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AI-driven Battery Management System for Electric Vehicles

ForthLithe is an AI-Neural Networks based Software Platform which accurately predicts Li-Ion battery charge (SOC) and health (SOH)

Executive Summary

Lithium-ion battery pack (LiB) is a major component within the car: its efficiency is a key factor for an increased car autonomy and for an extended pack life. Moreover, LiB requires a careful management and control to ensure its safe operation, to be performed by an embedded system called Battery Management System (BMS).

One of BMS's critical tasks consists of inferring battery's internal state from external measurements. Such state includes State of Charge (SoC), (remaining energy) and State of Health (SoH), (capacity performance of the current cell compared to its original condition.)

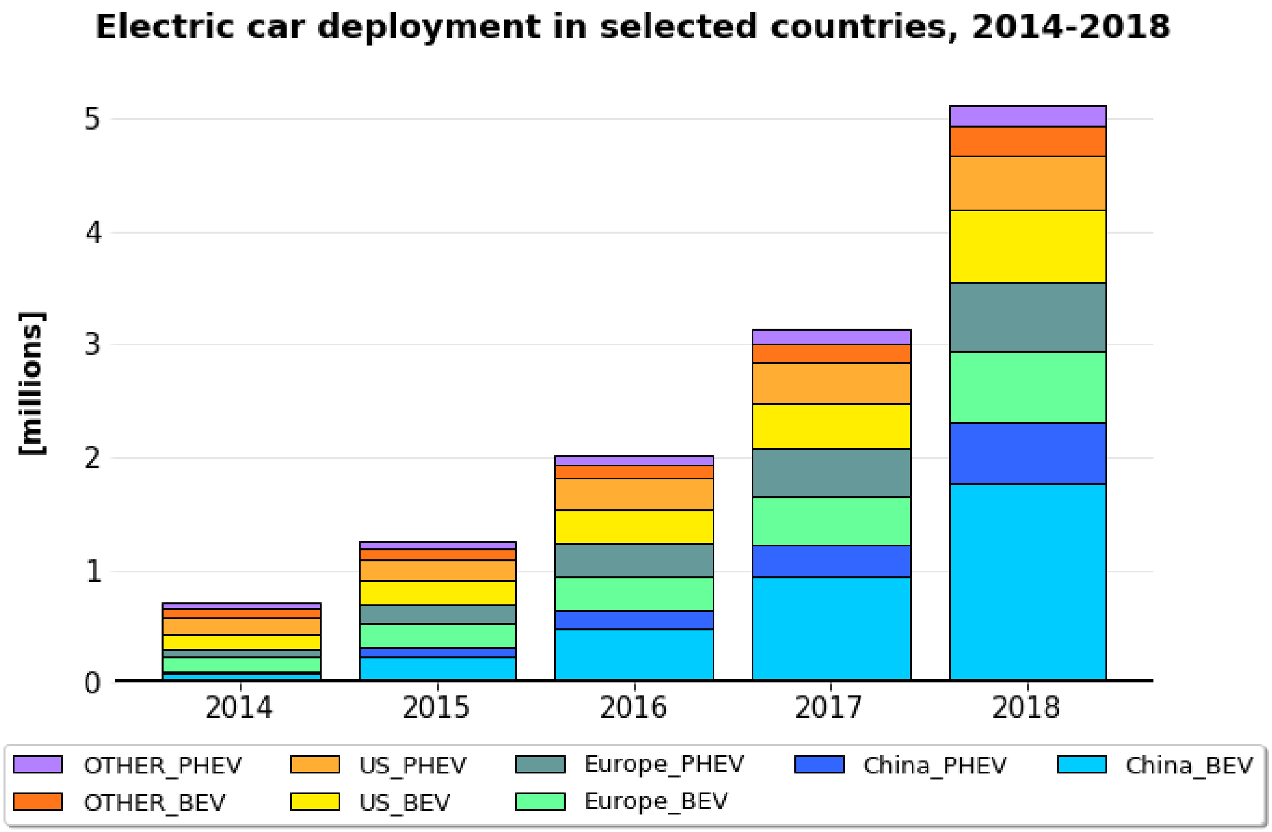
LiB states cannot be directly measured and several methods are available nowadays which compute SoC and SoH based on the theoretical model of the battery and on external measurements of voltage, current and temperature . The most widely used techniques usually rely upon an electrical equivalent circuit which is analytically solved with the measurements of external physical measurements.

ForthLithe software platform shows that with ML-Machine Learning (LSTM Neural Networks) at low frequency sampling and using few physical quantities (Current, Voltage, Temp) it is indeed possible to estimate battery health (SOH) and charge (SOC) with a very high precision without ever applying more expensive analytical techniques.

Electric Vehicles: economic landscape

The automotive industry is witnessing years of unprecedented disruptions and innovations. As world population keeps growing at a fast pace urban environments become the places where people demand for high quality transportation services and cheap and reliable vehicles. Worldwide markets push for cleaner and more sustainable technologies which will help reduce the environmental loads as well as the rate of pollution-related illnesses. Policies aim at boosting regional economic independence by fostering renewable energy sources and electrification. In this scenario Electric Vehicles (EV) play a major part within the automotive industry.

The Global EV Outlook drafted by the International Energy Agency (IEA) in 2019 [3] examines current and future scenarios of the EV growing market. According to the report the electric passenger cars increased by 63% in 2018 with respect to the previous year, adding up to a global 7% share in cars sales. International regulatory bodies and institutions are actively defining strategic plans to ensure that technical development efforts meet the financial resources allocated by public and private investors, to design and manufacture energy efficient products.



Picture 1: EVs deployment since 2014, BEV battery ev, PHEV plug-in hybrid ev

Picture 1 shows the increased deployment of EVs at the global scale both for battery charged fully electric vehicles (BEV) and for Plug-In Hybrid electric vehicles (PHEV). Despite the comparative advantage of EVs in terms of GHG emissions with respect to Internal Combustion Engines (ICEs), it is clear that the benefits of transport electrification on climate change mitigation is greater since EV deployment is taking place in parallel with the decarbonisation of power systems.

To push such a promising scenario further, back in 2017, the Clean Energy Ministerial (CEM) launched the EV30@30 campaign [4] aimed at promoting a joint action between public and private sectors and philanthropists in the effort to reach a 30% share for EVs by 2030. CEM members Canada and China lead the campaign; Finland, France, India, Japan, Mexico, Netherlands, Norway, Sweden and United Kingdom participate under the coordination of the IEA and of the Shanghai International Automobile City Group (SIAC).

In the same year (October 2017), the European Commission launched the "European Battery Alliance" (EBA) to take up the challenge of setting a proactive working platform for industrial stakeholders, interested Member States and the European Investment Bank to cooperate. According to the European Commission forecasts, the battery market will reach 250 bn of euros starting 2025: the EBA was established to promote the development of a sustainable and competitive value chain and to reach the so called goal of EBA250.
Through a series of workshops and conferences the EBA identified 43 necessary actions to be sought in the next future for reaching EBA250. Among them, 18 are regarded as high-priority areas [5]: they form the pool for starting concrete and strategic projects.

The project referred to in this report sets within action number 13 of the EBA250 framework:

"*Create a competitive advantage with constant incremental (e.g. lithium-ion) and disruptive (e.g. solid state) R&I linked to the industrial ecosystem. This applies to all the steps of the value chain (advanced materials, new chemistries, advanced manufacturing process, BMS, recycling, business model innovations)*"

Specifically, ForthLithe is an AI-driven innovative Battery Management System (BMS) for lithium-ion batteries for the accurate real-time computation of the State of Charge (SoC) and of the State of Health (SoH) of the battery.
Discover more about it in the next chapters.

ForthLithe: AI driven Battery Management System

Lithium-ion batteries (Lib) are extensively used to power end-consumer electronic devices such as mobile phones and laptops due to their high energy density compared to other types of electrical batteries. This makes Lib of increasing interest for applications with higher energy and power requirements, especially Electric Vehicles (EVs). The Lib pack is a major component within the car: its efficiency is a key factor for an increased car autonomy and for an extended pack life. Moreover, Lib require a careful management and control to ensure their safe operation. Battery monitoring and control is performed by an embedded system called a Battery Management System (BMS), which main purpose is to ensure that each battery cell within the pack operates in a safety window in terms of current (I), voltage (V) and temperature (T).

Another important function fulfilled by the BMS consists of inferring battery's internal state from external measurements. Such state includes the battery's State of Charge (SoC), which is the percentage remaining energy compared to the available energy in a fully charged battery, and State of Health (SoH), which expresses the performance of a degraded cell in terms of energy storage capacity compared to a cell in its original condition.

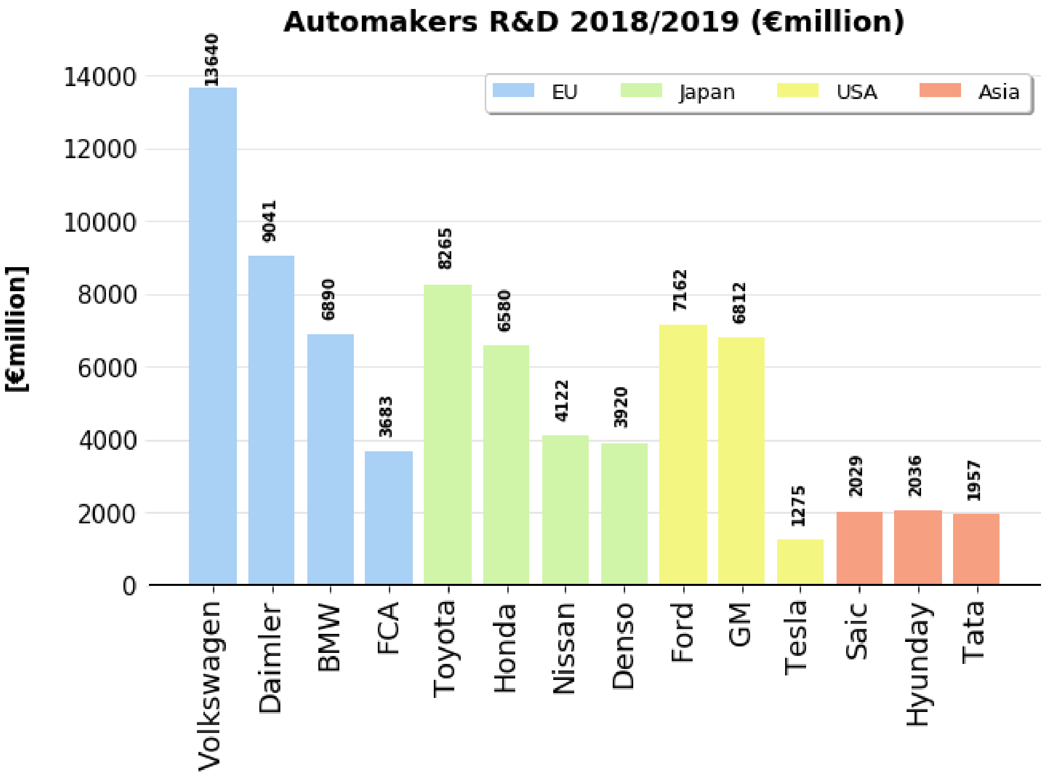
LiB states cannot be directly measured and several methods are available nowadays which compute SoC and SoH based on the theoretical model of the battery and on external measurements of voltage, current and temperature [6].
The most widely used techniques used today rely upon an electrical equivalent circuit which is analytically solved with the measurements of external physical measurements. Only highly complex models provide an accurate and reliable representation of the battery system, though due to their complexity they do not meet the hardware constraints posed by embedded systems on memory resources and computing power.

Data-driven approaches in the domain of BMS have not been fully exploited yet: the solution presented in this paper involves a machine learning approach and demonstrates how data-driven approaches meet the challenge of reaching high accuracy while being light and computationally efficient.

The "Randomized Battery Usage Data Set" from NASA Ames Prognostics Data Repository [7] was used for training and validating the algorithm. The trained model was subsequently tested on the SPC584B-DISP board from STMicroelectronics in order to prove its effectiveness within the resources constraints posed by an embedded system. The results indicate that this approach leads to an embedded BMS with enhanced accuracy and low execution timings.

Battery's states: Soc and SoH

Among lithium-ion batteries are several types of cells made of different chemical elements. This translates into a range of features and performances that make LiB technology suitable for urban driving environments, high-way long distances as well as race loads. For instance a LiB cell meant for sport EVs should have higher specif power and specific energy than passenger vehicles. This latter should instead be equipped with low cost and long lifespan battery packs. Aside the choice of the preferred LiB inner chemical components a lot can be done at operation time to avoid unwanted situations to occur and to slow down the degradation mechanisms of the cells. ForthLithe stands as the first fully AI-based solution addressing the problems of deployability and reliability of high accuracy solutions targeting real-time environments.



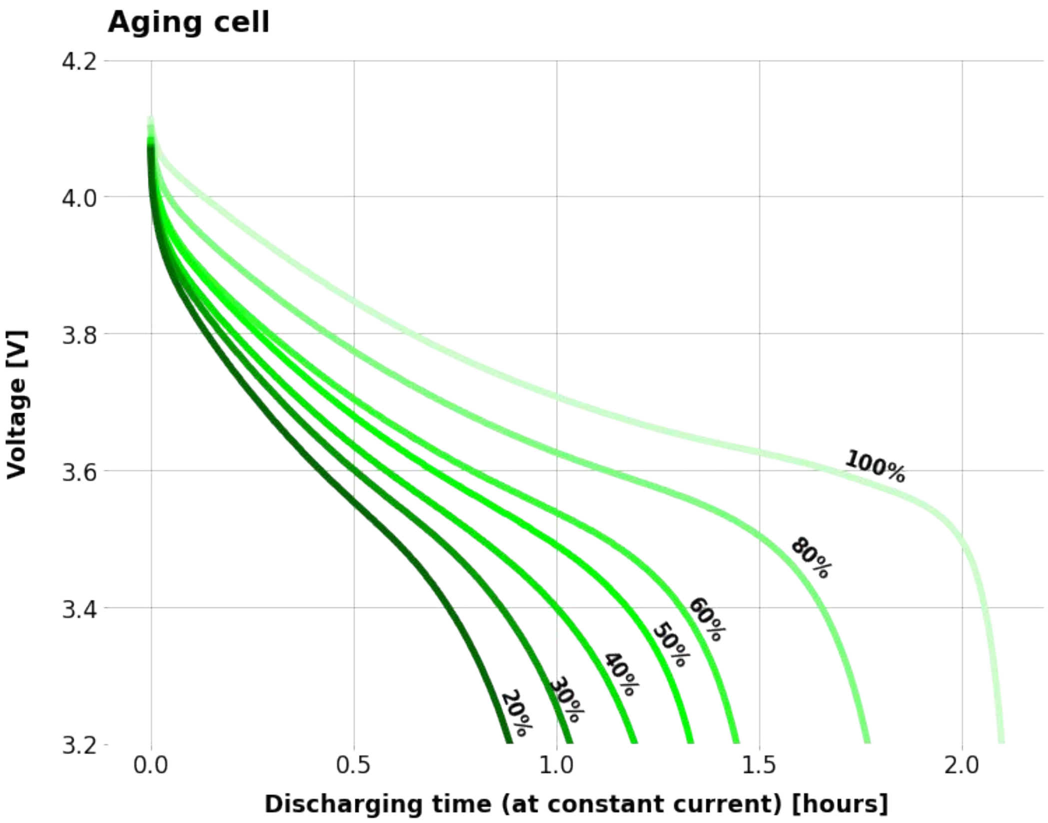
Picture 2: R&D expenditures for top automakers, global view 2018/2019

Automakers invested more than $125 billion globally on research and development in 2018, ranking the auto industry ahead of other technology-driven industries. However, it turns out that among all, automotive industry has the lowest net margins and securing high standards of operations' efficiency plays a major role. ForthLithe's architecture ensure the easiness of use and stands as a ready to use tool for R&D forces constantly dealing with timings and budgetary constraints while designing the next generation of AI-driven BMSs.
ISO 6469 Standard - Part 1 [8] sets safety specifications for the Rechargeable Energy Storage System (RESS) of electric vehicles. It defines several important parameters concerning LiB batteries and outlines the test procedures automakers should comply with when assessing such parameters.

The State of Charge is defined as "the available capacity of an RESS or RESS subsystem expressed as a percentage of rated capacity".
Whereas the capacity is defined as "the total number of ampere-hours that can be withdrawn from a fully charged RESS under specified operating".
The SoC definition provided by ISO refers to the rated capacity which is the Ah a fully charged battery can deliver under certain specified conditions:

- the voltage to which the battery is discharged, or end-voltage
- the current at which the battery is discharged
- the temperature during discharging

The rated capacity is a measure of the degradation grade of the cell. Aging of LiB cells is an unrelenting process affecting the cell both during use (i.e. at cycling) and at rest (and storage). Given the rated capacity at time zero, the State of Health can be calculated as the ratio between the actual rated capacity and the cell's rated capacity in its original condition.



Picture 3: battery autonomy degrading from a fully healthy state (100%)

Picture 3 provides a graphical representation of how aging affect cell's capacity: when the state of health is 100% (pristine cell) the time required to discharge the battery at constant current is more than 2 hours. The same parameter gets reduced with aging: for instance when the cell's SoH is 60% the discharging time is less than 1.5 hours, and when the SoH is 30% the SoH is around 1 hour.

Many factors affect the aging mechanism of a LiB cell: not only the chemical properties of its components, but also the environmental conditions (temperature and humidity) as well as the number of cycles and the loads dynamics. All of these non-linear dependencies make the analytical modeling of the cell's behavior a hard task which, upon success, faces the problem of too large model's dimensions and too high execution latency. The solution referred to in this paper adopts a customized neural-network based on convolution auto-encoders and recurrent LSTM cells to hit the goal of reducing dimensions and preserving accuracy of SoH and SoC estimations. The capabilities of the solution are demonstrated on a hybrid dataset, i.e. the "Randomized Battery Usage Data Set" from NASA Ames Prognostics Data Repository.

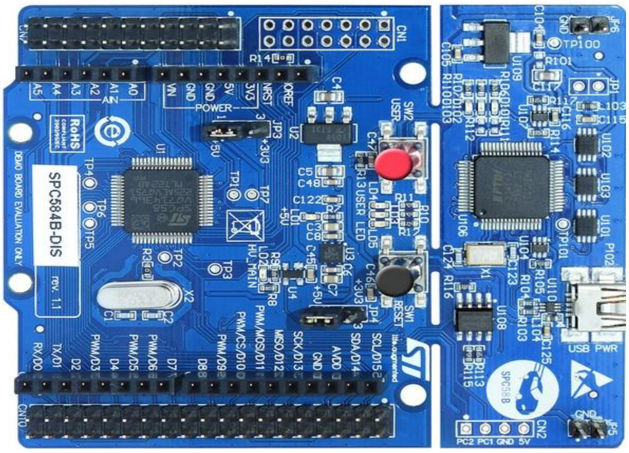
By using the term "hybrid" we refer to a dataset obtained from real measurements on real cells through a set of loads reproducing the loading conditions of a system operating in the field. A hybrid dataset differs from a pure simulated dataset which uses a simulation software instead of real equipment; and it differs from a real dataset for the construction of which data is collected directly from the field. A hybrid dataset is closer to a real dataset than a simulated dataset is. When assessing the training feasibility of a machine learning model the usage of hybrid or real datasets is preferable: simulated data might not hold physical patterns looked for by during back-prop. A downside of hybrid datasets is that they might lack of wideness and lead to a too narrow pre-trained model which could prove insufficient for deployment.

ForthLite platform powered by SPC5Studio.AI

ForthLithe software platform relies on SPC5Studio.AI, the Artificial Intelligence software extension from STMicroelectronics, and was deployed and tested on the SPC584 Discovery Board [10] .

The target board features SPC58 Chorus 4B Line microcontroller to address a wide range of automotive applications in which safety and security needs are growing. SPC58 Chorus 4B Line is designed to meet ASIL-B functional safety level, in compliance with ISO26262.

The SPC584B70E1 mcu is based on the 32-bit Power Architecture® Technology. It holds 2112 KB of on-chip flash memory (2048 KB code flash + 64 KB data flash) and 128 KB on-chip general-purpose SRAM (in addition to 64 KB core local data RAM).



Picture 4: SPC584 Discovery Board

ForthLite relies on SPC5Studio.AI, a software suite for Artificial Intelligence that allows a deep learning pre-trained neural network to be easily integrated into an application targeting SPC5 execution. SPC5Studio.AI enhances programmer productivity, avoiding time consuming code development and enabling a neural network software to run into a SPC5 environment.

SPC5Studio.AI by STMicroelectronics: is an AI software extension for the well-known SPC5Studio configuration and code generation tool that links high-level AI coding frameworks with the C/C++ development IDEs.
Based on the SPC5 target, SPC5Studio.AI takes the pre-trained model (for instance a .h5 format model generated with Keras) as an input and automatically generates a memory-optimized and computationally efficient NN library, checking for memory size consistency, being fully validated and providing static and run-time information. ST public APIs are exported as well, in order to expose the NN library resources to the high level application.

Encoding information, exploiting capabilities

As stated in the previous chapters the computation of the State of Health (SoH) is necessary to accurately estimate the State of Charge (SoC) further. The adopted approach is a full data-driven solution that performs the two steps in one pipeline. The intermediate result is the cell's SoH, which is then fed to the second half of the algorithm in order to get the final output, i.e. the SoC.

This chapter highlights the main components of the software architecture and provides additional details regarding the neural network design and training phases.But before diving into more technical facets, following are some general remarks worth stressing.

Accurate knowledge of the SoC is required to ensure a proper estimation of the car's autonomy so to allow the driver to timely schedule the trip's stops. On its own the SoC is not enough: the car's autonomy is computed by coupling SoC with SoH. The knowledge of the SoH is required not only for the accurate estimation of the car's autonomy, but also to infer the SoC itself, as mentioned in previous chapters. Moreover, the knowledge of the SoH allows to inform the driver and the automaker that the battery pack is reaching its end of life. According to the European Council for Automotive R&D (EUCAR) specifications BEVs and PHEVs SoH should not fall below 80% [9].

Having said that, let's unveil the mechanics of the software pipeline and discover how a deep learning approach can bridge the gap of reaching high accuracies estimations while meeting hardware constraints.

The type of neural network that best meets the needs of the embedded application depends on the data structure the application will crunch after deployment. This same structure should be the one characterizing the data used to train the model as well: the measurement system used for dataset creation should be designed to fit the system's mechanical, electrical and budgetary specifications. In other words: training a model on data collected with a highly intrusive, energy consuming and very expensive measurement system is completely useless, since we would not be able to collect those same data at run-time.

So, what kind of data are we able to measure from the cell's pack? Usually, a battery monitoring system relies upon voltage, temperature and current measurements coming from several or all of the cells of the battery pack. A continuous stream of data is better managed by recurrent neural networks (RNNs) that are capable of mining information from the data stream and to output a single vector as a result. This kind of RNN is called a sequence to vector network: it is the perfect choice for the second half of our pipeline aimed at computing the SoC of the cell starting from the (V, I, T) stream directly measured from the cell.

This begs the question of which is the optimal stream length (or sequence length) we should consider for our purposes. Actually, the sequence length is a hyper-parameter of the model and should be optimized alongside with the other hyper-params, i.e. number of cells, number of layers and learning rate, to name a few.

The sequence length should be long enough to hold relevant information from which to perform regression, and, at the same time, short enough not to lead to a too heavy, and therefore not deployable, neural network.
For instance, a (V,I,T) sequence of 20 seconds does not hold any information about the cell's inner dynamics: trying to compute the SoH of the cell from a so short sequence would prove a vain effort. On the other hand, a 5 min sequence holds salient information regarding the SoH: the correlation between the input data stream and the cell's SoH is there and we expect that a well designed neural network would spot it. Nevertheless, such a network would hold too many parameters and therefore would not fit our hardware constraints.

The solution comes from denoising auto-encoders: a deep learning model with the capability of compressing data and at the same time retain all and only relevant information, cleaning data from noise.
Auto-encoders are of particular interest in the domain of embedded products where dimensionality reduction is paramount and opens the doors to an entire new set of potentially disruptive innovations.

The first half of the ForthLithe pipeline is composed of a denoising auto-encoder that compresses a long data stream, long enough to hold meaningful information regarding the cell's SoH, into a shorter sequence, short enough so that the second half of the pipeline can afford available memory resources.
Here, the auto-encoder plays the major role of making the algorithm deployable to a resources constrained hardware.

Conclusions

The ForthLithe application task is to compute the State of Health (SoH) and the State of Charge (SoC) of a lithium-ion battery cell. The application is designed to output SoH and SoC from Voltage, Current and Temperature (V, I, T) data streams coming from the battery management system. The actual computation is performed by a deep learning pipeline composed of two main items:

- a denoising auto-encoder used to compress the data stream
- a recurrent neural network aimed at compute SoH and SoC

The auto-encoder performs dimensionality reduction and replaces analytical frameworks in the purpose of pre-processing data. Moreover it allows for a lighter model to be trained.

The ForthLithe application was trained on the "Randomized Battery Usage Data Set" from NASA Ames Prognostics Data Repository and subsequently tested on the target hardware: the SPC584b-discovery board from STMicroelectronics.

ForthLithe stands as a real case example of embedded data-driven battery management system and was developed with the use of SPC5Studio.ai: the new plugin from STMicroelectronics allowing for the integration of pre-trained neural networks within the embedded application targeting SPC5 mcu based products.

The development of this solution is prompted by one of the 18 high-priority areas outlined by the European Battery Alliance (EBA) aimed at directing R&I investments of European stakeholders acting in the battery market, in order to reach the target set by European Commission: ensuring a share of 250 bn euros in the global battery market starting 2025 onward.

About Bluewind

Bluewind, an independent engineering company, provides world-class products, engineering and software solutions in the domains of electronics, safety critical applications, and connected devices.
As a qualified partner for Artificial Intelligence technologies, Bluewind is actively involved in designing next generation products using STMicroelectronics technologies and platforms in the Automotive, Industrial and Medical industries.

About STMicroelectronics

ST is a global semiconductor leader delivering intelligent and energy-efficient products and solutions that power the electronics at the heart of everyday life. ST’s products are found everywhere today, and together with our customers, we are enabling smarter driving and smarter factories, cities and homes, along with the next generation of mobile and Internet of Things devices. By getting more from technology to get more from life, ST stands for life.augmented.

References

1. https://www.bluewind.it/case-study/vivaldi-edge-machine-learning/
2. https://www.youtube.com/watch?v=94tT9nlv5B8
3. https://www.iea.org/reports/global-ev-outlook-2019
4. http://www.cleanenergyministerial.org/campaign-clean-energy-ministerial/ev3030-campaign
5. https://www.eba250.com/actions-projects/priority-actions/
6. "State of the Art of Lithium-Ion Battery SOC Estimation for Electrical Vehicles", https://doi.org/10.3390/en11071820
7. https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/
8. https://www.iso.org/standard/68665.html
9. https://eucar.be/wp-content/uploads/2019/08/20190710-EG-BEV-FCEV-Battery-requirements-FINAL.pdf
10. https://www.st.com/en/evaluation-tools/spc584b-dis.html

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