Novel Technique for Developing Linearized Convex System Models from Experimentally Derived Data

Aadil Latif, Richard Bryce and Adarsh Nagarajan
National Renewable Energy Laboratory, Golden, Colorado

Introduction

Project partners

- National Renewable Energy Laboratory
- Sumitomo Electric (SEI)

Project background

- San Diego Gas and Electric (SDG&E) and Sumitomo Electric (SEI) initiated a 2MW / 8MWh vanadium red-ox flow battery (VRFB) storage pilot project in California.

Objectives

- Optimally dispatching a utility-scale vanadium redox flow battery (VRFB) energy storage system

Contribution

- A novel technique for generating a convex system model from an experimentally derived dataset which features variance among repeated measurements.

The convex hull approach for modeling system losses

The convex system model developed as a test case characterizes the dynamic system losses of a vanadium redox flow battery as a function of

- The active power output and,
- The battery state of charge.

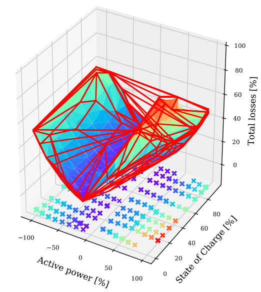

Figure 1: Surface plot for total system losses measured for battery operated at various levels of active power and state-of-charge. Projection on the Z axis shows regions sampled during experimental run.

Sources of systematic underestimation

- The hull forms on the extremities of experimental dataset.
- Noise within the dataset can significantly increase under estimation of system losses
- There may exist concave regions within predominantly convex datasets.

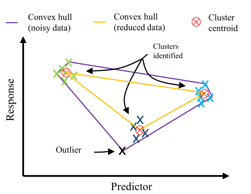

Figure 2: The illustration shows why outlier and natural variance in measured data systematic under estimation if not cleaned.

Clustering for outlier detection and error mitigation

- The storage system was charged and discharged at various levels of state of charge and active power over a period of three days, such that most of the state space was sampled.
- DBSCAN was used to identify clusters and outliers within the dataset. Centroids were then calculated for each cluster.
- Average silhouette score, number of scores less than zero and variance within the score, among others, were used to identify values of parameters for DBSCAN clustering

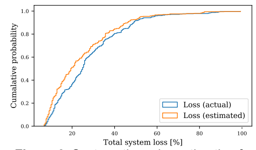

Figure 3: Systematic under estimation from the convex hull model

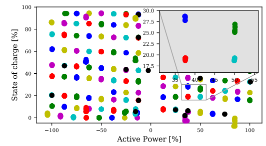

Figure 4: Clusters form using DB-scan.

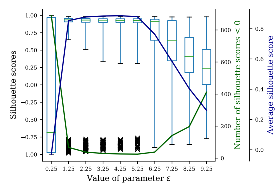

Figure 5: The plot shows the impact of varying tunable parameters for the DBSCAN algorithm in the silhouette scores

Algorithm development

- Tune clustering parameters, identify clusters and calculate cluster centroids.
- Form a convex hull around the calculated centroids.
- Identify the lower envelope of the hull and use the use set of hyper plane equations to model total system losses
- Identify boundary hyperplanes to allow extrapolation to losses for states not sampled in the experimental run

Algorithm 1: Pseudo code for calculation of system losses from the convex hull model

```
Input: C, P_m, S_m
Output: L_e // Estimated system losses
p_Dmin = empty list;
Losses = empty list;
Dmin = inf;
// Identify the planes that contain P_m, S_m
for each hyperplane h_abc = a.P + b.S + c.L + d = 0 forming convex hull C do
    Identify triplet (p_a, p_b, p_c) that bound the hyperplane h_abc ;
    Calculate K; projection of hyperplane h_abc onto L = 0 plane bounded by triplet (p_a, p_B, p_c) ;
    if (P_m, S_m) lies within the region K then
        Calculate losses l using the hyperplane h_abc;
        Append l to Losses
if length of list 'Losses' > 0 then
    L_e = min(Losses) // Return the loss value corresponding to the lower envelope of the hull
else
    // If P_m, S_m lie outside the hull C
    for each hyperplane h_abc forming hull C do
        Identify triplet (p_a, p_b, p_c) that bound the hyperplane h_abc ;
        if p_Dmin in triplet that bounds h_abc then
            // Identify point closest to measured values P_m and S_m
            for each point p_x in triplet do
                Calculate distance D between [P_m, S_m] and the project of point p_x on L = 0 axis;
                if D < Dmin then
                    Dmin = D;
                    p_Dmin = p_x
    // Extrapolate to estimate losses
    for each hyperplane h_abc forming hull C do
        if p_Dmin in triplet that bounds h_abc then
            Calculate losses l using the hyperplane h_abc;
            Append l to Losses
    remove outliers from Losses;
    L_e = avg(Losses)
```

Validation of developed methods

- Pre-cleaning via clustering procedure significantly reduces this mean bias error and the variance of the residuals.
- The global accuracy metrics show that the clustering procedure results in a model which better predicts the total system losses of the flow battery

TABLE I: The first four moments of the distribution of the residuals

Evaluation metric	Convex hull model for noisy data	Convex hull model for reduced data
mean	-25.279	-11.472
variance	604.914	466.690
skewness	-1.176	-1.989
kurtosis	0.247	3.160

- By reducing the clusters to representative centroids, the complexity of the developed piecewise linear model can be reduced. In this case its **more than 27%.**

TABLE II: Addition metrics use to to compare the developed models

Evaluation metric	Convex hull model for noisy data	Convex hull model for reduced data
R2 score [%]	90.1	95.3
Number of hyperplanes	190	138
Number of vertices	97	71

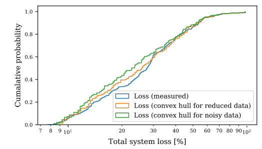

Figure 6: Loss model performance with and without the intermediate clustering step

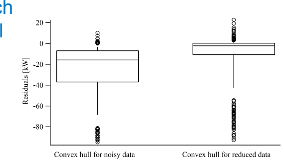

Figure 7: Box and whisker plots of residuals of each model relative to the measured data.

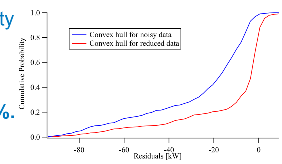

Figure 8: Cumulative probability density plot of residuals of the convex hull models based on the noisy data and the reduced data set.

Conclusions and future work

- In this paper, a novel method for developing piece-wise linear model using a convex hull is presented
- The method makes use clustering techniques to remove outliers and mitigate measurement noise and significantly improves model accuracy
- Lower envelope of the convex hull formed using centroids of identified clusters has been used to define the piece-wise linear model
- The algorithm is also capable of extrapolating outside defined region and estimating values for states that lie out the region enclosed by the hull
- The proposed formulation allows us to embed piece-wise linear models into ReOpt, a MILP, and solve the optimal dispatch problem very quickly considering loss dynamics of the battery, which will be part of future work.

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by New Energy and Industrial Technology Development Organization (NEDO), Japan. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

IEEE Power Engineering Society General Meeting 2019 (PESGM)
Atlanta, GA, USA
August 4th - 8th, 2019
NREL/PO-5D00-74510