Li-Ion Batteries State-of-Charge Estimation Using Deep LSTM at Various Battery Specifications and Discharge Cycles

Kei Long Wong, **Michael Bosello**, Rita Tse, Carlo Falcomer,
Claudio Rossi, Giovanni Pau

澳 門 理 工 學 院
Instituto Politécnico de Macau
Macao Polytechnic Institute

ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

UCLA
Computer Science

Lithium Batteries

Battery technology is one key enabler for the green energy transition

- Everything that can be electrified will be electrified within a decade (according to EU)

Li-ion battery is the most popular power supply of EV

- high energy density
- long lifespan
- lightweight
- low self-discharge rate

Battery Management Systems (BMS) ensure security and reliability

State of Charge (SOC)

$$SOC = \frac{Q_t[Ah]}{Q_0[Ah]} \cdot 100(\%)$$

Estimating SOC is one of the core duty of the BMS

The BMS adjust its functioning according to the estimated SOC

A robust SOC estimation

- Ensure battery reliability
- Prevent failures and hazards
- Prevent over-charge and over-discharge
- Informs the user about the charge

SOC Estimation

- It cannot be measured

Direct methods	• It can be precisely computed in laboratory conditions
Model-based (+filters)	• Physical models are difficult to be designed • electrochemical reactions are non-linear
Data-driven	• Better results in complex applications • They do not require expert knowledge about the degradation phenomena • Computational efficient (during inference) – essential for execution on BMS • They open to SOC forecasting

Proposed Method

Deep(er) LSTM — able to learn the SOC trend

- Time series as input: voltage (V), current (I), and temperature (T)
  - V, I, T are measurable and related to SOC
- Use of two high-quality wide datasets
  - One with original data from real batteries collected by UNIBO
  - One publicly available

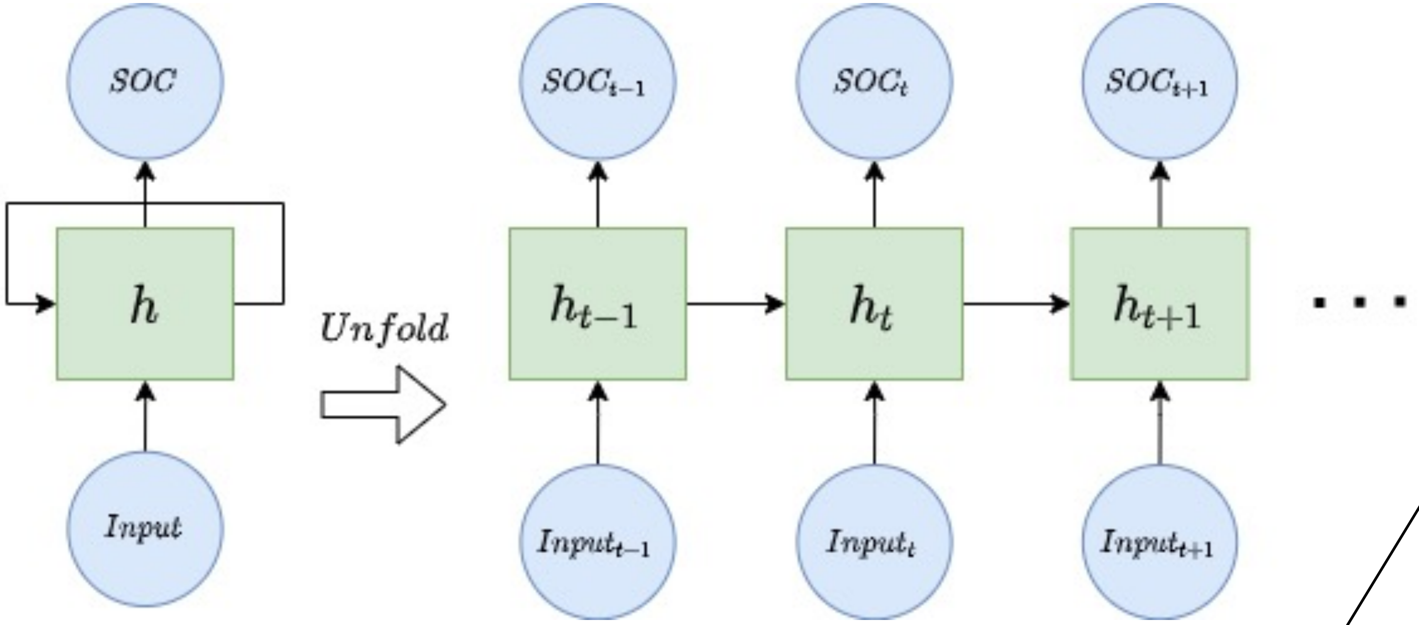
Related works

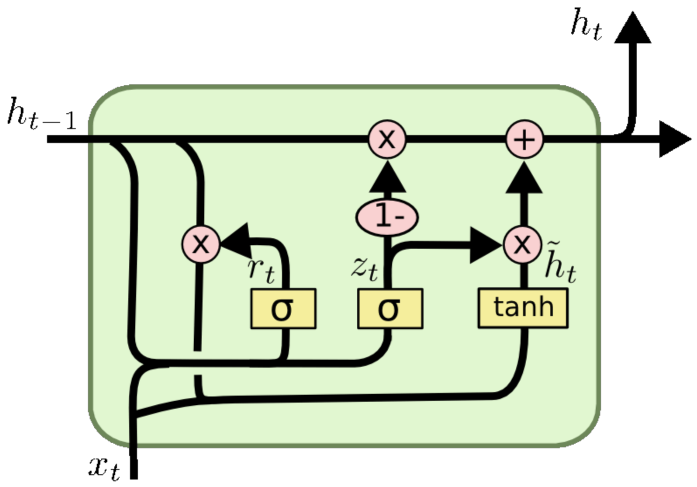
- Some works already used LSTMs for SOC estimation
  - Their datasets contain only one or a few batteries with one setup

Datasets

- UNIBO Powertools Dataset (first publication)
  - 27 batteries cycled in laboratory
  - CC-CV Discharge, three tests: standard, high current, pre-conditioned
  - **Different manufacturers**
  - **Several nominal capacities**
  - **Cycling is performed until the cell's end of life**
    - Useful to assess how SOC is affected by the cell's age
    - Useful to validate the model under different health status
- LG 18650HG2 Li-ion Battery Data
  - One battery tested
    - At different temperatures
    - With several driving profiles

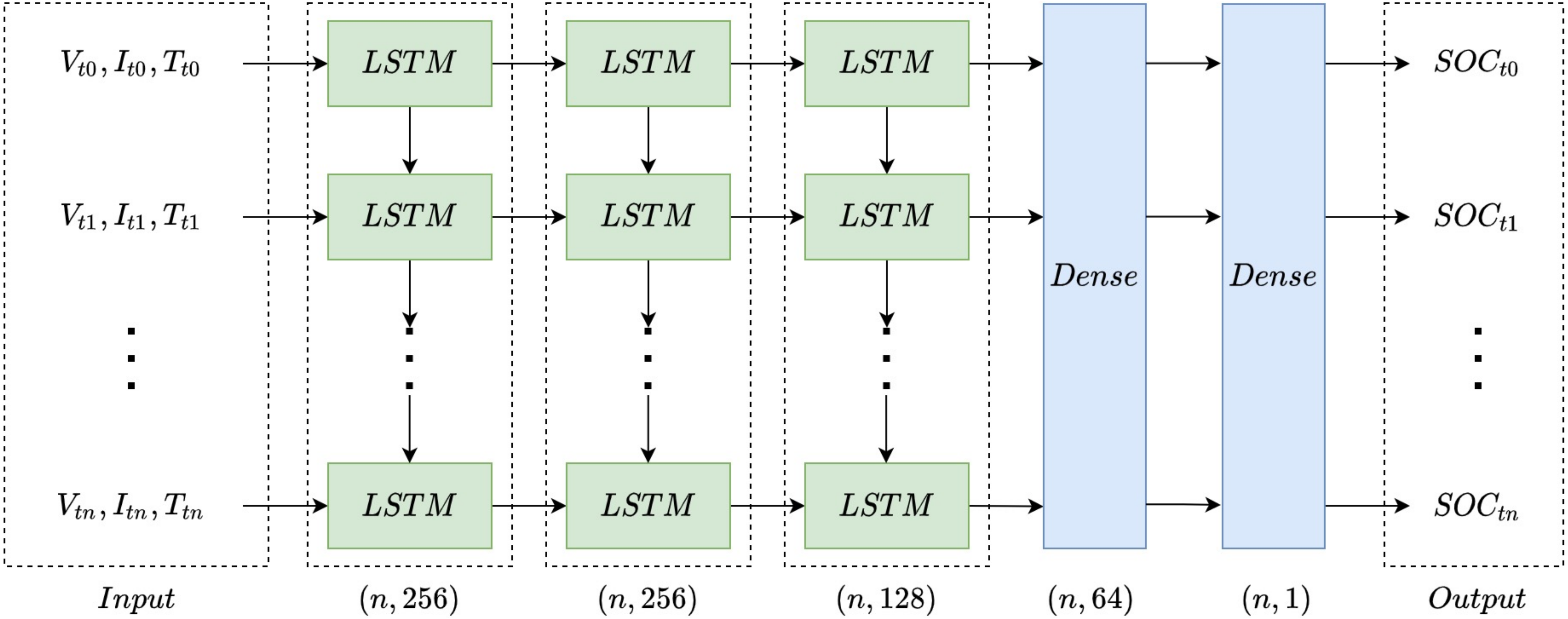
Recurrent Neural Networks and Long-Short Term Memory



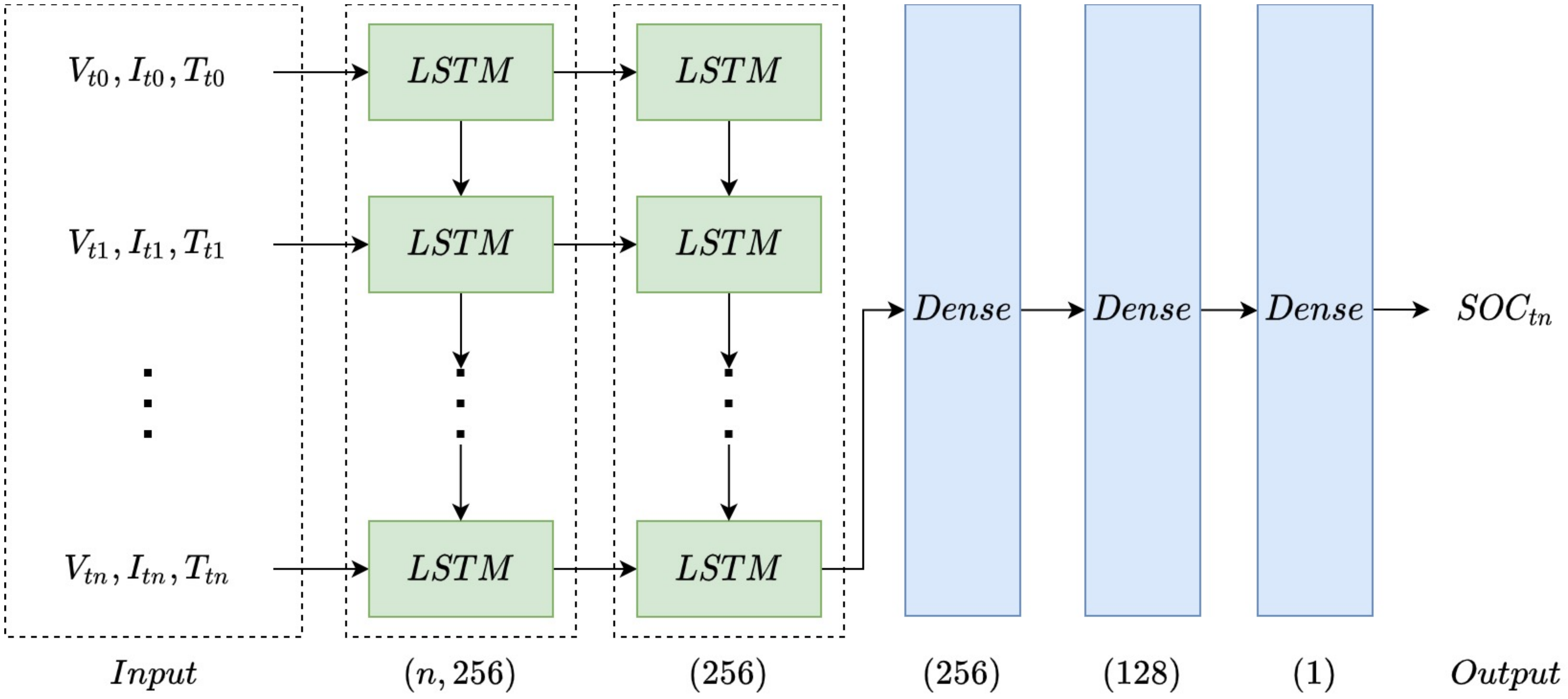


Credits: https://colah.github.io

Model for UNIBO Data



Model for LG Data



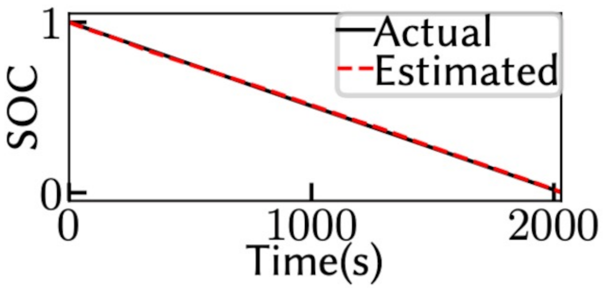
Results: UNIBO Powertools Dataset

- Testing on 1 cell for each test type and nominal capacity (20 train, 7 test)

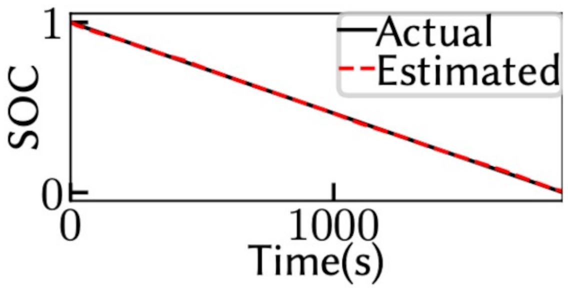
✓MAE: 0.69%, RMSE: 1.34%

  - MAE < 0.6%, RMSE < 0.8% for all test type but two (not having enough data)

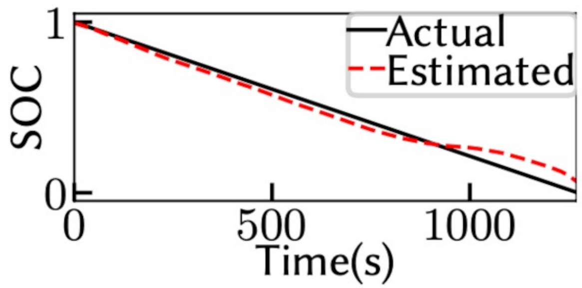
✓SOC accurately estimated under different **battery health statuses**



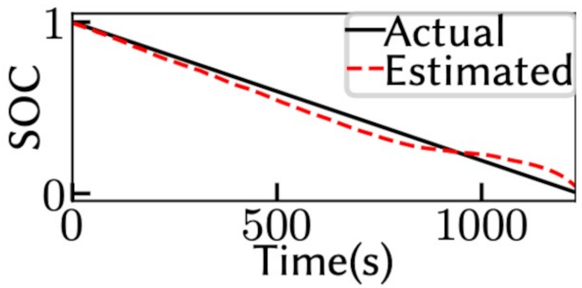
(c) Standard 2.85Ah (first cycle)



(d) Standard 2.85Ah (last cycle)



(a) High current 2.85Ah (first cycle)



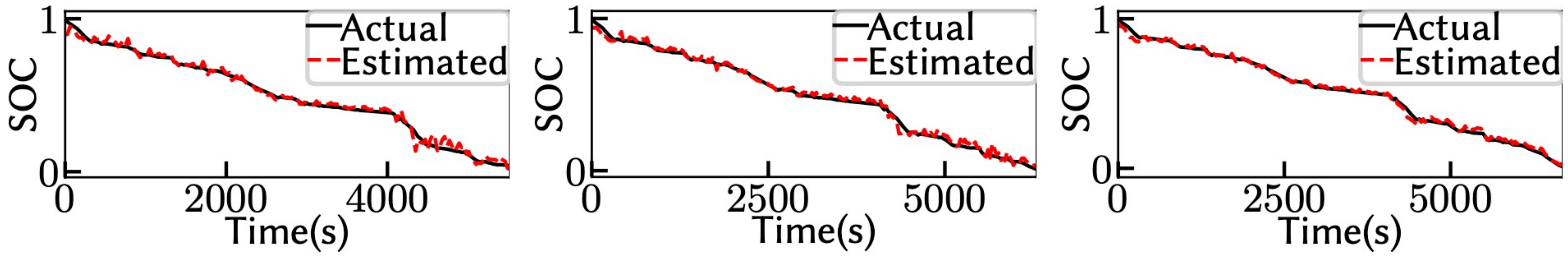
(b) High current 2.85Ah (last cycle)

Results: LG 18650HG2 Li-ion Battery Data

- Training on 6 mixed driving cycle for each temperature
- Testing on UDDS, LA92, US06 + 1 mixed driving for each temperature
- Different time series lengths tested — the best is 300 step ~50sec

✓MAE: 1.47%, RMSE: 1.99%

✓SOC accurately estimated under different **temperatures** (0°C, 10°C, and 25°C)



(g) 0°C (300 steps) (d) 10°C (300 steps) (a) 25°C (300 steps)

Thank you

- Code
  https://github.com/KeiLongW/battery-state-estimation
- UNIBO Powertools Dataset
  https://data.mendeley.com/datasets/n6xg5fzsbv/1
- Contact
  michael.bosello@unibo.it