BATTERY STATE-OF-CHARGE ESTIMATION

MATLAB DESIGN TOOL BASED ON DATA DRIVEN LEAST-SQUARES SUPPORT VECTOR MACHINE METHOD

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Acknowledgements: Research supported by the Scottish Enterprise Can Do Innovation Challenge programme for Zero Emissions Heavy Duty Vehicles

Scottish Enterprise

Contents

Introduction

- Hybrid HDVs with electric power zero-emissions
  - Involve battery energy storage supplying electric vehicle
  - In conjunction with other power sources, e.g. Fuel Cells
  - Green revolution highlights importance of batteries and Battery Management Systems (BMS) in transport applications
- Development of estimators is critical aspect of BMS design
  - Algorithms compute estimates of battery characteristics that are unmeasurable
  - E.g. for battery equivalent capacity, battery resistance & battery State-of-Charge (SoC)
- BMS estimator design is complex and time-consuming task
  - Due to variety of battery technologies, architectures, and uncertainties
  - Several data-driven and combined data-driven/model-based methods have been proposed to solve BMS SoC estimation problem
  - Including Neural Network (NN), Fuzzy Logic, KF-based algorithms, combining ML and model-based approaches

Philosophy

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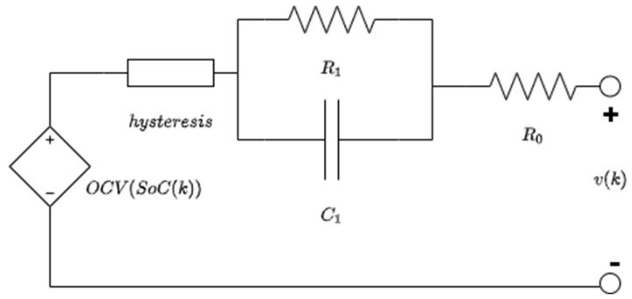
- Purely data-driven design methodology to perform battery estimation
  - Focus is on battery State-of-Charge (SoC) estimation problem
  - Method combines modern data-driven Least-Squares Support Vector Machine (LS-SVM) with data pruning procedure for efficient computations
  - Method uses Particle Swarm Optimization (PSO) to tune algorithm
- Pruning method selects important samples from training dataset
  - Reduces computational complexity and memory footprint of algorithm
  - Whilst maintaining performance
- Dataset collected by emulating battery using Enhanced Self-Correcting (ESC) battery simulation model
  - Baseline estimator was also developed for comparison with model-based approach
    - Extended Kalman Filter (EKF)
  - Estimators compared in simulation
    - In terms of performance and computational complexity

Battery Model



Battery State-of-Charge

SoC of *i*-th battery cell is defined as:

$$SoC_i(k) = \frac{\theta(k) - \theta_{0\%}}{\theta_{100\%} - \theta_{0\%}}$$

where $\theta(k)$ is average lithium concentration stoichiometry at discrete-time k defined as:

$$\theta(k) = \frac{c_{s,avg,k}}{c_{s,max}}$$

This should remain between *0%* and *100%*

- Although possible to violate limits in over-discharge or over-charge situation
- Presently no way to measure concentrations to calculate stoichiometries and SoC
- Therefore necessary to infer or estimate SoC using only measurements of cell terminal voltage, current, and temperature

Data-Driven SoC Estimator

Pruning Procedure

One of main issues in LS-SVM identification is size of training dataset

Estimate is computed iteratively by comparing training dataset information with measurements from real system

Two issues:

1) Computational burden increases with dataset size; when training dataset is large, iterative computation of estimate can be prohibitive in real-time;
2) To use LS-SVM on real systems, training data must be stored in memory, reducing possibility of porting algorithm onto hardware with limited resources

Possible solution for reducing training dataset size is so-called *pruning method*

Method involves iteratively performing LS-SVM identification, reducing training dataset size at each iteration

By gradually omitting least significant training data

- Lowest Lagrangian multipliers

Method allows a priori definition of maximum size of data subset to consider

- Or equivalently, acceptable value of identification performance degradation

Data-Driven SoC Estimator

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Pruning Procedure

1) Considering original dataset of size N & train LS-SVM
2) Remove number of points (e.g. $\Delta N = 5\%$ of N) corresponding to smallest values in $|\alpha_k|$ (data point 'influence') spectrum
3) Train LS-SVM with new reduced dataset
4) Return to point 2 until identification performance degradation threshold is exceeded

Data-driven SoC Estimator

Data-Driven Design Procedure

Data-driven estimator design is based on ML and statistical methods

To limit computational complexity, following design procedure was defined:

- Phase 1: Perform first LS-SVM training based on PSO & original training dataset to compute estimator calibration parameters
- Phase 2: Perform Pruning Analysis with calibration parameters of Phase 1 & select pruned dataset size to consider for final estimator training
- Phase 3: Perform final LS-SVM training

Data-driven SoC Estimator Design Tool

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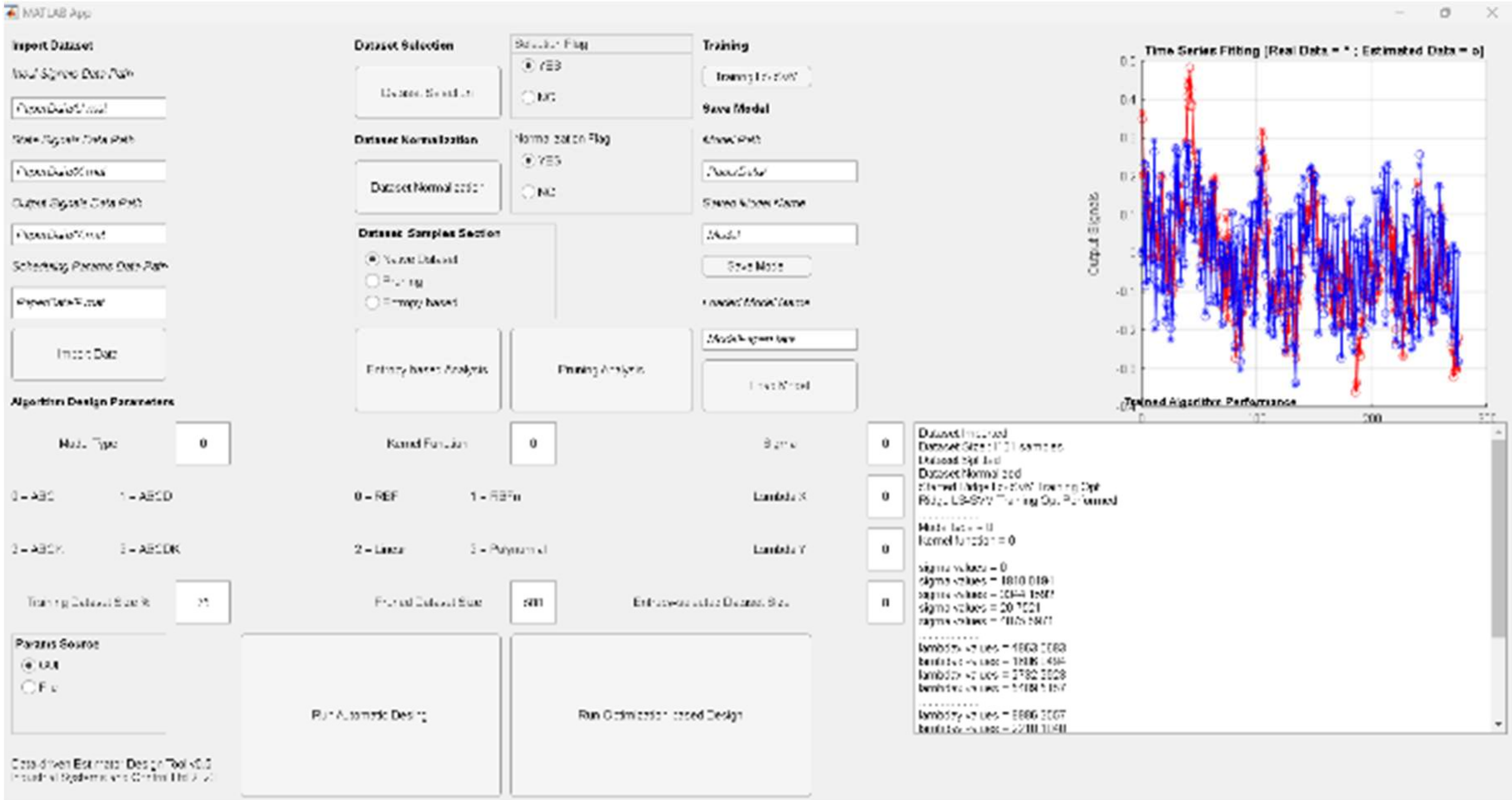
Design approach is implemented in Data-driven Estimator Design Tool

- Developed by ISC to simplify development
- Software generates data-driven estimator
  - Includes tuning parameters for training and pruning procedure
- GUI provides feedback to user
  - Estimation/pruning graphical results & identification of performance statistics
- GUI shows inclusion of set of common data manipulation methods e.g. data normalization & Entropy-based Analysis



Performance Criteria

Performance indices to compare estimators:

- **Mean Absolute Error** (MAE)
- **Root Mean Square Error** (RMSE)
- **Execution Time** (ET) in seconds

Estimators Comparison

Data-driven estimator design: Phase 2

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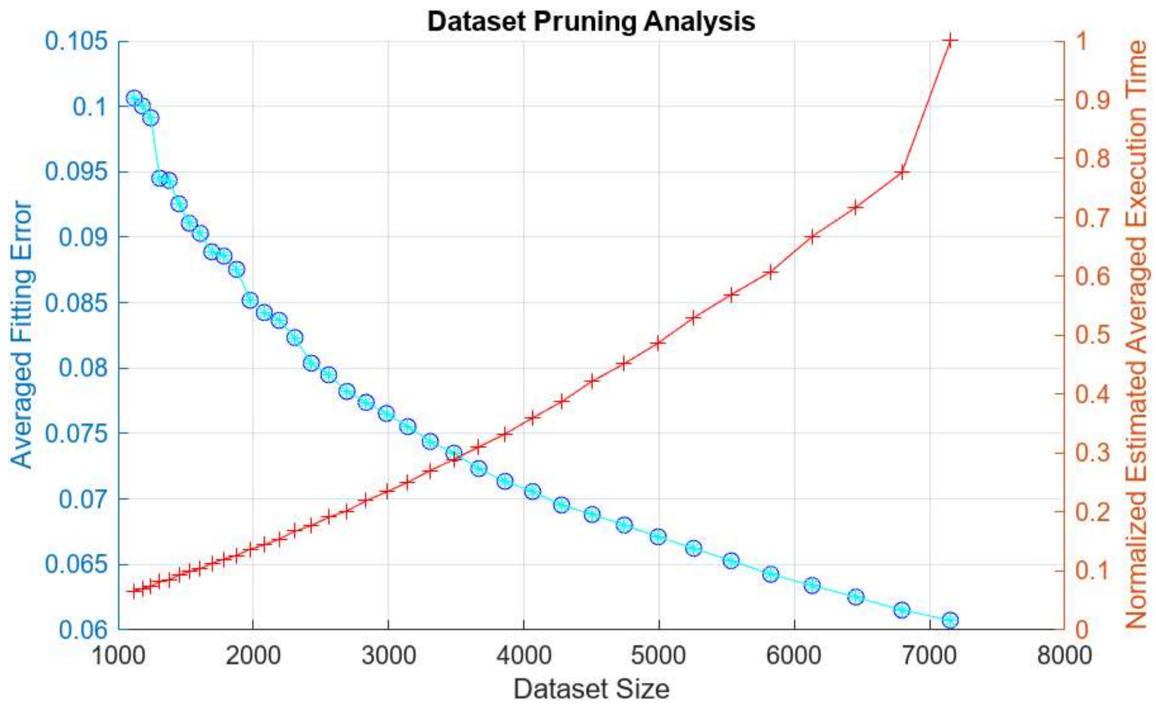
- In Phase 2, pruning was applied to dataset from Phase 1
- Figure: Result of analysis with averaged fitting error with respect to size of selected dataset, plus normalised averaged execution time
- Analysis enables evaluation of trade-off between fitting error increase and related execution time reduction
- From this, size of pruned dataset for Phase 3 is selected as 5000 samples
- Reduces computational burden by 50%, with expected 12% increase of fitting error



Estimators Comparison

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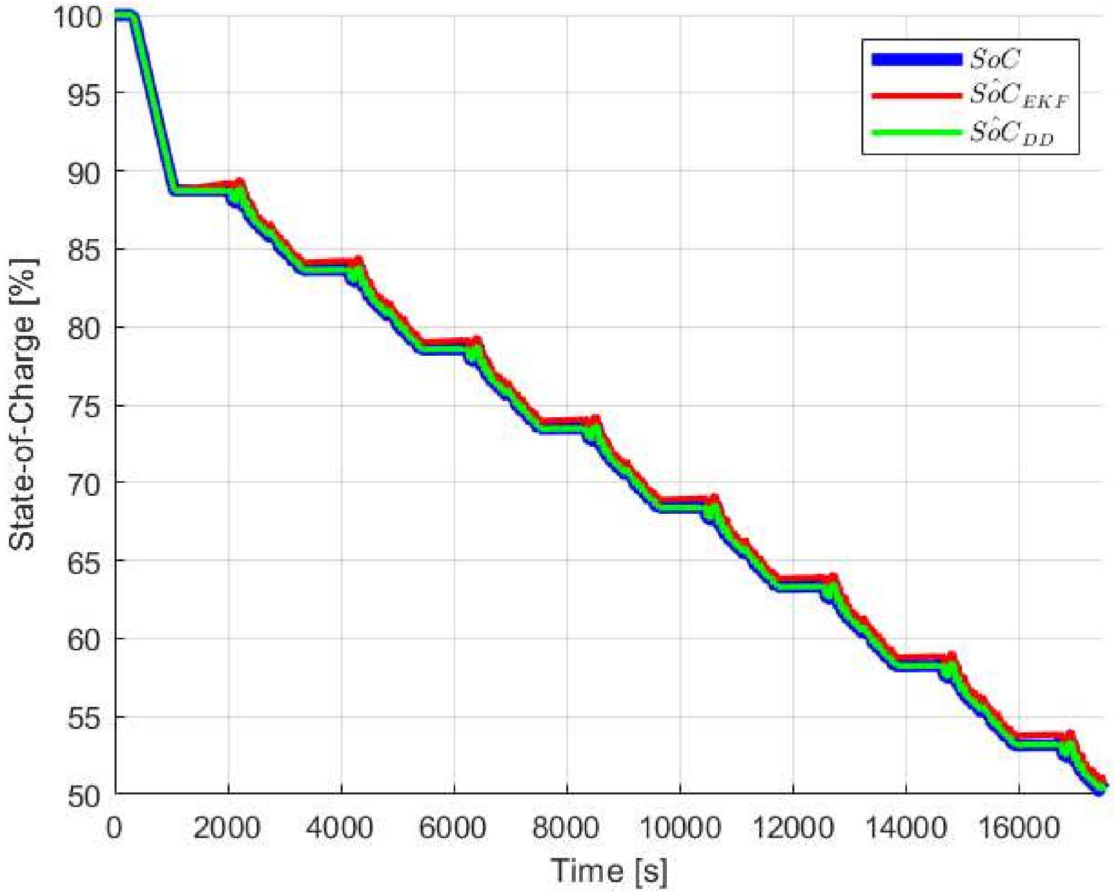
Performance of data-driven estimator vs. baseline EKF

Figure: estimator performance for scenario with SoC varying from 100% to 50%



Estimator	RMSE	MAE
EKF	5.1049×10^{-3}	4.8496×10^{-3}
LS-SVM	4.7922×10^{-3}	2.9855×10^{-3}

Conclusions

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- Battery State-of-Charge (SoC) estimation method developed
  - Exploiting capabilities of data-driven Machine Learning (ML) techniques
- Approach/tool can be used for more general applications
  - Combines Least-Squares Support Vector Machine (LS-SVM) identification technique with Pruning Dataset Selection procedure
  - Uses Particle Swarm Optimization (PSO) method
- **Automatic procedure combining these techniques has been developed and implemented within Data-driven Estimator Design Tool**
  - **Developed to reduce effort in battery estimation**
- Estimator approach achieves good performance with limited computational complexity
- Performance of algorithm compared against baseline EKF estimator
  - Results demonstrated that proposed estimator overcame limitations of model-based methods whilst reducing computational burden