile. Voltage, quantity of charge, current, cell and ambient temperature have been fed to the network as input features, while the target, i.e., the output value, has been the percentage SoC.

IV. Experimental Activity

As previously described, this paper aims to treat the implementation of ML algorithms like a measurement process, to associate a rigorous uncertainty evaluation with the algorithms' results. Therefore, the following subsections describe the designed case study, the adopted measurement setup, and the uncertainty evaluation process, respectively.

TABLE I. SPECIFICATIONS OF THE TESTED LFP CELL

Feature	LFP
Shape (-)	Cylindrical
Weight (g)	86
Nominal capacity (Ah)	3.2
Set-point voltage (V)	3.65
Minimum discharge voltage (V)	2.5
Cut-off current (A)	0.032
Temperature limits (°C)	–20 to 45

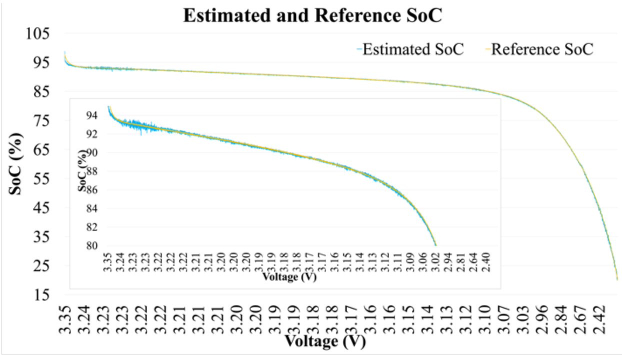

Fig. 2. Estimated and reference SoC values

TABLE II. METRICS VALUES OF THE NARX MODEL

Metric (-)	Value (-)
MAE	$9.6x10^{-6}$
MSE	$3.8x10^{-10}$

A. *Case study*

The case study selected to explore the uncertainty evaluation of the ML algorithm is the battery SoC estimation. To this purpose, the measurements performed in the controlled laboratory environment with accurate instrumentation are used as a reference. On the contrary, the algorithm estimations are treated as the set of measurements on which to run the uncertainty estimation to be compared with the reference values. The comparison of the confidence intervals of the estimated and reference quantities will prove when and in which circumstances the estimations can be considered accurate.

B. *Reference Tests and Setup*

The experimental setup employed in this work comprises a power supply (TDK Lambda GEN 10-240) with a rated output of 10 V and 240 A for voltage and current, respectively, and a DC electronic load composed of two Agilent N3306A modules, with operative limits of 60 V and 240 A for voltage and current, respectively [22]. The power supply and the DC load are controlled by a software developed in LabVIEW2018 through a National Instruments data acquisition Board (NI PCIe 6553). The battery voltage was acquired at its poles with an accuracy of 981 µV. The experimental system was completed with three “copper disc” k-thermocouples to measure the temperature at the battery poles and shell and with a standard thermocouple to measure room temperature, whose signals are acquired with NI 9211 modules (only two thermocouples provide the model input measurements, i.e. cell and ambient temperature). To gather reference values for uncertainty evaluation during SoC estimation, one Lithium Iron Phosphate battery – LFP – cell was subjected to a constant current discharge at 2C, according to the manufacturer’s indications. Battery specifications are reported in Table I. During the discharge, each quantity was acquired every 0.1 seconds for a total of 18432 acquisitions. The voltage measurements have been used to compute the respective reference SoC percentage values, based on the nominal capacity of the battery (corresponding to a SoC equal to 100 %) and the chosen depth of discharge (80 %). Of note, with the aim to assess the role of uncertainty in SoC prediction, we conducted a pilot test on a small-size battery in an extremely controlled environment. However, the obtained findings can be then used to predict the behavior on large-size batteries [23].

C. *Uncertainty Analysis*

As previously mentioned, the uncertainty analysis has been conducted through the metrological comparison of reference and estimated SoC values. The reference SoC is obtained from the voltage measurements (as described in previous sections) at each time step. Its confidence interval was fixed according to the accuracy specifications of the voltage sensor (a type B evaluation of the uncertainty). As for the estimated SoC, a quasi-Monte Carlo method was applied. Specifically, 10, 100, and 1000 datasets were generated by modifying the values of voltage and current input features. The choice of the minimum value has been made considering an acceptable number of measurements performed by a Battery Management System (BMS) per minute, while the maximum value aims to confirm the goodness of the method. Regarding the generation, each value has been randomly extracted from a uniform distribution centred on the original value. The upper and lower limits are fixed both at ± 0.1 % and ± 1 % of the original value. In other terms, the random values were generated first with an uncertainty of 0.1 % and then with 1 %. The idea is that, in realistic applications, the voltage/current is measured with sensors featuring various accuracy values (depending on the budget available for the distributed measurement system). Consequently, for every voltage/current value, a distribution of 10, 100, or 1000 estimated SoC values is obtained and the mean value is calculated. In addition, the 95 %-confidence interval is extracted and then compared with the one of the reference SoC. A small note on the training and testing of the method. The reference SoC can be obtained from voltage and current measurements, or both. Therefore, the algorithms can be trained and tested using one or both quantities.

In the first place, the NARX model has been trained and tested using the original dataset, i.e. the dataset composed of input features measurements and SoC reference values (the acquisition and computational details are given in subsection IV.B). Figure 2 depicts the SoC reference values (yellow line) and those estimated by the NARX model (blue line), trained with 80 % of the dataset and tested with the remaining portion (a zoomed view is added in the graph). Table II presents the achieved values of the Mean Absolute Error (MAE) and Mean Squared Error (MSE) metrics, defined in equations (1) and (2) with y_i the

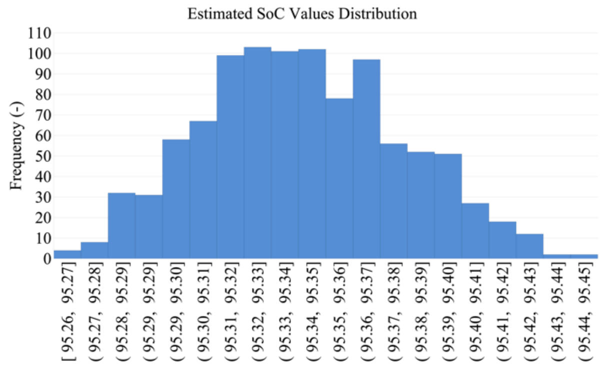

Fig. 3. Distribution of the estimated SoC values

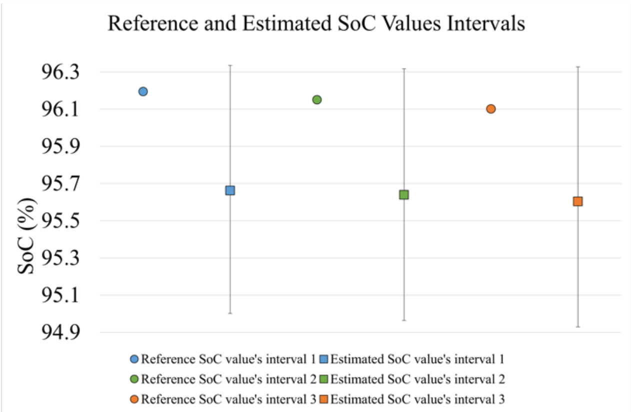

Fig. 4. Comparison between estimated and reference SoC values intervals

TABLE III. PERCENTAGE OF OVERLAPPED SOC INTERVALS

Iterations (-)	Uncertainty (%)	
	0.1	***1.0***
10	39.31 %	95.74 %
100	58.25 %	99.66 %
1000	58.49 %	99.69 %

generic reference SoC value, $\hat{y}_i$ the corresponding estimated SoC value, and n the total number of SoC estimations. It is crucial to note that the MAE e MSE metrics refer to the accuracy of the NARX model in estimating the SoC and are not associated with the measurement uncertainty and the metrological evaluation of the model.

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n}, \tag{1}$$

$$MSE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|^2}{n}. \tag{2}$$

In the second place, the simulations of the quasi-Monte Carlo method have been executed. Figure 3 graphs the distribution of estimated SoC values in the case of uncertainty equal to 0.1 % and 1000 generations of datasets. In terms of the metrological evaluation of the NARX model, the results obtained from comparing the 95 %-confidence intervals of the estimated and reference SoC values are reported below. Figure 4 illustrates a comparison of three pairs of intervals. In each pair, the first interval (circle-shaped) is centered on the reference, while the second (square-shaped) is centered on the corresponding estimated value. The points were consecutively chosen from the results obtained in the case of uncertainty equal to 1 % and 100 iterations. In this instance, all three intervals overlap. A note from the figure, the confidence intervals of the reference values cannot be seen because they are too small compared to the estimated ones. However, they are included in the intervals generated with the 95 %-confidence limits of the estimated values.

Table III displays the percentage of overlapping 95 %-confidence intervals in all simulated cases. Logically, the percentage increases with both the rise in uncertainty applied to the input values and the increase in the number of dataset generations. Table III demonstrates that, by employing highly accurate sensors to collect measurements, even AI features are insufficient for accurately estimating the SoC. However, in realistic applications, a 0.1 % accuracy sensor is seldom deployed (due to its cost).

From all results, it is possible to conclude that (i) the quasi-Monte Carlo method is a valid solution to metrologically confirm the results from the implementation of AI algorithms for the estimation of the SoC; (ii) it is possible to treat AI estimations as measurements and assess them properly with the basic metrology theory; (iii) defining a priori target uncertainty, considering also the available equipment, is fundamental to perform a realistic uncertainty evaluation on a specific application.

V. CONCLUSION

This paper presents a novel procedure for treating measurement uncertainty in AI-driven estimation systems. To ensure a rigorous analysis of artificial intelligence and machine learning models, it is crucial to assess their performances from a metrological perspective. The objective is to validate the NARX model's application in estimating the state of charge of batteries. In this context, the machine learning algorithm is treated as a measurement tool, and a quasi-Monte Carlo method is applied for assessment. The obtained results not only affirm the validity of the method but also provide valuable metrological insights for AI-based state of charge estimation systems. Furthermore, the derived considerations can guide decisions regarding the selection of measurement instruments installed in the BMS.

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