**IOSUD - Universitatea Politehnica Timişoara**
**Şcoala Doctorală de Studii Inginereşti**

# RECHARGEABLE BATTERIES STATE OF HEALTH ASSESMENT FOR BATTERY POWERED EMBEDDED SYSTEMS

**PhD thesis – Summary**

for obtaining Doctorate degree at

Politehnica University of Timișoara

in the field of Computer Science

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# 1. Introduction

Due to recent technological development the number of battery powered devices has increased. Therefore, there is a tremendous need to maximize the battery health by monitoring the battery parameters and also to decide with very high accuracy when the battery cannot be used anymore and has to be replaced.

Battery management systems play a key role for this problem and their complexity has grown nowadays from simple charge/discharge monitors to complex systems which monitor different battery parameters, provide SoH estimation and control the battery operating temperature.

## 1.1 Research topic and fields

This thesis deals with problems from multiple interconnected fields, the most important ones being:

- The field of batteries – a complex field facing a tremendous growth in last decade because of the technological improvement of manufacturing the chemical compounds
- The field of battery powered embedded systems – because of latest battery improvements the battery powered devices became ubiquitous in all areas: military, automotive, aerospace, medical, consumer electronics.

Taking into consideration these two primary fields, the research focuses on the following secondary fields:

- Battery management systems
- Battery state of health estimation methods
- Deep learning – neural networks

The topic of this research work is “Rechargeable batteries state of health assesement for battery powered embedded systems”.

## 1.2 Research aims and objectives

The main goal of the research work is to find improved solutions to current problems related to battery state of health estimation for rechargeable batteries.

The following paragraph will describe the complete list of aims and objectives:

- Define a new method for rechargeable battery state of health estimation with the following properties:
    - High accuracy in terms of SoH estimation
    - Has the ability to be implemented and executed on embedded platforms with limited resources (processing power, power consumption. Etc).

- Define a framework for performance evaluation of estimation methods based on neural networks. It should follow the following criteria:
    - Precision and accuracy
    - Algorithm complexity
    - Processing resources (CPU, memory, power consumption)

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## 1.3 Thesis structure

The following paragraphs will detail the thesis structure.

Chapter 2 will cover some theoretical foundation used in the scope of this work. Among the most important ones are: detail description and structure of a battery management system, battery state of health definition, battery models and recurrent neural networks used for time series estimation.

Chapter 3 contain a detailed literature review in the field of battery state of health estimation methods. A complete battery management system implementation with second order polynomial regression for state of health estimation method is presented in chapter 4. Chapter 5 describes a novel estimation method based on gated recurrent unit neural networks. In chapter 6 the framework for performance evaluation of estimation methods is detailed using well defined evaluation criteria.

Chapter 7 covers a detailed analysis of the proposed estimation method: results on PC simulation, comparison with other estimation methods and embedded systems implementation results.

Chapter 8 contains the conclusions and future perspectives.

The final part of the thesis contains the list of references, the list of publications and annexes.

# 2. Theoretical foundations

In this chapter I have presented the most important theoretical aspects related to battery management systems, battery state of health, battery models and least but not last the aspects related to time series estimation and neural networks used for time series estimation,

# 3. State of the art

In literature there is a tremendous interest related to rechargeable battery state of health estimation [1]-[3]. There are multiple ways to classify estimation methods, the most common ones being: classification based on complexity, classification based on estimation parameters, classification based on method type.

Using the complexity criteria, the methods can be classified in:

- Simple methods – one estimation method is used
- Hybrid methods – the estimation is done using a fusion of one or more estimation

methods (usually simple).

Based on battery parameter we have the following estimation methods:

- Battery capacity used for SoH estimation
- Internal battery resistance used for SoH estimation
- Battery capacity and internal resistance used for estimation

Using the estimation type the methods can be classified as follows:

- Real time data methods
- Based on stochastic filters
- Deep learning methods

Other classification criteria which are worth mentioning are: battery type, computational complexity, estimation time.

In the following paragraphs i will summarize the most relevant battery state of health estimation methods.

Coulomb counting is one of the most used estimation methods [4]-[5]. This method computes the battery capacity by integration of battery voltage and charge/discharge current in time. State of heath estimation is done most of the time using regressions [4].

OCV method [6] provide battery state of health estimation by using a relation between battery open circuit voltage and battery health. To asses this dependency extensive tests are conducted in special labs.

The authors in [7] use an estimation method based on fuzzy logic. This type of method is used in combination with impedance spectroscopy (EIS). The battery state of health estimation is done using high number of datasets based on internal battery resistance.

The estimation methods based on Kalman filters [8]-[10] or particle filters [11]-[12] use parametric battery models. These models can be electrical, electrochemical, mathematical. The model parameters are estimated using these types of filters.

Deep learning methods like SVM/RVM [13]-[14] and neural networks [15], [16] use offline training data to provide state of health estimation. The greater number of datasets are used, the better the estimation performance.

A novel estimation method is presented in [17]. It uses a relation between DV/DQ curves and battery health. The inflection points of these curves output the points where the battery provides a considerable change in terms of health.

Other estimation methods which can be mentioned are: [18] in which the authors use the magnetic field to characterize battery health; in [19]-[20] probabilistic and statistics methods are used to predict the battery state of health.

# 4. Battery state of health estimation based on polynomial regression

This online method is based on second order polynomial regression: the battery curve capacity is obtained at each discharge cycle and based on this function the capacity related to future cycle can be estimated. For a given cicle k, we have $C_k$ the corresponding capacity:

$$C_k = ak^2 + bk + c, \ a < 0$$

If we consider the values obtained for n charge/discharge cycles, we can obtain function parameters using the following relation:

$$\begin{cases} a\sum_k k^2 + b\sum_k k + cn = \sum_k C_{\mathrm{k}} \\ a\sum_k k^3 + b\sum_k k^2 + c\sum_k k = \sum_k kC_{\mathrm{k}} \\ a\sum_k k^4 + b\sum_k k^3 + c\sum_k k^2 = \sum_k k^2 C_{\mathrm{k}} \end{cases} \quad . k = \overline{1,n},\, n \geq 3$$

This system can be solved by computing the determinants below:

$$\Delta = \begin{vmatrix} \sum_k k^2 & \sum_k k & n \\ \sum_k k^3 & \sum_k k^2 & \sum_k k \\ \sum_k k^4 & \sum_k k^3 & \sum_k k^2 \end{vmatrix} \qquad \Delta_{\mathrm{a}} = \begin{vmatrix} \sum_k C_{\mathrm{k}} & \sum_k k & n \\ \sum_k kC_{\mathrm{k}} & \sum_k k^2 & \sum_k k \\ \sum_k k^2 C_{\mathrm{k}} & \sum_k k^3 & \sum_k k^2 \end{vmatrix}$$

$$\Delta_{\mathrm{b}} = \begin{vmatrix} \sum_k k^2 & \sum_k C_{\mathrm{k}} & n \\ \sum_k k^3 & \sum_k kC_{\mathrm{k}} & \sum_k k \\ \sum_k k^4 & \sum_k k^2 C_{\mathrm{k}} & \sum_k k^2 \end{vmatrix} \qquad \Delta_{\mathrm{c}} = \begin{vmatrix} \sum_k k^2 & \sum_k k & \sum_k C_{\mathrm{k}} \\ \sum_k k^3 & \sum_k k^2 & \sum_k kC_{\mathrm{k}} \\ \sum_k k^4 & \sum_k k^3 & \sum_k k^2 C_{\mathrm{k}} \end{vmatrix}$$

In final step, the polynomial function parameters are obtained using the relations:

$$a = \frac{\Delta_{\mathrm{a}}}{\Delta},\ b = \frac{\Delta_{\mathrm{b}}}{\Delta},\ c = \frac{\Delta_{\mathrm{c}}}{\Delta}.$$

For faster computation the recurrent relations are used. These relations are well suited for implementation in embedded systems with low resources.

$$S_{\mathrm{k+1}} = S_{\mathrm{k}} + (k+1),\ S_{(\mathrm{k+1})^2} = S_{\mathrm{k}^2} + (k+1)^2,\ \text{etc.}$$

Given the capacity function we can compute the first cycle m for wich the battery capacity is bellow a specific level $F \cdot C_{nominal}$ for which battery state of health is considered 0%.

The value of m can be computed by solving the inequality:

$$F \cdot C_{\mathrm{nominal}} > ak^2 + bk + c$$

because $a < 0$, $m$ can be obtained by:

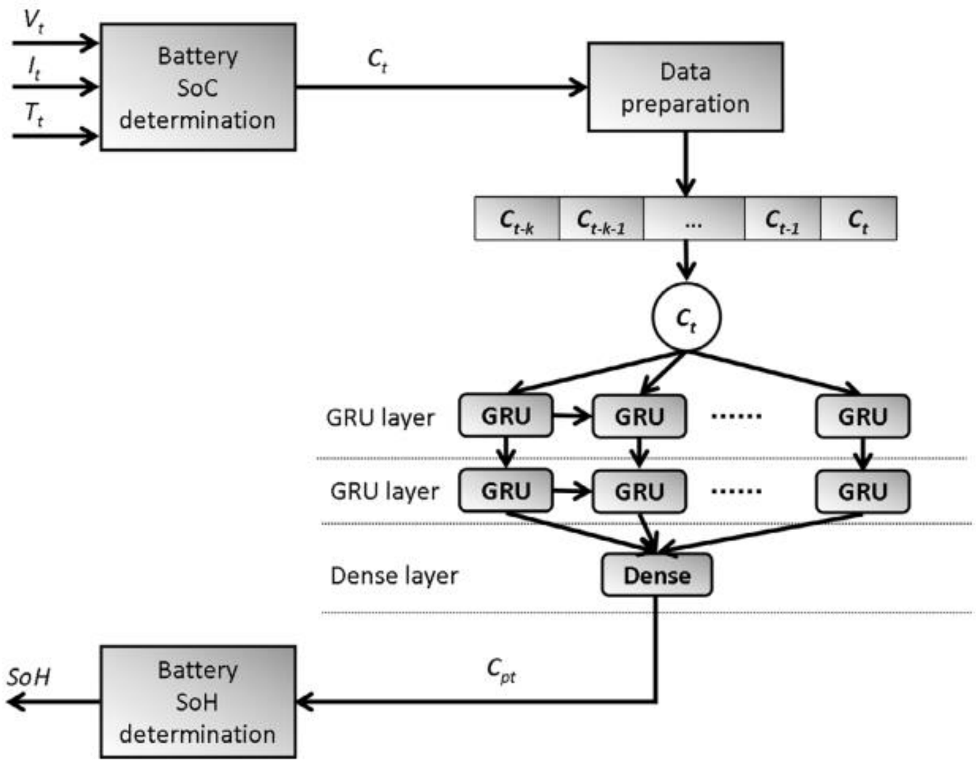
$$m = \left\lfloor \frac{-b - \sqrt{b^2 - 4ac}}{2a} \right\rfloor,$$

in which $\lfloor x \rfloor$ is the integral part of $x$.

This method provides very good estimation accuracy when the capacity curve follows a linear trend. The accuracy decreases when nonlinearities are present in battery capacity data.

# 5. Battery state of health estimation based on GRU cell recurrent neural networks

The following figure details the structure of a typical battery management system which uses an online battery state of health estimation method:




Estimation method based on gated recurrent units GRU

The system has the following structure:

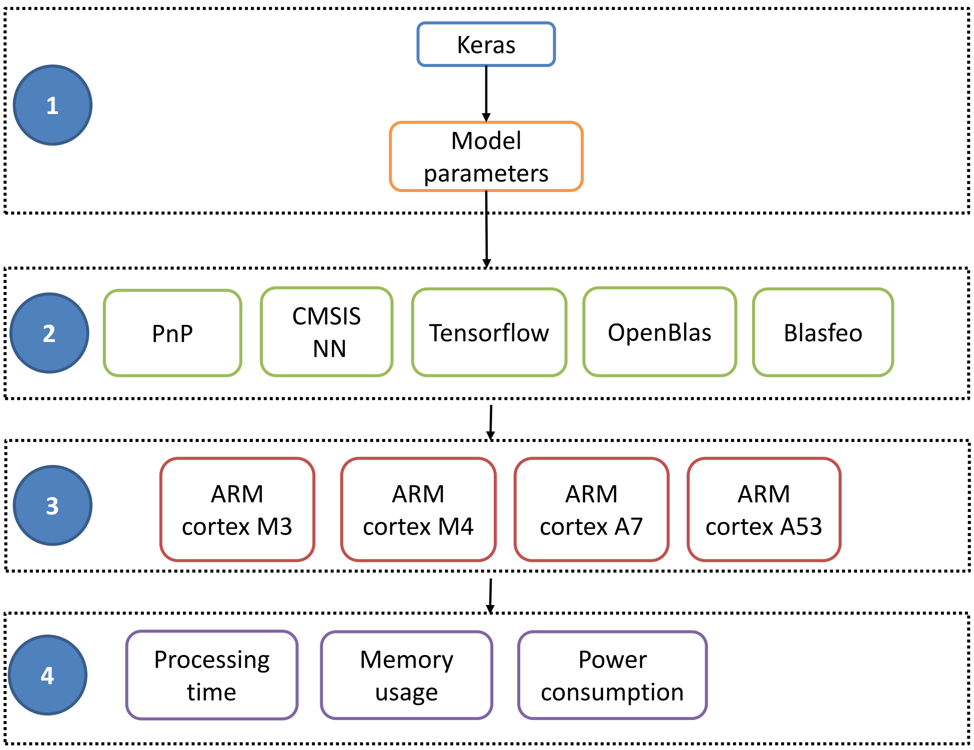
- SoC computation subsystem – this module computes in real time the output parameter, in this case battery capacity at time instance t, $C_t$ based on the input parameters – in this case battery voltage, battery current and battery temperature.
- Data preparation module – transforms input data into sequences which are used at the input of the neural network.
- Recurrent neural network
- SoH computation module – transforms the value of the estimated capacity into SoH value. Using the following relation:

$$SOH[\%]=\begin{cases}100\%, & \dfrac{C_{bat}}{C_{nom}}>1\\ \left(1-\dfrac{1-\dfrac{C_{bat}}{C_{nom}}}{SOH_0}\right)\cdot 100[\%] & \\ 0\%, & \dfrac{C_{bat}}{C_{nom}}<SOH_0\end{cases} \quad (56)$$

# 6. Framework for performance evaluation of battery state of health estimation methods based on neural networks

The structure of the performance evaluation framework is a layered one:

- layer 1 – denotes the model representation layer. For simplification I have used Keras for the representation with help of Python programming language.
- layer 2 – denotes the computational layer on embedded systems. One can choose between computational libraries: PnP (Paper and Pencil), Tensorflow etc.
- layer 3 – denotes the HW layer. Here one can choose the hardware platform in which the performance needs to be evaluated.
- layer 4 – denotes the output layer in which the performance metrics are computed and evaluated.



The evaluation criteria and performance metrics used in layer 4 are the following:

- processing time – period of time computed in ms, elapsed for each estimation output. The processing time depends on the CPU frequency and the number of threads on which the algorithm runs.
- memory usage – depending of the chosen HW platform there are multiple types of memories: flash (for constants), SRAM and DRAM for algorithm variables.
- power consumption – used for each estimation at each discharge cycle. The unit of measurement used to compute the value is mAh.
- estimation error – it is the relative percentage error obtained after providing test data. This can be compared with the error obtained on PC to check if there is some difference.

# 7. Performance evaluation

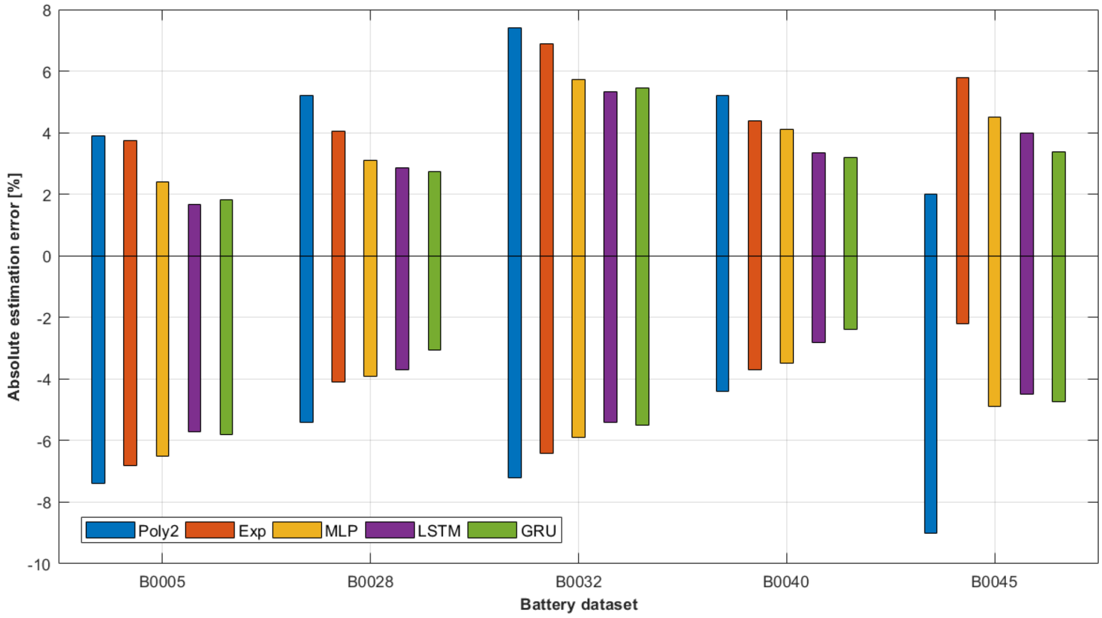
Neural network-based estimation methods provide the best accuracy [3]. The range of the error is near the values 1% – 1.5%. These values were obtained by running the algorithm on datasets in which the batteries were cycled at room temperature of 25 degrees Celsius, charging and discharging performed using constant current. I have confirmed this result using experimental scenario 25-DEG-CC-SF. Thus, using a dataset which contains real life scenario, having variable discharge currents and different operating temperatures, I have obtained an error range similar to the median error of most common methods.

Compared to other memory neural networks [21] such as LSTM, the GRU method has the advantage of having a simpler structure. This means the number of model parameters is 25% less than the number of parameters in LSTM model. This is very important for the learning process and also for the physical implementation on a embedded device with reduces resources.

The following table summarizes the comparison between the GRU model and LSTM model.

| **Criteria** | **LSTM** | **GRU** |
|---|---|---|
| No. of model parameters | 30651 | 23001 |
| Learning median error | 0.270 | 0.264 |
| Relative percentage error range for ALL-DEG-CC scenario | [–5.02, 5.24] | [–5.13, 5.32] |

In [21] I used a dataset similar to ALL_DEG_CC, in which I have considered the end-of-life battery capacity between 60% and 70% of nominal capacity. Using this dataset, I have compared the GRU method with the most common neural network-based methods and also with the ones base on polynomial and exponential regression. The results are detailed in the next figure.




Comparative study of different estimation methods [21]

The estimation methods based on polynomial and exponential regression provide good estimation results when the battery capacity curve has the trendline of a polynomial or exponential function. In most of the cases the nonlinearities of the battery make the estimation error to increase, e.g., [-7.5%, 4%] and [-7%, 3.8%] for battery B0005.

The estimation error is smaller when taking into consideration methods based on neural networks: starting with MLP, with an error range of [ -6.5%, 2.5%] and end with LSTM and GRU for with the estimation error is in range of [-5.5%, 2%] for battery B0005. The improvement is due to the internal structure of LSTM and GRU cells which contain lon and short memory.

When the battery capacity has multiple regeneration points, the estimation error gets worse even for LSTM and GRU, and the difference between them is no so relevant. This can be seen with battery B0032. Even if the error increases, it is in an acceptable range for this type of estimation methods.

# 8. Conclusions and future perspectives

The thesis ‘Rechargeable batteries state of health assessment for battery powered embedded systems’ represent the doctoral study research advised by Professor Dr.-Eng. Mihai V. Micea.

The first object was met by implementation of the battery state of health estimation method described in chapter 5, based on neural networks with GRU cells. In addition, I have detailed an optimization for batteries which present regeneration effect. This method is an improvement for the method presented in chapter 4, in which a full BMS was implemented. The method described in chapter 5 can be implemented on embedded platforms ranging from the simplest ones to complex ones.

The second objective was met by defining and implementing the performance evaluation framework for the estimation methods. The purpose if this framework is to output the relevant metrics to help analyze the performance comparison of different estimation methods based on neural networks.

There are several improvement perspectives for future development. These can be grouped tacking into consideration the thesis objectives. The list of the improvement related to the battery state of health estimation method are described as follows:

- Transform the model into a dynamic one which performs the parameter update at each battery cycle.
- Combine the method with another one in order to obtain more performance in terms of estimation error.

For the second objective we can list the following future improvements:

- Extend the embedded devices which can run the method
- Add new SW libraries for mathematical operations
- Define a general performance score for method comparison

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