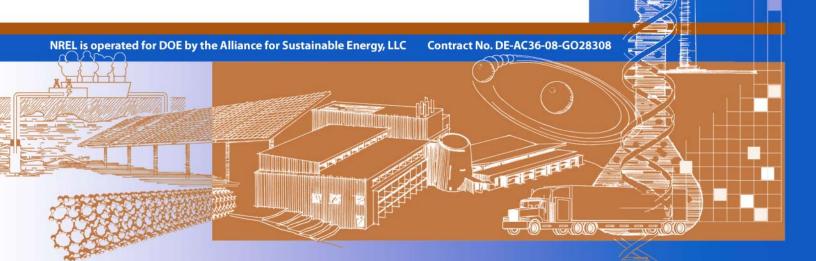


Innovation for Our Energy Future

Fuel Cell Vehicle Learning Demonstration: Study of Factors Affecting Fuel Cell Degradation

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FUEL CELL VEHICLE LEARNING DEMONSTRATION: STUDY OF FACTORS AFFECTING FUEL CELL DEGRADATION

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ABSTRACT

The 5 year "Controlled Hydrogen Fleet and Infrastructure Demonstration and Validation Project" (or Fuel Cell Vehicle Learning Demonstration) was initiated by the U.S. Department of Energy (DOE) in 2004. The purpose of the project is to conduct an integrated field validation that simultaneously examines the performance of fuel cell vehicles and the supporting hydrogen infrastructure. Four industry teams are currently operating more than 92 vehicles and 14 refueling stations throughout the United States. More than 40 additional vehicles and several additional refueling stations will be added to the project through 2009.

At the National Renewable Energy Laboratory (NREL), on-road driving and refueling data are analyzed to assess the technology status and progress, as well as to provide feedback to the hydrogen research and development community. A new/updated set of public results, in the form of composite data products (constructed to protect the intellectual property of the four teams), is released twice a year in the spring and fall. In addition to the public results, detailed analyses results are shared with each participating team.

One of the analyses studies fuel cell degradation. The study includes following the fuel cell performance degradation trends, e.g. identifying fuel cell stacks that are decaying at a different rate than others of a similar design and in the same fleet, and explores connections between the real world data and fuel cell degradation. This study differs from other degradation studies in a lab setting or at the single cell level because this study uses full scale fuel cell stacks in vehicles with on-road driving and refueling.

In the study, researchers investigate degradation factors by applying multivariate analyses for each individual team and for the combination of all four teams. Detailed results are reviewed with the individual teams in an effort to improve each analysis iteration and comprehension of the results. This paper will detail NREL's study of fuel cell degradation factors by describing the process, reviewing the latest public results, and reporting on any observed dominant factor groups affecting fuel cell degradation.

FUEL CELL VEHICLE LEARNING DEMONSTRATION PROJECT

Hydrogen fuel cell vehicles are being developed and tested for their potential as commercially viable and highly efficient zero-tailpipe-emission vehicles. Using hydrogen fuel and high-efficiency fuel cell vehicles provides environmental and fuel feedstock diversity benefits to the United States.

Hydrogen can be derived from renewable sources, natural gas, coal, or nuclear energy. This versatility would enable the United States to reduce emissions and decrease its dependence on Numerous technical barriers remain before foreign oil. hydrogen fuel cell vehicles are commercially viable. Significant resources from private industry and government are being devoted to overcoming these barriers.

The Department of Energy (DOE) is working with industry partners to develop these technologies through its Hydrogen, Fuel Cells & Infrastructure Technologies (HFCIT) Program. This multi-faceted program simultaneously addresses hydrogen production, storage, delivery, conversion (fuel cells), technology validation, deployment (education), market transformation, safety, and codes and standards.

The 5 year "Controlled Hydrogen Fleet and Infrastructure Demonstration and Validation Project" (or Fuel Cell Vehicle Learning Demonstration) was initiated by the DOE in 2004. The purpose of the project is to conduct an integrated field validation that simultaneously examines the performance of fuel cell vehicles and the supporting hydrogen infrastructure. Four industry teams are currently operating more than 92 vehicles and 14 refueling stations throughout the United States. More than 40 additional vehicles and several additional refueling stations will be added to the project through 2009. Automotive OEMs are leading three of the four teams, and an energy provider leading the fourth. Figure 1 shows the teaming arrangement of the four teams along with their first-generation fuel cell vehicles. The major companies making up the four teams are as follows:

- Chevron and Hyundai-Kia
- Chrysler and BP
- Ford Motor Company and BP
- General Motors and Shell



FIGURE 1: FIRST GENERATION VEHICLES WITH OEM & **FUEL SUPPLIERS IDENTIFIED**

The objective of the Fuel Cell Vehicle Learning Demonstration Project is to conduct parallel learning demonstrations of hydrogen infrastructure and fuel cell vehicles to allow the government and industry to assess progress towards technology readiness. We are accomplishing this objective by validating the vehicle and infrastructure as a complete integrated system. The quantity and breadth of data collected and analyzed enables researchers to evaluate technology status against DOE program targets, as well as provide feedback to DOE-funded research and development as appropriate. The ability to feed results back into research and development efforts as an integrated part of DOE's program makes this project unique compared to typical demonstration projects.

TABLE 1: KEY HYDROGEN LEARNING DEMONSTRATION TARGETS

Performance Measure	2009*	2015**
Fuel Cell Stack Durability	2000 hours	5000 hours
Vehicle Range	250+ miles	300+ miles
Hydrogen Cost at Station (untaxed)	\$3/gge	\$2-3/gge

^{*} To verify progress toward 2015 targets

The targets listed in Table 1 address key barriers to successful market entry. Fuel cell stack durability is critical to customer acceptance of fuel cell vehicles, and will be discussed in this paper. Although 2,000-hour durability in 2009 is considered acceptable to validate progress, a 5,000-hour lifetime (equivalent to approximately 100,000 miles) is estimated as a requirement for market acceptance.

Fuel Cell Degradation Study

The project has passed its mid-point and there are fuel cell stacks with more than 1,000 operating hours. NREL becomes more confident about projections of fuel cell degradation as more data and operating hours are added. Which factors affect fuel cell degradation is an important question to investigate because fuel cell degradation has been identified as a key technology hurdle along the path of fuel cell commercialization. For this reason, fuel cell durability is a key metric in the FCV Learning Demonstration project. As specified in Table 1, the DOE has established fuel cell performance targets for 2006 and 2009, with the general expectation that approximately a 5,000 hour operation time will be

necessary for commercial fuel cell vehicles.

^{**} Subsequent projects to validate 2015 targets

Objectives

A number of degradation experiments are based on single cell testing in a laboratory environment and there is a gap in translating single cell degradation experiment findings to full scale, real world applications. Within the FCV Learning Demonstration project, we have access to a large data set of onroad fuel cell vehicle trips. (As used here, an FCV trip is a key on, key off scenario. The vehicle may not have gone anywhere, but there was at least a signal to start the fuel cell.) Studying these data may allow us to bridge the gap between single cell laboratory experiments and full scale applications.

The foundation of this degradation study is built on trying to learn if there are any observable relationships between the FCV Learning Demonstration real world data and fuel cell degradation. The available data may not be sufficient to identify all of the possible degradation factors, but a vast amount of data has been collected in this project and these data can be

processed to look at driving patterns and conditions, as well as fuel cell performance. It has already been observed [1] that fuel cells are not decaying at the same rate when compared among the project partners. In addition, fuel cells are not degrading at the same rate within fleets or within similar designs. This study is looking for general factors affecting degradation as well as attempting to answer why there are varying rates of fuel cell degradation.

Because of the highly proprietary nature of fuel cell performance, many analysis details are protected. Public results are presented in a manner that will provide the findings of the degradation study while protecting intellectual property and identity of the project partners. There is a separate analysis for each team and those results are shared in detail with each team. Collaboration between NREL and the teams is critical for increasing the value of this degradation study. Many questions, experiences, and ideas are raised during individual conversations between NREL and the teams. NREL

also hopes to supplement and/or complement existing team efforts to identify contributors to fuel cell degradation. Table 2 has a list of objectives for the study of factors affecting fuel cell degradation.

TABLE 2: FUEL CELL DEGRADATION STUDY OBJECTIVES

Investigate relationship between on-road data and fuel cell degradation								fuel	
Address			full	scale	fuel	റലി	de	arada	ation

Address lack of full scale fuel cell degradation analyses/experiments

Investigate reasons for differing fuel cell decay rates

Collaboration with project partners

Public reporting of any findings

Data Collection

NREL's approach to accomplishing the project's objectives is structured around a highly collaborative relationship with each of the four industry teams. We receive raw technical data from both the hydrogen vehicles and refueling infrastructure that allows us to perform unique and valuable analyses across all four teams. Our primary objectives are to feed the current technical challenges and opportunities back into the DOE Hydrogen R&D Program and assess the current status and progress toward targets. To protect the commercial value of these data for each company, we established the Hydrogen Secure Data Center (HSDC) to house the data and perform our analyses. Figure 2 shows the flow of data and results, along with the quantity of data received per month since September 2004. To date, NREL has received data from more than 203,000 individual vehicle trips, amounting to more than 49 GB of raw, on-road data.

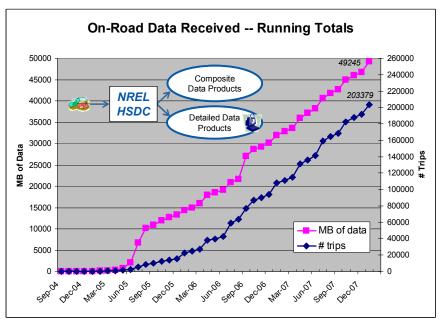


FIGURE 2: PROCESS FLOW FOR HYDROGEN SECURE DATA CENTER ANALYSES AND RESULTS

To ensure that we are providing value to the hydrogen community, we publish composite data products (CDPs) twice a year at technical conferences. These data products report on the progress of the technology and the project, focusing on the most significant results. Additional CDPs are conceived as additional trends and results of interest are identified. NREL has created a web site to house all of the current composite data products at: http://www.nrel.gov/hydrogen/cdp_topic.html. We also provide our detailed analytical results privately back to each individual company in order to maximize the industry benefit from NREL's analysis work and obtain feedback on our methodologies and results.

Approach

Why did we apply a multivariate analysis method for the degradation study? First, the data set (as can be seen from Figure 2) is large, with many different types of data including length of trip, ambient temperature of trip, and fuel cell voltage and current. Data from this project are not controlled specifically for a degradation experiment; therefore we do not have the advantage of analyzing a data set that is truly independent. Parts of the data may be redundant, correlated with other data sections, and relationships or patterns may be hidden in the complexity and size of the data. A multivariate analysis will look for these relationships and highlight variations as well as similarities within the data set. Initially, a single factor study was established to look for isolated, dominant factors contributing to fuel cell degradation one variable at a time. Not surprisingly, no single factor was identified. The uncontrolled data set, interdependencies within the data, and a belief that in real world applications degradation would be affected by factor combinations, directed us to a multivariate analysis.

There are many multivariate methods that we could apply to this data set. We started out by looking at Principle Component Analysis (PCA) and Factor Analysis (FA). PCA results for this data set would look for any linear combination of variables that identified differences among the samples. After a few iterations, it became obvious that while we may be highlighting relationships within the data, we were not targeting the relationship we were after – the relationship between the variables and fuel cell degradation.

The next step was to attempt to fit a regression model to the data set. The regression model looks specifically for relationships between two data sets, in our case, fuel cell decay rate and the driving data. Partial Least Squares (or Projection to Latent Structures, PLS) is the specific regression method used. A PLS analysis allows us to focus on any relationships between fuel cell degradation and the driving data because a PLS model is built to explain the maximum amount of variance in the decay rate. (PLS method is based on the PCA method and many results can be interpreted in the same way.) A Latent Variable (LV) is a linear combination of variables that account for decay rate variance. The decay rate estimates are the primary observation (or Y, the dependent data set) and the driving data variables are the predictors (or X, the independent data set). Currently the PLS models are used as a tool to identify and describe possible correlations between the data set and decay rate. It is not used as a prediction tool (a common use of PLS models) for new samples, although this is a possible long term goal for this study. Figure 3 depicts the process we have used for the degradation study.

FUEL CELL DEGRADATION ANALYSIS PROCESS

Data Processing

We spent some time identifying possible variables that could, or should, be included in the degradation study. The

initial variable list was limited to data that were already being provided to the NREL, which varies by team. Input data for the degradation study were organized by fuel cell stack and many variables were broken down into sub-variables or bins. An example of a variable that was broken down into bins is length of trip. For one collection of fuel cell data, trip length may vary substantially. Using an average value may not be a true indication of the driving patterns. Instead of one average trip length, all trips were collected into multiple trip length bins; 0-5, 5-10, 10-20, 20-30, and greater than 30-minute long trips.

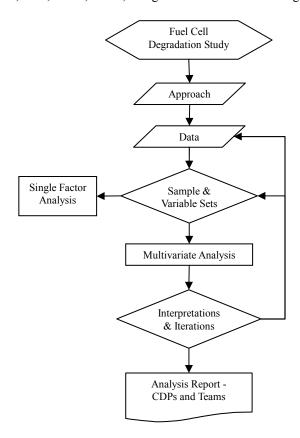


FIGURE 3: NREL MULTIVARIATE DEGRADATION STUDY FLOW CHART

The data are collected in actual driving situations with real-world data acquisition issues. It was necessary to use some filters to clean up the data set to ensure the inclusion of only trips with fuel cell operation. There are also differences in the supplied data and fuel cell systems of each team. Therefore each team has a separate data set and regression model and a combined data set for all teams is used for the DOE fleet level regression analysis, for a total of five analyses that are updated regularly.

A critical variable in the multivariate data set is the fuel cell decay rate. The method for estimating a fuel cell stack decay rate is as follows (graphically represented in Figure 4 and Figure 5). First, the fuel cell voltage, current, and operating

hours are collected from the on-road trip data files. Every x points (x may vary based on the team and data) a non-linear fit is applied to the voltage (V) and current (I) points. A high

current point has been selected for each team. The voltage is stored at this current point on each fit.

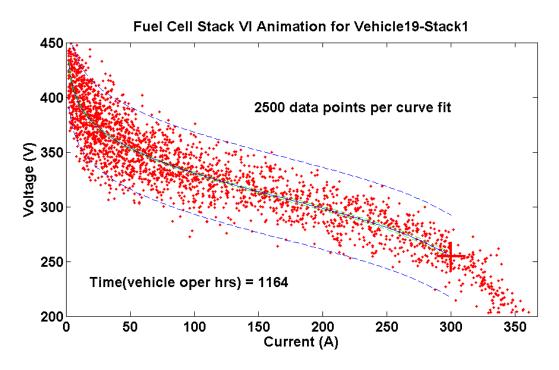


FIGURE 4: EXAMPLE OF VI CURVE FIT

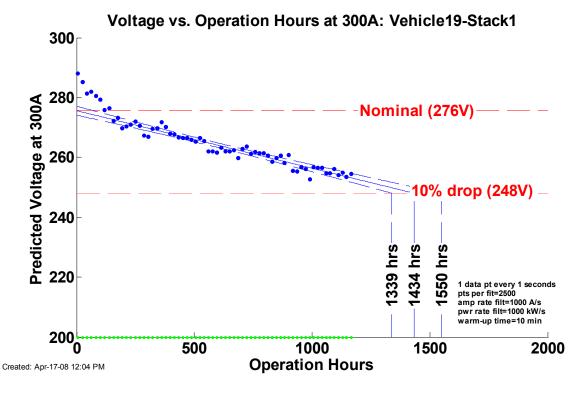


FIGURE 5: EXAMPLE OF DECAY RATE ESTIMATE

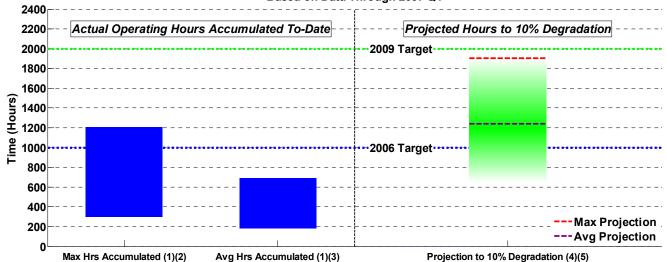
The voltage points are plotted against the fuel cell operating hours and a linear fit is applied. The slope of the fit is the decay rate estimate. The nominal voltage is the y-intercept of the line and the projection to 10% drop is the operating hour point where the line reaches 90% of the estimated nominal voltage.

Our goal for this multivariate degradation analysis is not to predict how long the fuel cell will be able to meet the vehicle demands. The 10% mark is a DOE target or benchmark to evaluate the status and progress of the fuel cells in the project. The method for estimating the fuel cell decay rate is the same for all the fuel cell stacks and may not be sufficient for predicting the time until end of life, but it does provide a fair comparison of how quickly the performance of each fuel cell is degrading. The decay rate estimate also allows us to compare the rate of one fuel cell to another fuel cell and identify high decay rate fuel cells.

Figure 6 combines all the fuel cell operating hours and degradation estimates into one figure that protects the teams' identities and details. The maximum accumulated hours on a fuel cell stack, without stack repair, has surpassed the 2006 target of 1,000 hours and the range of maximum operating hours is approximately 300-1200 hours. The range of average accumulated operating hours is approximately 200-650 hours.

The range is set by the span between teams, where each team has one point. The data presented in Figure 6 are from first generation fuel cell vehicles. Second generation systems will be compared against the 2009 targets. The range of projections to a 10% drop in voltage crosses the 2006 target of 1,000 hours, with the average projection exceeding the 2006 target.





- (1) Range bars created using one data point for each OEM.
- (2) Range (highest and lowest) of the maximum operating hours accumulated to-date of any OEM's individual stack in "real-world" operation.
- (3) Range (highest and lowest) of the average operating hours accumulated to-date of all stacks in each OEM's fleet.
- (4) Projection using on-road data -- degradation calculated at high stack current. This criterion is used for assessing progress against DOE targets, may differ from OEM's end-of-life criterion, and does not address "catastrophic" failure modes, such as membrane failure.
- (5) Using one nominal projection per OEM: "Max Projection" = highest nominal projection, "Avg Projection" = average nominal projection. The shaded green bar represents an engineering judgment of the uncertainty due to data and methodology limitations. Projections will change as additional data are accumulated.

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FIGURE 6: CDP #1 - ACCUMULATED HOURS AND PROJECTION TO 10% VOLTAGE DROP

Sample & Variable Set

Criteria for including the samples and variables started out as a wide net, looking for any and all possible data. Some filters were required to focus in on samples and variables that would accurately represent the fuel cell data set. Samples were included based on available data, operating hours, and confidence in the decay rate estimate. Variables were included based on available data and possible relevance to fuel cell degradation. As the study evolved, variables that did not appear to be contributing to the model were removed (like region and filling station). Variables were also added, removed, or modified based on communications with the teams. Processing improvements were made and samples and variables were added or removed with each iteration in an effort to improve the interpretation of the results. Table 3 has a list of possible variable categories and Figure 7 is a data set example with 'n' number of stacks and 'i' number of included variables. The variable categories attempt to include variables that are thought to contribute to fuel cell degradation; including variables such as the number of starts/hour and extreme voltage and current operating time.

TABLE 3: EXAMPLE OF VARIABLE CATEGORIES

Fuel Cell Voltage and Current
Install Date
Starts per hour
Idle Time
Time between Trips
Trip Length
Ambient Trip Temperature
Speed
Fill Data
Location

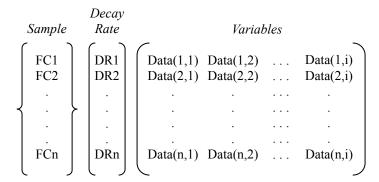


FIGURE 7: EXAMPLE OF MULTIVARIATE DATA SET WITH 'n' SAMPLES AND 'i' VARIABLES

Multivariate Analysis

As mentioned earlier, the multivariate method applied here is PLS. The observation (Y data set) is the samples' decay rate and the predictors (X data set) are the sample driving data

submitted to NREL from on-road fuel cell vehicle trips. The data are scaled and mean-centered in a pre-processing step because of the wide range of variable values possible in the data set, which includes data through December 2007.

In the HSDC, we have created a graphical user interface (GUI) called "Correlate" (see

Figure 8) that is part of a suite of interfaces designed to process large amounts of data efficiently and to provide a common location to view results and perform additional analyses.

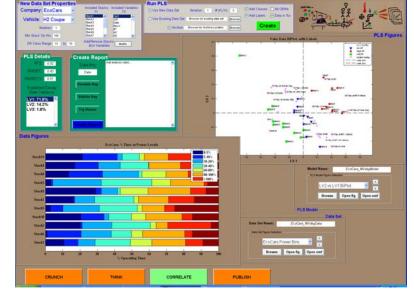


FIGURE 8: NREL FAT CORRELATE GUI

The Correlate GUI can be broken into three sections; inputs (top left in Figure 8), outputs, and additional interfaces (lower left in Figure 8). In the inputs section of the GUI, the user can include and adjust the creation setting of the data set and PLS model. Data settings include: company, vehicle type, minimum operating hour sample filter, data set iteration, range for decay rate classification, and the option to view and modify the included samples and variables. PLS model settings include: data set selection, whether the data is input as percentages or as actual values, model iteration, and the number of latent variables (LVs) used to construct the model. In the outputs section, the user can easily view figures for the data and the model plots, as well as the model statistics. The outputs section also has an area where notes can be collected and a report on the analysis can be created.

The settings, samples, and variables may vary for each team, analysis iteration, and addition of new data. A classification was applied to samples, in part because of team variations. The classification is based on the decay rate within a fleet's samples and is broken into three classes, high, average, and low. The classification of samples based on decay rate allows for a simple, visual check for groups of either high or low decay rate samples.

Because of the proprietary nature of issues related to fuel cell degradation and the fuel cell system, the actual analysis will not be described in detail, except for the publically available CDPs on this subject. Instead, a simulated example will be described and discussed in an effort to highlight the interpretation and iteration step.

Interpretation and Iterations

The intention of the regression model applied to the fuel cell vehicle data is to provide insight into any correlations between fuel cell decay rate and the driving data. A regression model may also be used as a tool for predicting the outcome for additional samples, but that is not the purpose of this study.

The PLS model is assembled in a way that places the focus on expressing hidden links relating the data and fuel cell decay rate. We will discuss a few of the model outputs that are necessary for interpreting the model.

There are a number of model outputs that will help highlight any correlations. In general, creating the model is more straightforward than interpreting the model results. A latent variable (LV) is created in the model as a collection of the input variables, collected together to explain variance in the decay rate; this is shown as a percent of explained variance. The amount of explained variance is useful for evaluating the contribution of a LV and thus the contributions of the input variables in that LV. The contribution of an input variable in a LV is measured by the variable loading. If a variable is important in the makeup of a LV, it will have a high variable loading (positive or negative). Loadings will also draw attention to interactions (similar and opposite) of variables. With a non-designed data set (the input variables are not necessarily independent of one another) like the one in this study, dependent relationships within the input variables may also be found by viewing a loadings plot. A loadings plot can be viewed as a single LV and against other LVs.

Just as the input variables are partly described by the LV loadings, the samples are partly described by the LV scores. A high (positive or negative) sample score on a LV implies that LV explains that sample. Sample relationships can be identified with scores. Samples with similar scores will have commonality within their input variables. Groups of samples with high decay rates are particularly interesting in this study because if those high decay rate samples are isolated from the remaining samples, the reason for a high decay rate may be found in differences of the sample driving data. Scores can also be plotted with a single LV and against other LVs. As the magnitude of a score or loading increases, the amount of variance captured by a LV increases.

When trying to make the connection between sample groups and the relationship to the input variables, one must look at both the sample scores plot and variable loadings plot. One graphical representation of the combined details is a biplot,

which overlays the sample scores on the variable loadings, Figure 9. If a sample has a higher than average value in a variable when that variable has a high positive loading on a LV, then the sample has a high, positive score on that same LV. If a group of high decay rate stacks exists, we look for the variables in the same area, or directly opposite. These variables may be the link between the data and a partial explanation of decay rate variance. Figure 9 through Figure 11 are examples created from a simulated data set in an attempt to help depict the interpretation methods. Figure 9 highlights some possible sample groups and the corresponding variables, and identifies an outlier.

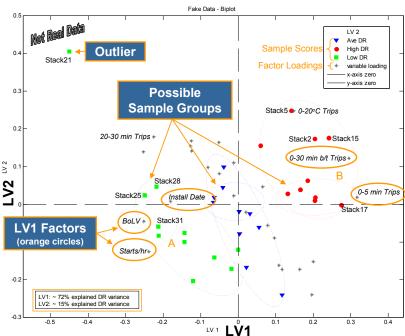


FIGURE 9: SIMULATED DATA - BIPLOT EXAMPLE

The PLS model is a linear regression fit of the data and there is a regression coefficient for each variable. The regression coefficient is another output that helps the user understand how the variable is contributing to the overall model, as well as the directional relationship between the variables and the decay rate. These regression coefficients are not used without evaluation at the LV level because there may be variables with a low regression coefficient that could still tell a story about a relationship between the variables and decay rate for a LV. Because we are using PLS as a tool to identify and describe the relationships, variables with low regression coefficients will not be removed simply based on the regression coefficient. Figure 10 is an example of a regression vector, $y_{pred} = x*a$, where 'x' is the sample data and 'a' is the regression vector.

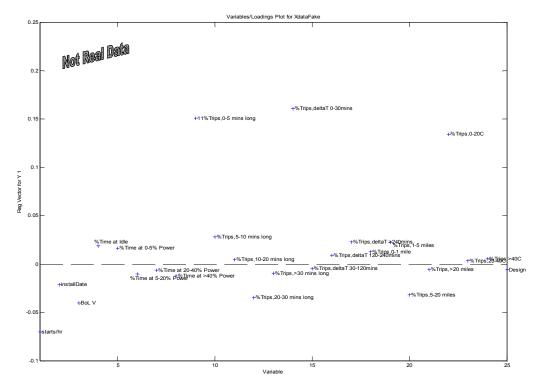


FIGURE 10: SIMULATED DATA - REGRESSION VECTOR EXAMPLE

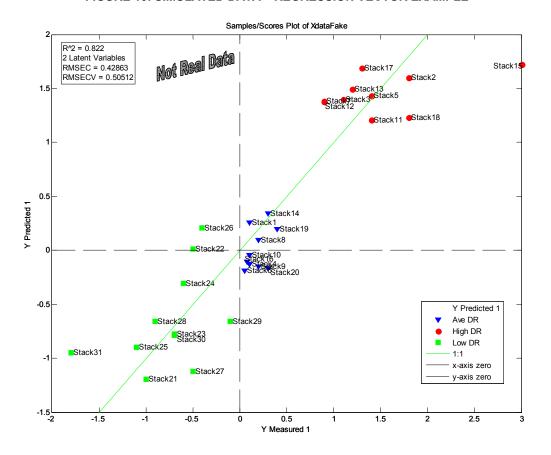


FIGURE 11: SIMULATED DATA - PREDICTED VERSUS MEASURED EXAMPLE

9

When interpreting regression model results, there are a couple of points to watch out for. The model may be over-fitting the data and giving a false sense of model accuracy, or the model may not be able to separate the noise from the relevant correlations, if there are any. This may be especially possible in a study where the data is not accumulated in a controlled, design of experiments, manner. The model statistics and sample outliers can be a signal of potential problems with the model.

A couple ways to find outliers can be done by looking at the sample scores and/or residuals. Outliers can be an important step in interpreting a model because an outlier may truly be different than the rest of the samples and contain key data patterns that will help unlock the meaning of other sample groups. An outlier could just as easily be a sample with data errors or a sample that should not be compared with the rest of the samples. An outlier may be disproportionately influencing the model and may have to be removed to have a more accurate interpretation of the model. Figure 9 shows an outlier in a scores plot and Figure 11 shows the predicted versus measured example plot. You can see that an outlier in one plot is not necessarily an outlier in another plot.

Model statistics are another way to check how well the model is describing the data. The explained variance, correlation coefficient, cross validation, and root mean square errors will all help determine how good the model is. A high correlation coefficient (R²), typically greater than 0.7, is a signal that the model is doing a good job of fitting the data. The use of a cross validation method (in this study the cross validation method is "leave one out"), will help measure the model's ability to predict the dependent variable. With a cross validation method included, there will be two error numbers for the model; Root Mean Square Error of Calibration (RMSEC) and Root Mean Square Error of Cross Validation (RMSECV). Ideally, the RMSECV would be within two times the value of the RMSEC. If the RMSECV is much greater than the RMSEC, the model is not robust and may be highly dependent on a few of the samples. These statistics must be used with one another to provide an overall picture of the model's validity.

While interpreting the analysis results, there are many questions that are looked at by running the analysis again but with variations on the inputs. A number of iterations are typically needed to improve the interpretation of the model and develop conclusions.

Analysis Reporting

Public Results We make every effort to create public degradation results that are detailed and significant. There are a number of hurdles with the public version of the degradation results. One is that all public results must protect team identity and intellectual property. A second hurdle is the analysis complexity and our ability to form a clear and concrete conclusion. The majority of value added from this analysis is within the individual team conversations covering the details of the analysis variation and interpretations. There are two current

CDPs relating to the multivariate degradation analysis, CDP#48 and CDP#49.

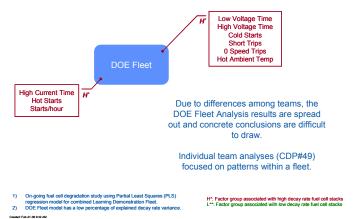
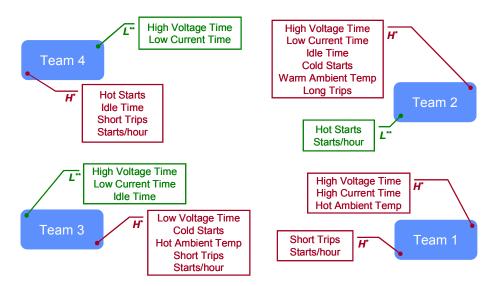


FIGURE 12: CDP#48 – VARIABLE GROUPS ASSOCIATED WITH FUEL CELL DEGRADATION FOR COMBINED DOE LEARNING DEMONSTRATION FLEET

Figure 12 depicts a summary of the spring 2008 DOE fleet-level degradation analysis, which is just one piece of the degradation study. We are looking for groups of samples and groups of variables, specifically within the extremes of the samples' decay rate range. There are two boxes of input variables specified in Figure 12. Each box sets apart a variable group that is attached to either high or low decay rate sample groups. In general, if a box is associated with a high decay rate sample group, those samples have higher than average time (or # of trips) for the variables listed in the box. The box of variables is a reminder that the potential relationships between the input variables and fuel cell decay rates are based on a collection of variables, not the impact of an isolated variable.

The number of boxes labeled in CDP#48 and CDP#49 depend on the analyses results. If there were groups of variables that could be considered the opposites of those variable groups already categorized, they were not specifically labeled in CDP#48 and CDP#49. For example, variable groups associated with low decay rate samples are only labeled if the opposite group for high decay rate samples is not already specified.

The DOE fleet analysis explains a lower overall decay rate variance than the individual team analyses, primarily because of the differences among the teams. The thought process of trying to connect the analysis results to a strong correlation with fuel cell degradation is more straightforward in the team analyses, than in the LD fleet analysis. However, the team analysis results still remain scattered and it is difficult to determine tangible patterns and correlations with the data and fuel cell degradation. Figure 13 is a summary of the individual team analyses. There is no one dominant variable group among all four teams, which emphasizes the earlier statement that the combined DOE fleet is more difficult to interpret because of differences between the teams.



- On-going fuel cell degradation study using Partial Least Squares (PLS) regression model for each team.
- Teams' PLS models have a high percentage of explained decay rate variance, but the models are not robust and results are scattered.

FIGURE 13: CDP#49 - VARIABLE GROUPS ASSOCIATED WITH FUEL CELL DEGRADATION FOR EACH TEAM

Even though there are no clear, common variable groups among the four teams, a handful of variables, like starts per hour and high voltage and current are listed with all teams. Each team's fuel cell system may be configured differently and will therefore react differently to the range of vehicle demands. The interaction between vehicle demand and how the fuel cell system responds relative to fuel cell degradation, could be one possible summary statement. For example, how a fuel cell system responds to vehicle demand may make it more susceptible to hard driving cycles. Impacts of driving patterns (and the fuel cell system's sensitivity to different drive tendencies) may partly answer the question of why fuel cell stacks in a fleet and of a common design are decaying at different rates. The individual team analyses have a higher correlation coefficient than the DOE fleet analysis and seem to fit the data better, but all the analyses have a high RMSECV value and are not yet robust models.

Detailed Results Detailed descriptions and data on each team analysis are sent as a supplement packaged with CDP#49 to the teams. As can be seen in Figure 13, individual team analyses are varied and not all team analyses have clear distinction among the samples, variable groups, and driving data. We discuss the interpretations and possible analysis iterations with each team. The process of running through many analysis iterations is helped along by the creation of the correlate GUI which provides more flexibility to change, review, and comment on the analysis iterations. The GUI allows this degradation study to evolve over time.

CONCLUSIONS

The Fuel Cell Vehicle Learning Demonstration project has completed over two years of operation, data accumulation, and of reporting detailed composite data products. In spring 2008 there were 47 CDPs were released [4]. All CDPs, previous versions. and papers presentations can be viewed at http://www.nrel.gov/hydrogen/proj learning demo.html. The amount actual operating accumulated on the fuel cell stacks continues to increase, as does NREL's confidence in the fuel cell degradation projections and trends as well as NREL's ability to apply this degradation to the second generation fuel cell vehicles, for which we have just

begun receiving data. The maximum fuel cell operating hours have surpassed the first actual operating hours target of 1,000 hours and the average projection of fuel cell operating hours to 10% voltage degradation has surpassed the first degradation target of 1,000 hours.

We have processed data from over 203,000 trips to create a condensed data set designed to look for correlations between on-road driving data and variations in fuel cell degradation by applying a multivariate regression model, PLS. The degradation study is still in the early stages and continues to evolve with the addition of new data, understanding of multivariate analysis tools, and most importantly, close collaboration with the teams. Results from the PLS models continue to be complex and difficult to interpret, especially with the combined, DOE fleet analysis. Scatter in the model results continue to hinder the formation of clear and dominant correlations and conclusions, but we continue to look for ways to improve the analysis and have plans to look into variations such as transients, hybridization impacts, and changes to input samples and variables. NREL is striving to construct a meaningful multivariate degradation study that provides value to the participating teams and looks for significant correlations to fuel cell degradation that can be presented to the hydrogen and fuel cell research and development community.

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H*: Factor group associated with high decay rate fuel cell stacks

*: Factor group associated with low decay rate fuel cell stacks

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