

Training a Multi-task Neural Network for Anomaly Detection & Forecasting

Summary: With the increased usage of green energy to sustain ample environmental conditions, the use of electric vehicles has tided over Internal combustion engines. The race for efficiency in terms of storage and adequate employment of energy is underway. There is one name commonly heard, the Lithium-ion battery with its different chemistries (LFP, NCA, NMC, Solid-State), commonly used in Electric Vehicles due to its high energy density, long life cycle and reliability. This research investigates the said attributes within a few factors that are believed to be influential for a battery's longevity and efficiency.

Background: The groundwork previously laid for this purpose includes early detection of anomalous degradation behaviour in Lithium-ion batteries, where two datasets were employed under specific operating conditions to return 800 ~ 900 cycles for cells in dataset 1 containing 12 samples of 3260 mAh Li(NiMnCo)O₂ batteries and 1400 ~ 1500 cycles for dataset 2 containing 23 samples of 350 mAh batteries with the same cathode chemistry (Diao et al., 2020). This research concluded that standard deviation was a cause for delay in anomaly detection as dataset 1 had a considerably larger valued std compared to dataset 2. No account of the variables involved is provided. Bringing us to our lower level of groundwork, this research considering charge/discharge current rate, depth of charge/discharge & temperatures as driving metrics in battery degradation in EV data elicited through Shanghai Electric Vehicle Public Data Collecting, Monitoring and Research Centre (SHEVDC) (Song et al., 2020). Where a Feed Forward Neural Network was employed to estimate State of Health (SOH) of 300 Battery Electric and 400 Hybrid Electric passenger vehicles, equipped with Lithium Nickle Manganese Cobalt Oxide (NMC) batteries, popular for balancing performance & cost. The researchers concluded the average SOH value to be 0.45% with Root Mean Squared Error & Mean Absolute Error estimations to be 1.976 Ah and 1.521 Ah respectively for Battery Electric Vehicles and 0.14 Ah and 0.1157 Ah for Hybrid Electric Vehicles. The framework possesses huge development prospects but is bound to a specific set of parameters for the time being.

Research Question: Can multi-task neural networks efficiently detect anomalous charge/discharge behaviour and predict state of charge over time simultaneously?

Objectives:

- Elevate understanding of Machine Learning with various methodologies including Mathematical Expression, Calculus, Statistics & Probability, Python Programming, Exploratory Data Analysis & Problem Solving.
- Train Long-short Term Memory Models to capture time dependencies in data, specifically the decline of State of Charge over usage patterns, charging and ambient temperature.
- Employ Neural networks (Autoencoders/Variational Autoencoders) to reconstruct input data and define expected behaviours of historical charge & discharge.
- Merge the mentioned facets in a single Neural Network to facilitate shared feature learning and producing a multi-faceted output to return both anomalous behaviour and state of charge forecast.

Task List:

As mentioned below the tasks are divided into 3 milestones spanning over 3 fortnights of work assuming a laminar flow from one task to the next, which may vary depending upon the need for re-evaluation of the selected methodologies with respect to the project and time-line compatibility.

❖ Data Preprocessing: 15th October – 1st November

- Combining two datasets containing vehicle data and charging/discharging behavioural data.
- Filter data to meaningful features by unifying identifiers and removing duplications.
- Evaluating basic dataset parameters through visualization and description.
- Applying data manipulation for easier pattern recognition through normalization or log transformation.
- Implementing pipelines through TensorFlow.

❖ Separate Model Training: 1st November – 15th November

- Choosing separate Neural Network models for Anomaly Detection & Forecasting.
- Implementation of chosen architecture and model through Keras.
- Training models to the most realistic achievable accuracy. (Goal 80%+)
- Noting down effects of tuning parameters and model behaviours.
- Visualizing model behaviours along different sets of tuning parameters.
- Applying model efficiency methodologies to reduce time cost.
- Documenting results and comparing with available literature.

❖ Training Multi-task Model: 15th November – 25th December

- Using inferences from previous evaluations to redefine model architecture.
- Implementing model architecture with one input and 2 output heads.
- Fine tuning of model through observed effects from separate models.
- Monitoring effects of the applied changes through visualization.
- Tuning model parameters to achieve highest possible realistic accuracy.
- Documentation of model behaviours and comparison with available literature.

❖ Gathering Additional Research Parameter: 25th December – 5th January

- Conducting thorough literature review to evaluate project completion over the acquired results.
- Improvement of project documentation through outlined formatting principles.
- Identifying future applications of methodology implementation in the event of project fruition, on the contrary, conducting research to identify shortcomings and required improvements.

❖ Parallel Tasks:

- Evaluating and applying ethical parameters over the span of the project implementation.
- Partaking in Ethics lectures and assessments for project implementation.

Data Management Plan:

Datasets to be used in the research have been acquired from the links provided in references 3 & 4.

The data consists of 2 parts:

Vehicle Data (9.34 mb): Elicited from ~230 electric vehicles over a 1–3-year timespan using on board data loggers installed by the project team or preinstalled by the original equipment manufacturer, which was made accessible via an online web portal/API, this dataset contains trip-level or daily data during a vehicle's standard operations.

Variables to be employed include:

Date (MM/DD/YY): Over which the data was aggregated.

Number of Trips: Taken each Day.

Total Distance (Miles): Driven Each Day.

Idling Time (hours): Static time of the Vehicle

Total Run Time (hours): Time with Key on each day.

State of Charge Used (%): Total amount of SOC (aggregated level decreases over a day)

Total Energy Consumption (kWh): Energy used by the vehicle in the day.

Average Ambient Temperature (F): Average daily outdoor temperature.

Max SOC: Max level of State of Charge.

Min SOC: Min level of State of Charge.

Charge Data (1.30 mb): Elicited from the EV supply equipment (Charger), on-board equipment, utility submeter. Many chargers provide software that allows for the collection and reporting of charging session data. If unavailable, data may be recorded by the charging vehicle's onboard systems. If neither of these options is available, data can be acquired from utility submeters that simply track the energy flowing to one or more chargers.

Variables to be employed include:

Date (MM/DD/YY): Date over which data was aggregated.

Charging Time (Hours): Time the vehicle is actively charging.

Average Power (kW): Total energy divided by the length of charge.

Max Power (kW): Maximum power provided by Charger.

Total Energy Delivered (kWh): Amount of energy charged during date.

SOC Charged (%): Total amount of SOC charged during the charging session.

Document Control: Progress will be committed to Github on milestone progress basis and with minor contributions in the given link:

<https://github.com/MShoaibManzoor/Advanced-Research>

ReadMe File: This project elaborates the detailed working of a Multi-task Neural Network for Anomaly Detection & Forecasting, trained and perfected on EV data acquired from the link provided.

The files will be uploaded to One Drive for data security which can be accessed [here](#).

References:

1. **Early detection of anomalous degradation behaviour in lithium-ion batteries** Diao W, Naqvi I, Pecht M *Journal of Energy Storage* (2020) 32 101710
<https://www.sciencedirect.com/science/article/pii/S2352152X20315474#bbib0001>
2. **Intelligent state of health estimation for lithium-ion battery pack based on big data analysis** Song L, Zhang K, Zhang Y *Journal of Energy Storage* (2020) 32 101836
<https://www.sciencedirect.com/science/article/pii/S2352152X2031673X#abs0001>

3. *Livewire Data Platform (LDP). calstart/charging. Maintained by Livewire Data Platform for U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy. DOI: 10.15483/1989855. Accessed: <18 10 2024>. <https://livewire.energy.gov/ds/calstart/charging>*
4. *Livewire Data Platform (LDP). calstart/vehicle. Maintained by Livewire Data Platform for U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy. DOI: 10.15483/1989853. Accessed: <18 10 2024>. <https://livewire.energy.gov/ds/calstart/vehicle>*