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Adaptive RAS/SPS System Settings for Improving Grid Reliability and Asset Utilization through Predictive Simulation and Controls

A Use Case for Transformative Remedial Action Scheme Tool (TRAST): Jim Bridger RAS Evaluation and Analysis

December 2019

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U.S. DEPARTMENT OF ENERGY

Prepared for the U.S. Department of Energy
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Pacific Northwest National Laboratory
Richland, Washington 99352

Executive Summary

The Pacific Northwest National Laboratory (PNNL) project team has developed innovative mathematical and advanced computing methods for adaptively setting Remedial Action Scheme/Special Protection Scheme (RAS/SPS) coefficients with the consideration of realistic and near real-time operation conditions. In this report, the Jim Bridger RAS served as the use case for testing and validating the proposed methodology and the corresponding prototype, Transformative Remedial Action Scheme Tool (TRAST).

Acknowledgments

The project team at PNNL would like to thank Dr. Alireza Ghassemian, DOE Advanced Grid Modeling (AGM) project manager, for his insightful suggestions and comments to ensure the quality delivery of this project.

The team would like to thank our industry partners, Mr. Song Wang from PacifiCorp and Dr. Orlando Ciniglio from Idaho Power Company, for their technical advice and continuous supports to this project.

The team also would like to recognize the technical contribution of former PNNL staff member Dr. Ruisheng Diao for shaping the concept of this project and providing early technical input.

The authors also acknowledge our colleagues Francis Tuffner and Peter Christensen at Pacific Northwest National Laboratory for their support, comments, and review of this work.

Acronyms and Abbreviations

BA	balancing authority
BES	bulk-electric system
CSV	comma-separated value
CDF	cumulative density function
EMS	energy management system
HPC	high-performance computing
LHS	Latin hypercube sampling
OPF	optimal power flow
PDC	phasor data concentrator
PDF	probability density function
PMU	phasor measurement unit
PNNL	Pacific Northwest National Laboratory
PPF	point percentage function (or inverse cumulative distribution function)
RAS	Remedial Action Scheme(s)
RTCA	real-time contingency analysis
SE	state estimator
SOL	system operating limit
SPS	Special Protection Scheme(s)
TOP	transmission operator
TRAST	Transformative Remedial Action Scheme Tool
TSAT	Transient Stability Assessment Tool
WECC	Western Electricity Coordinating Council
WSM	West-wide System Model

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1.0 Background

Remedial Action Schemes (RAS) or Special Protection Schemes (SPS) are used throughout the bulk transmission system as a non-wires method of increasing transmission transfer capability. Traditionally, the RAS/SPS settings are determined using offline study; no existing automation tool can assist planning and protection engineers with adaptive settings of the RAS/SPS systems, such as the Jim Bridger RAS that operated by PacifiCorp. Furthermore, the computational speed is not fast enough in today's commercial tools to perform a full-scale study to calculate RAS parameters (e.g., arming level) and validate the control performance in a preventive way.

Since August 2017, the Pacific Northwest National Laboratory (PNNL) project team has been working its industry partners, PacifiCorp and Idaho Power Company, to develop a prototype named Transformative Remedial Action Scheme Tool (TRAST). It provides innovative mathematical and advanced computing methods for adaptively setting RAS/SPS coefficients with the consideration of realistic and near real-time operation conditions.

In this report, the Jim Bridger RAS served as the use case for testing and validating the proposed methodology and the corresponding prototype. The Jim Bridger RAS was placed into service in 2009, based on a limited set of conservative settings from the prior scheme and engineering judgment. The Jim Bridger RAS is owned, operated, and maintained by PacifiCorp. It is an event-based scheme; an open-loop control scheme is applied to trigger fast generation dropping and to stabilize the Bridger West transmission path. All RAS actions initiated by this scheme are pre-planned, based on offline studies of various system operating conditions [1].

PacifiCorp has performed regular economic analysis for the existing Jim Bridger RAS. There are at least two ways to examine the performance of the Bridger RAS with the existing settings: the number of Bridger unit trips, and the impact of the settings on the Bridger West capacity. The *2011 Jim Bridger Plant: Remedial Action Schemes (C&D) Technical Review* determined that the financial cost to restore generation after the Jim Bridger RAS triggers unnecessary trips was significant. The combined estimated benefit is on the order of several hundred thousand dollars per year. There are other un-quantified benefits, including a reduction in reliance to change or modify RAS states, as well as the opportunity to better understand the limits of the system, which can be used to help address future modifications to the RAS.

In this project, a comprehensive evaluation of existing Jim Bridger RAS design was performed, and the full functions of TRAST were explored to derive the RAS coefficients that adaptively adjust the control actions based on various system operating conditions.

2.0 Control Logic Review for Jim Bridger RAS

The Jim Bridger RAS increases the transfer capability of the east-to-west transmission path by protecting against potential oscillations following system events. With the Jim Bridger RAS in operation, the Bridger West Path limit is reported to be 2400 MW for east-to-west rating, while the complete loss of the Jim Bridger RAS for any reason requires that the Jim Bridger Power Plant be reduced to 1300 MW [1].

WECC Transmission Planning Criterion TPL-001-WECC-CRT-3 requires that, following fault clearing, the voltage at each applicable bulk-electric system (BES) bus recover above 80%. Additionally, the voltage at each applicable BES bus serving load must not dip below 70% of pre-contingency voltage for more than 30 cycles, or remain below 80% of pre-contingency voltage for more than 2 seconds [2]. This criterion will be used to evaluate the performance of the Jim Bridger RAS design.

The Jim Bridger RAS control system performs the following critical functions:

- Calculation of arming levels for 33 *N* events
- Calculation of generation tripping amounts for 33 *N* events, considering special conditions and remote inputs from Idaho
- Selection of unit(s) to trip
- Reactive elements insertion on at multiple close-by high voltage substations

Figure 1 provides a flow chart to illustrate the Jim Bridger RAS logic.

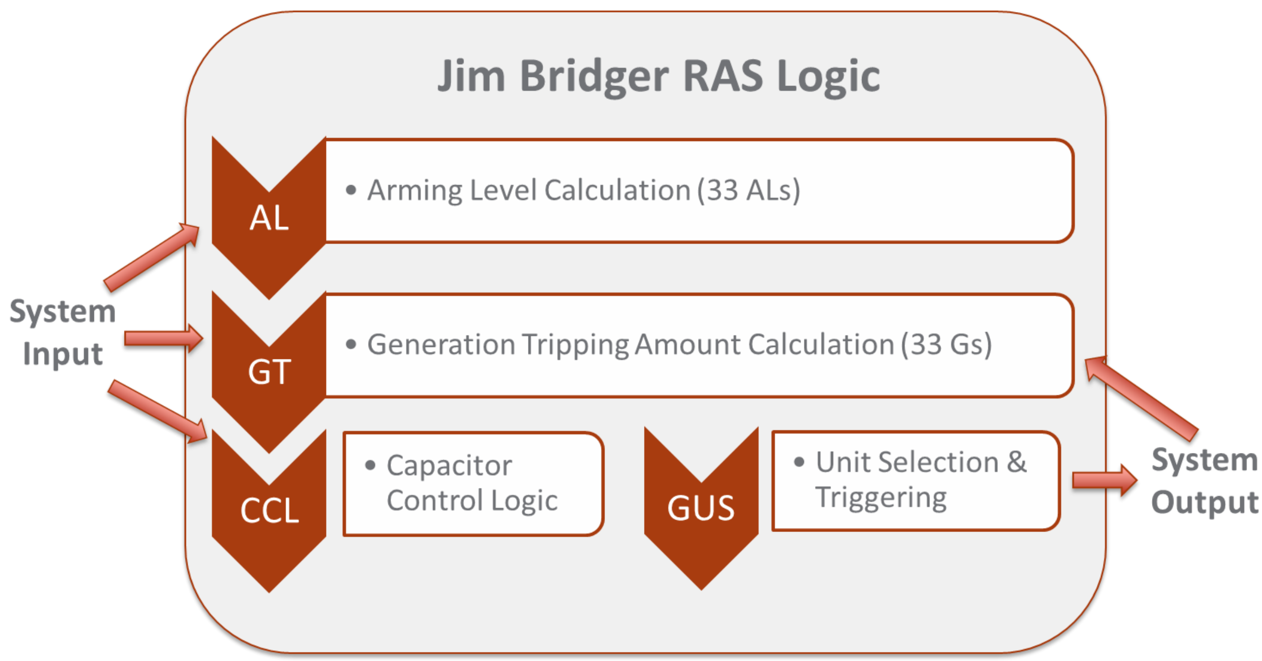

Figure 1. Flow chart illustrating the Jim Bridger RAS logic.

Figure 2 provides a flow diagram to illustrate the arming-level calculation in the Jim Bridger RAS logic. For each different power system operating state, considering the grid topology and equipment status, a specific "S State" can be identified in the RAS logic, then corresponding coefficients are used to calculate the RAS arming levels. Those arming level results are used to decide the online RAS actions.

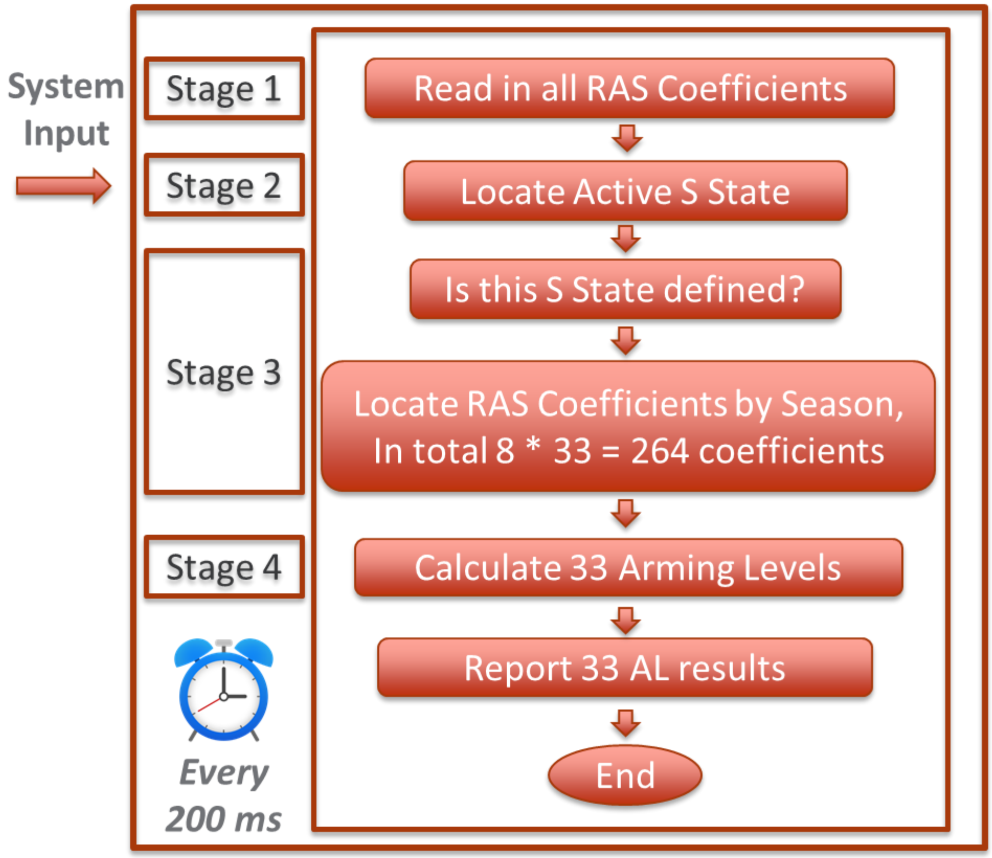

Figure 2. Flow chart illustrating the arming-level calculation logic for Jim Bridger RAS.

3.0 A Use Case for Transformative Remedial Action Scheme Tool (TRAST): Jim Bridger RAS Evaluation and Analysis

To demonstrate the value of calculating RAS parameters in an adaptive way, the team at PNNL has been collaborating with PacifiCorp and Idaho Power Company to develop a research prototype, Transformative Remedial Action Scheme Tool (TRAST). It provides an end-to-end solution for a comprehensive and transformative RAS analysis. In this process, PNNL followed the guidance of “ABCDE” design concept and adopt it into TRAST:

- “A” stands for advanced algorithms developed and integrated in the Jim Bridger RAS analysis.
- “B” stands for “Big Data” challenges taken on through in-depth collaboration with industry collaborators.
- “C” stands for the HPC techniques and Microsoft cloud computing techniques explored and implemented.
- “D” stands for the power engineering domain knowledge applied and improved.
- Lastly, and most importantly, “E” stands for the industry ecosystem that PNNL developed for a generic and transformative RAS analysis and improvement methodology.

Figure 3 conceptualizes how the ABDCE approach encompasses the development of TRAST.

Figure 3. Illustration of “ABCDE” design concept for Transformative Remedial Action Scheme Tool (TRAST).

3.1 Overview of TRAST

TRAST aims to provide an end-to-end solution for the RAS design, study, and evaluation process. It originates from the utility data analysis and evolves with the guidance of domain knowledge from power engineers. More importantly, the automatic/semi-automatic functionalities that are integrated in TRAST could significantly simplify and shorten the RAS design and study process. Additionally, continuous improvement and validation could be realized based on the proposed evaluation methodology. Here are the high-level capabilities of TRAST, they are given as follows:

1. Advanced statistical data analysis
2. OPF-based automated power flow case generation
3. Customized dynamic simulation in HPC/cloud platform
4. Machine-learning-based RAS coefficient prediction
5. A reliable RAS validation strategy in multiple commercial platforms

Figure 4 provides an overview of data-driven analytical functionalities in TRAST.

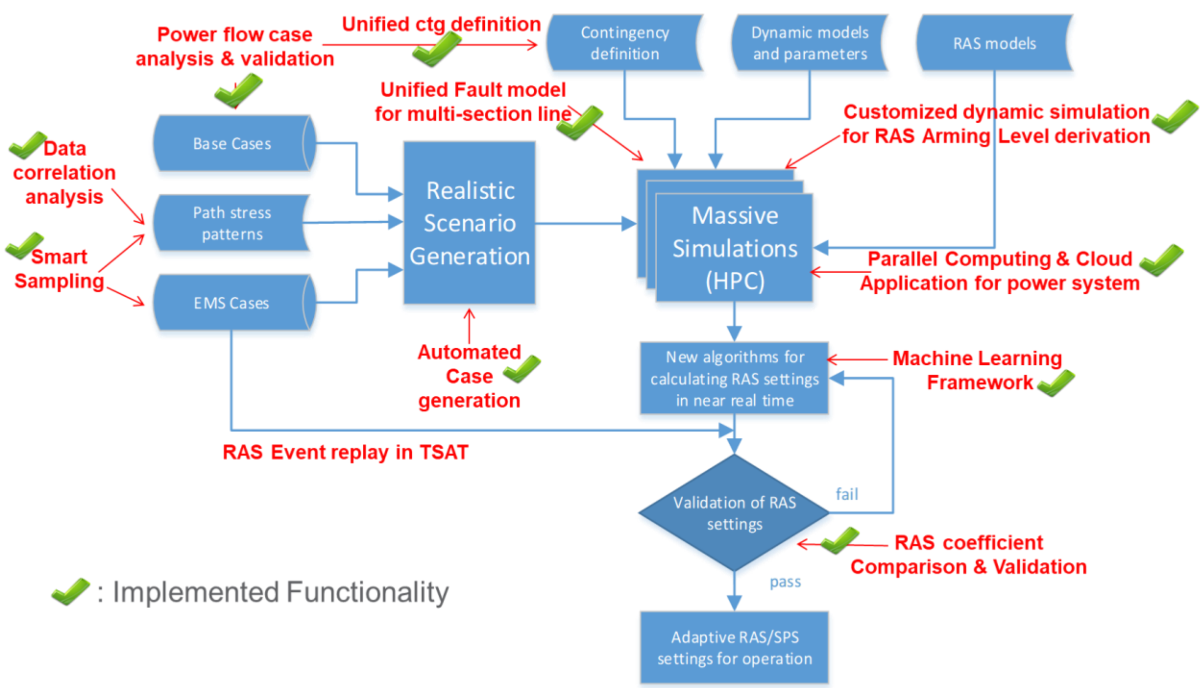

Figure 4. Overview of data-driven analytical functionalities in TRAST.

Traditional power system planning studies rely on power system planning cases that are provided by interconnection authorities or internal planning engineers. Usually, the total number of those planning study cases is limited and can only represent several power system operation conditions, such as “heavy summer,” “harsh winter,” and so forth. In contrast, Jim Bridger RAS requires a more comprehensive set of different power flow scenarios, as well as power system contingencies, which should be validated against a comprehensive pool of power system planning cases as input. TRAST has been developed by the team at PNNL to address this challenge, and uses comprehensive historical operational data to ensure a solid and repeatable study procedure. Figure 5 provides an overview of utility data integration in TRAST and its application for Jim Bridger RAS analysis.

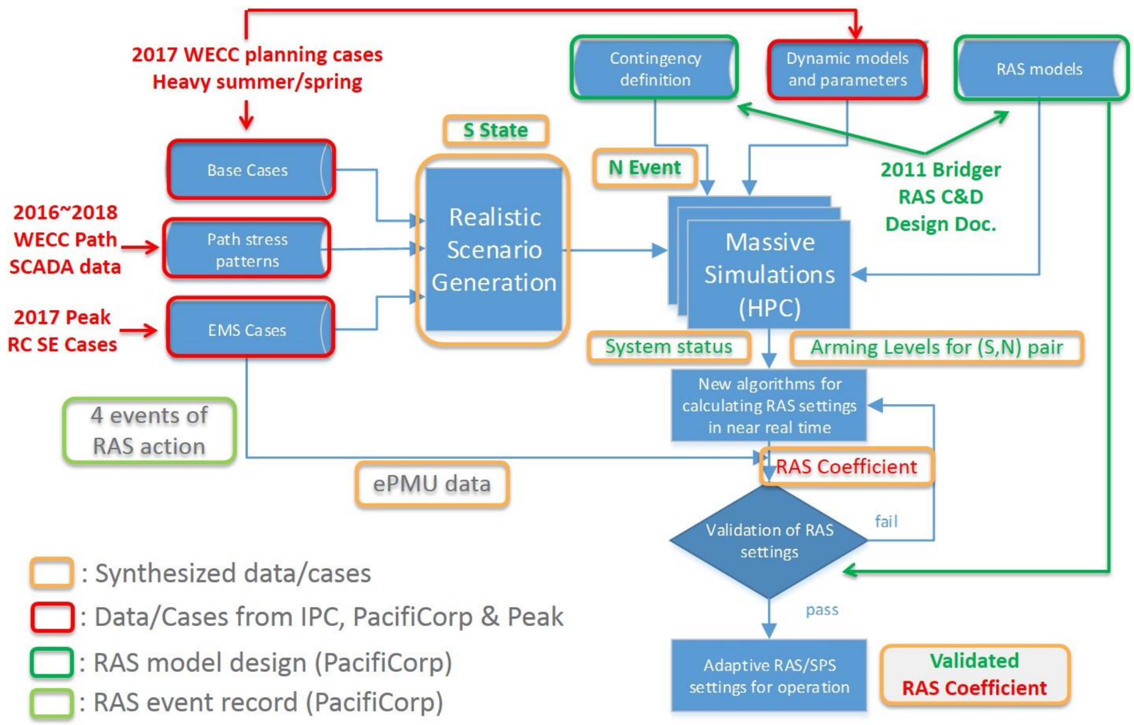

Figure 5. Overview of utility data integration in adaptive RAS setting framework.

3.2 Statistical Analysis for Utility Data

TRAST includes a comprehensive statistical analysis for full-year SCADA data set, which were provided by PacifiCorp and Idaho Power Company. The SCADA data set contains seven variables that are essential for the existing Jim Bridger RAS model; those power-system attributes/variables were referred to as P1-P7. These variables include active power measurements from selected transmission lines and power plants, as well as other related reactive compensation equipment status. P1-P6 are continuous variables representing power, while P7 is discrete variable representing seven distinct levels of series compensation. Temporal factors, such as season and month, have significant effects on SCADA data variability; therefore, season and month are also included as supplementary features.

Cross-correlation is a standard measure of similarity between two ensembles. The pairwise correlation coefficients are calculated between each pair of the seven variables and illustrated in Figure 6. Strong correlations (correlation coefficient > 0.7) are observed between P1 and P3 (Figure 7), P1/P3 and P7, while P5 and P6 are moderately correlated. P1 and P3 are positively correlated with strong linear relationship across all four seasons, as well as all 12 months. This indicates these relationships can be represented by a generalized linear regression model.

Moreover, P7 is a discrete variable representing seven distinct combinations of series compensation levels (e.g., C1-C7) in pre-determined transmission lines; the box plot in Figure 8 clearly indicates the inter-relationship between P3 and P7. Multinomial logistical regression method has been utilized to analyze this inter inter-relationship, which could provide equations with coefficient values that can be used directly by the users to calculate the probabilities in categories; the probability of each outcome is expressed as a nonlinear function of the predictor variables. For example, between P3 (predictor variable) and P7 (response), MLR can be used to predict the probability that P7 falls into a categorized value, given a value of P3.

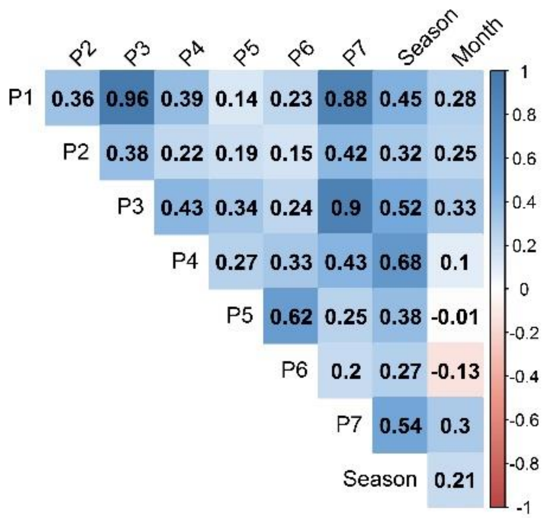

Figure 6 Pairwise correlations of the seven variables and two additional temporal variables.

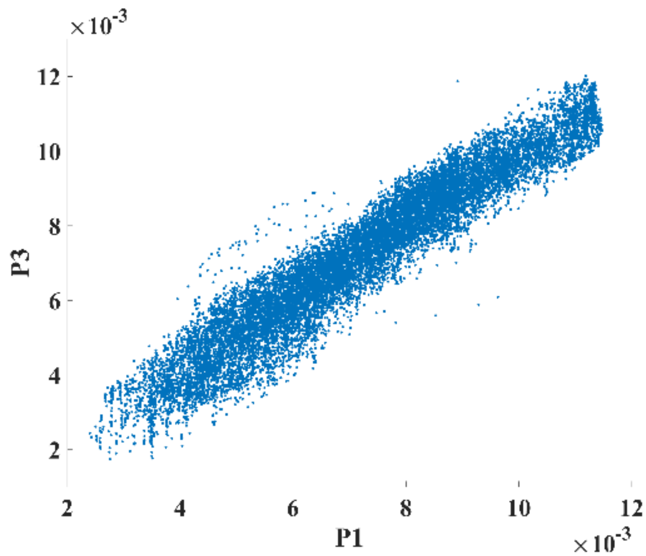

Figure 7 Scatter plot between normalized P1 and P3.

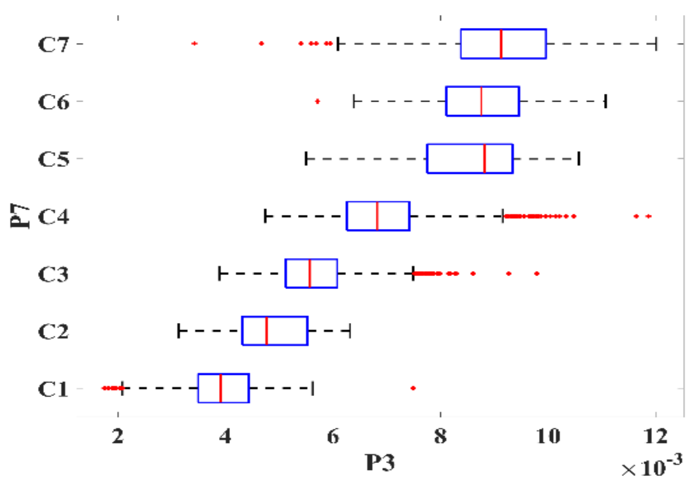

Figure 8 Box plots between normalized P3 and P7 showing seven categories.

It has been shown that there are evident inter-relationships among the abovementioned seven variables, including the capability for some of them to be represented and predicted by linear regression or multinomial logistic regression methods. As a result, when designing the power-system control scheme for utility-planning studies, the selection of the input features should be reviewed based on the proposed methodology. It is expected that with a minimized number of inputs features, the performance and reliability of power system control scheme should be improved. Further analysis on the feature selection for Jim Bridger RAS input could be found in [6].

In addition, comparisons are performed between SCADA data and the corresponding power flow data extracted from West-wide System Model (WSM) state estimator (SE) cases. The project team at PNNL has received about 10,000+ EMS SE cases (PTI RAW V30) from Peak Reliability; they were exported from the State Estimator (SE) in Peak's energy management system (EMS). Figure 9 showed consistency between different sources for the investigated power flow conditions.

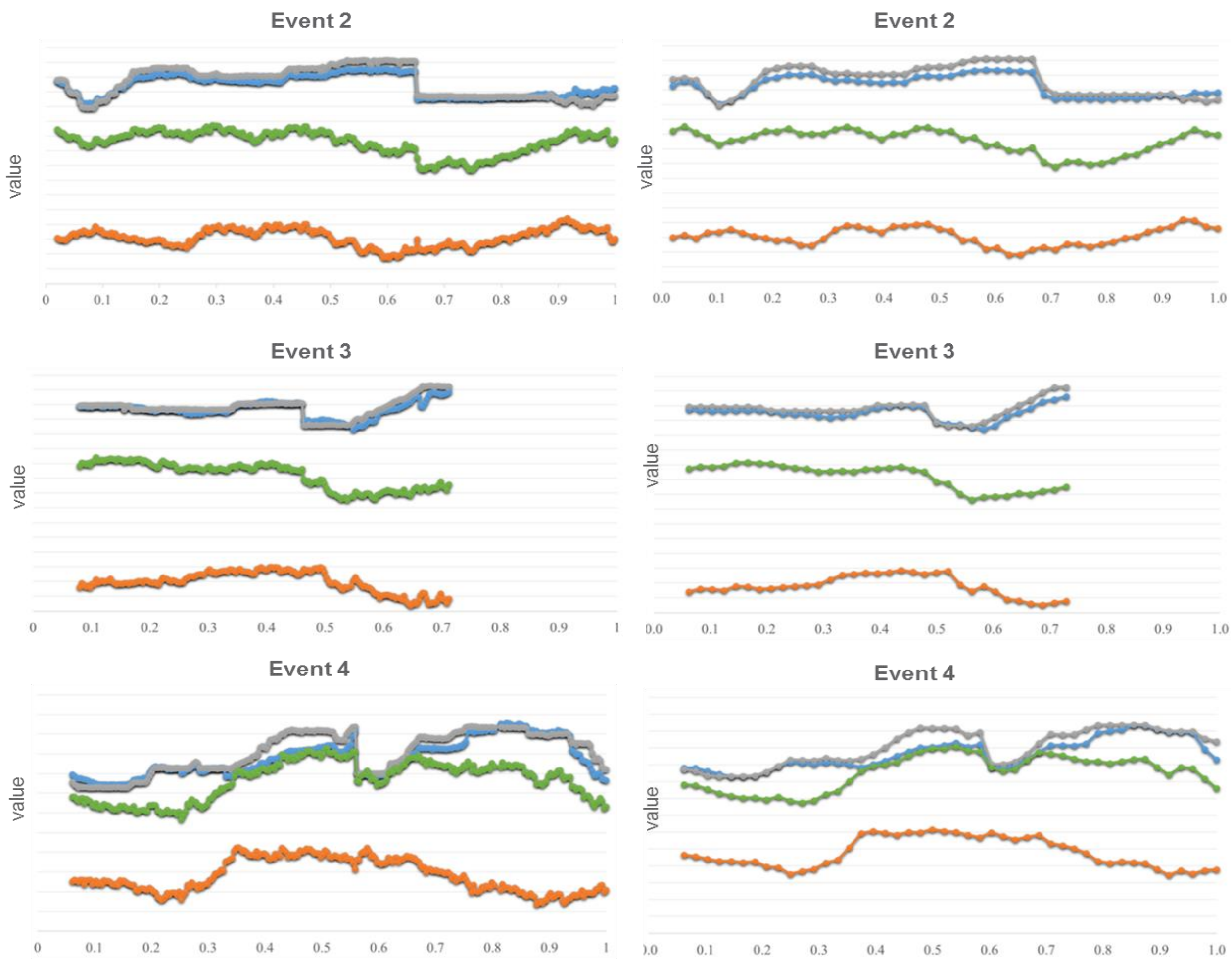

Figure 9 Comparison between Peak SE extracted data (left, normalized) and SCADA data (right, normalized) of Event 2, 3, 4. The time points (normalized) are represented by the x axis.

3.3 Smart Sampling for Power System Planning Case Generation

The major objective of smart sampling is to represent the probability distribution according to the original data using many fewer samples for each variable, all while honoring the data-dependency among the variables. The output of this smart sampling approach can then be used to guide the automated generation of power system planning cases. By applying the smart sampling method, the large volume of power flow cases required for dynamic simulations could be significantly decreased, while the main purpose of power system planning study for Jim Bridger RAS could still be fulfilled with confidence.

TRAST includes a more flexible and more general method [4] that can be adopted by any probability distribution, particularly when the number of observations is large, which is the case for the Jim Bridger RAS evaluation (17520 data points from SCADA data). PNNL used TRAST to sample the seven SCADA variables. It is also shown that a sample size of 365 could serve the balance between accuracy and computation burden of the smart sampling approach (Figure 10).

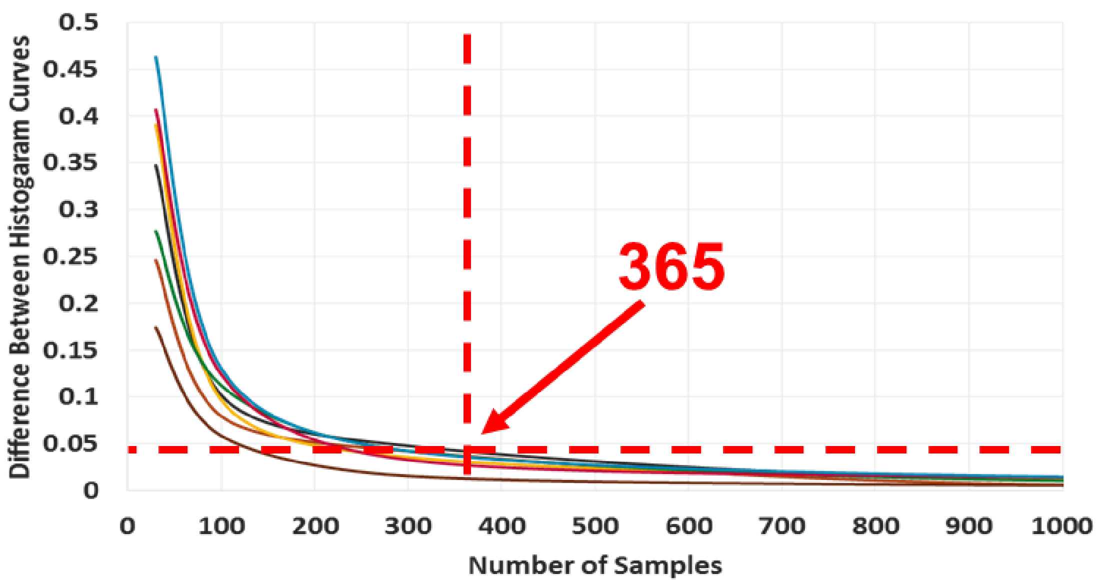

Figure 10. Accuracy of samples (difference between original and sampled histogram curves) as the number of samples, different colors representing different variables.

It should be noted that the inter-dependency among the variables has been preserved during the sampling process. Cholesky decomposition has been adopted to ensure the consistency of statistical properties between the 17520 SCADA data points and 365 smart sampling points. Figure 11 and Figure 12 provide examples to illustrate the smart sampling process in the time domain and the probability domain. It can be safely concluded that Smart Sampling provides an effective way to evaluate power system control design under various power flow condition. A rough estimate of the speed gain is 17520/365, which is about 48 times improvement.

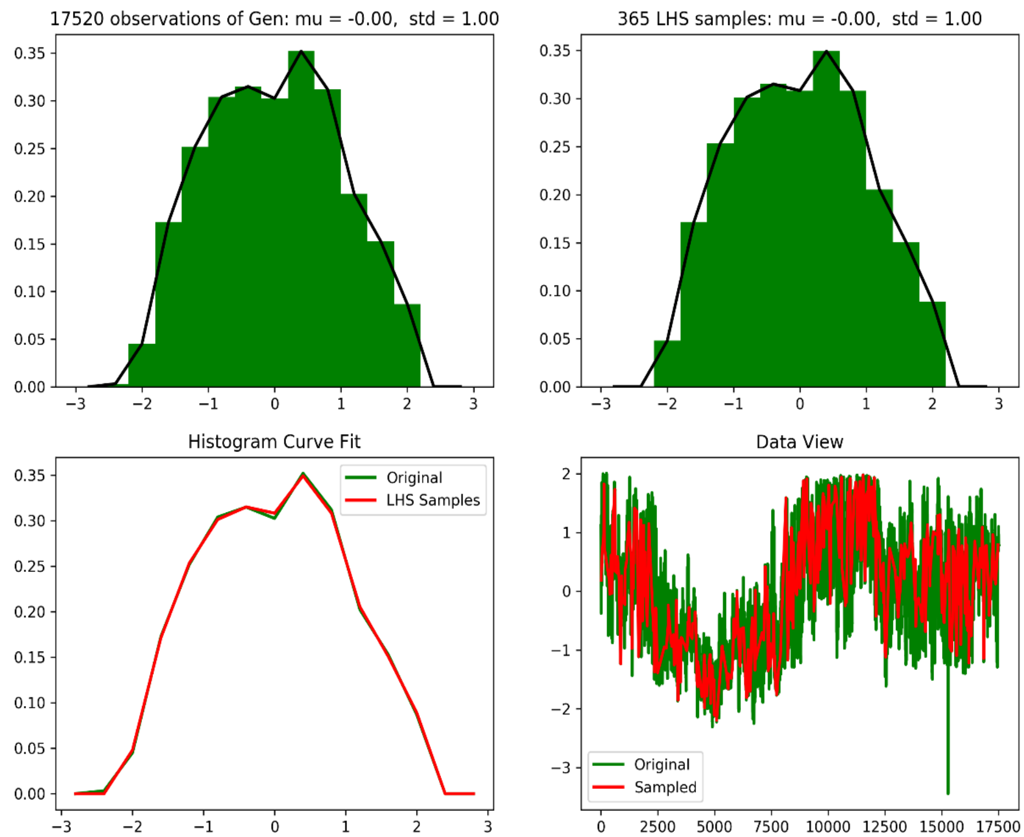

Figure 11 Results of Gen samples considering data dependency.

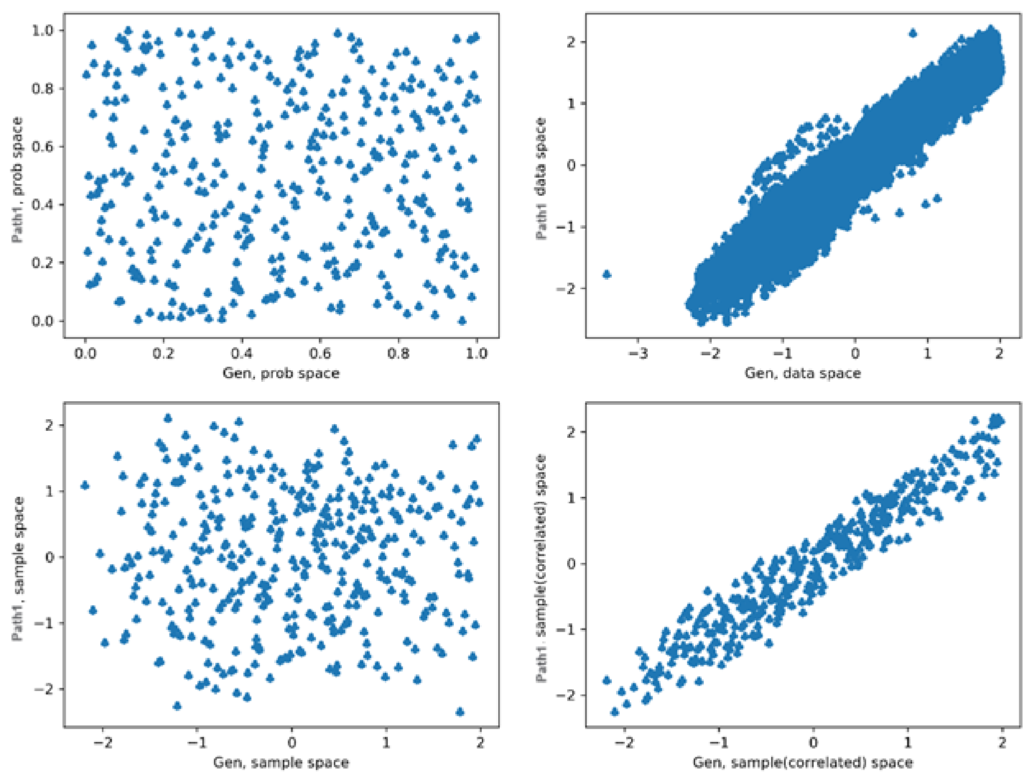

Figure 12 Samples of Gen and Path1 displayed in 2D space considering correlation.

3.4 Automated Power System Planning Case Generation

It is a well-recognized challenge for power system planning engineers to create different power flow cases to represent different operation conditions considering generation and load variations, as well as specific system stress conditions. Figure 13 illustrates a system stress pattern that considers two transmission paths. To address this challenge and facilitate the Jim Bridger RAS design and evaluation, the team at PNNL proposed an OPF-based methodology.

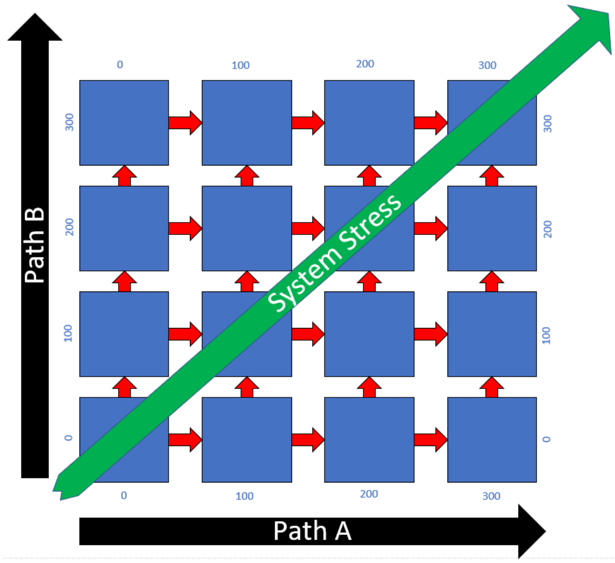

Figure 13. System stress pattern on different transmission paths.

TRAST applies the OPF-based methodology to a Western Interconnection power system planning case multiple times, each time incrementing a single path constraint by some value until the OPF does not solve. For the Jim Bridger RAS study, the Jim Bridger power plant is permitted to respond to the system conditions [i.e., Jim Bridger is set to respond via automatic generation control (AGC) option within the OPF]; moreover, the automated power system planning case generation increases (or decreases) power transfer across the Path 1 by using OPF to represent realistic operating conditions within the case. The output of this process is therefore a series of power flow cases with different loading, generation, and power transfer conditions.

In summary, for the Jim Bridger RAS evaluation and analysis, the PNNL research team used TRAST and developed more than 11,500 modified planning cases, generated from the WECC 2017 Heavy Summer planning case. Table 1 provides the summary of case generation process at each stage for Jim Bridger RAS evaluation and analysis.

Table 1 Total number of power flow cases created at each stage for Jim Bridger RAS.

Procedure	Starting point	Step 1 & 2	Step 3 & 4	Step 5 & 6	Step 7 & 8	Smart Sampling
Total # of Planning Cases	1 for 2017 HS	6	80+	1,200+	11,500+	295 out of 365 (ideal)

It should be noted that the Jim Bridger RAS mainly focuses on the power system instability that is caused by the loss of the radial transmission lines that deliver power from the Jim Bridger Power Plant. Its arming-level calculation algorithm has been structured such that it incorporates the measured real and reactive power generation (local inputs) from the Jim Bridger Power Plant, the compensation level of the 345 kV lines (remote inputs) from the reactive elements, and several important related path flows (local and remote inputs). Therefore, when using the full-scale WECC planning cases to validate its design, it is critical to understand how the selected WECC paths relate to the whole system power flow condition, more specifically, other major WECC paths.

To examine this relation to other paths, the PNNL research team also received the 2017 full-year SCADA data, at 1-hour resolution, that were available for 22 WECC paths [7]. Cross-correlation in TRAST has been adopted for this data; the pairwise correlation coefficients were calculated between each pair of the 22 variables and illustrated in Figure 14. Strong correlations (correlation coefficient > 0.7) are only observed between Path X and Path Y, while there are some moderate level correlations (correlation coefficient between 0.3 and 0.7) for other paths. Further review showed that Path X and Path Y were evolved from one “retired” Path definition in 2012; this partially explains the strong correlations among them [7]. Therefore, it is safe to draw the conclusion that the proposed OPF-based method satisfies the needs of Jim Bridger RAS evaluation and analysis. It should be noted that the WECC paths are groups of key transmission lines and generally understood by power industry professionals and broader stakeholders; it provides a comprehensive and effective medium for congestion- and transmission-expansion-related discussion at the interconnection-wide level.

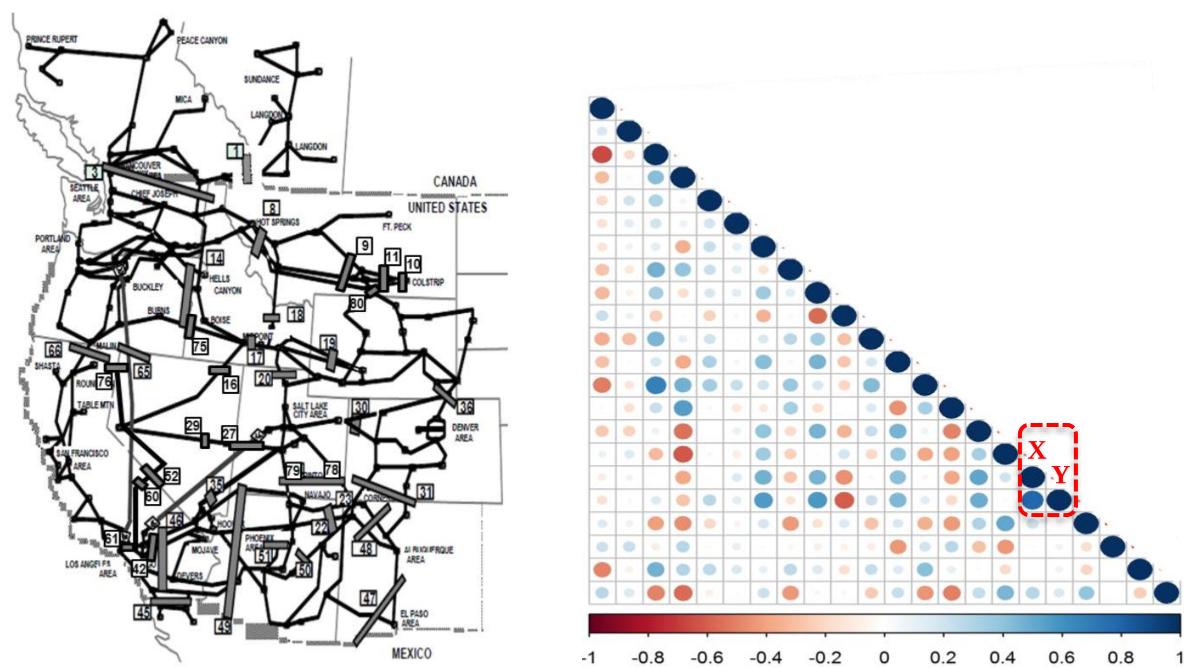

Figure 14 WECC path illustration [7] and pairwise correlations of the 22 variables that representing 22 WECC paths.

There are, in total, 11670 power flow cases that were automatically generated based on the 2017 WECC Heavy Summer Planning cases; all those cases are shown in Figure 15, with one red star representing one generated case. It can be seen that the generated power flow case pool has a complete coverage for the considered variables, e.g., Gen, Path 1, Path 2; moreover, the inter-relationships among different variables are also preserved. It is expected that those inter-relationships should be preserved in the next step of TRAST, Smart Sampling.

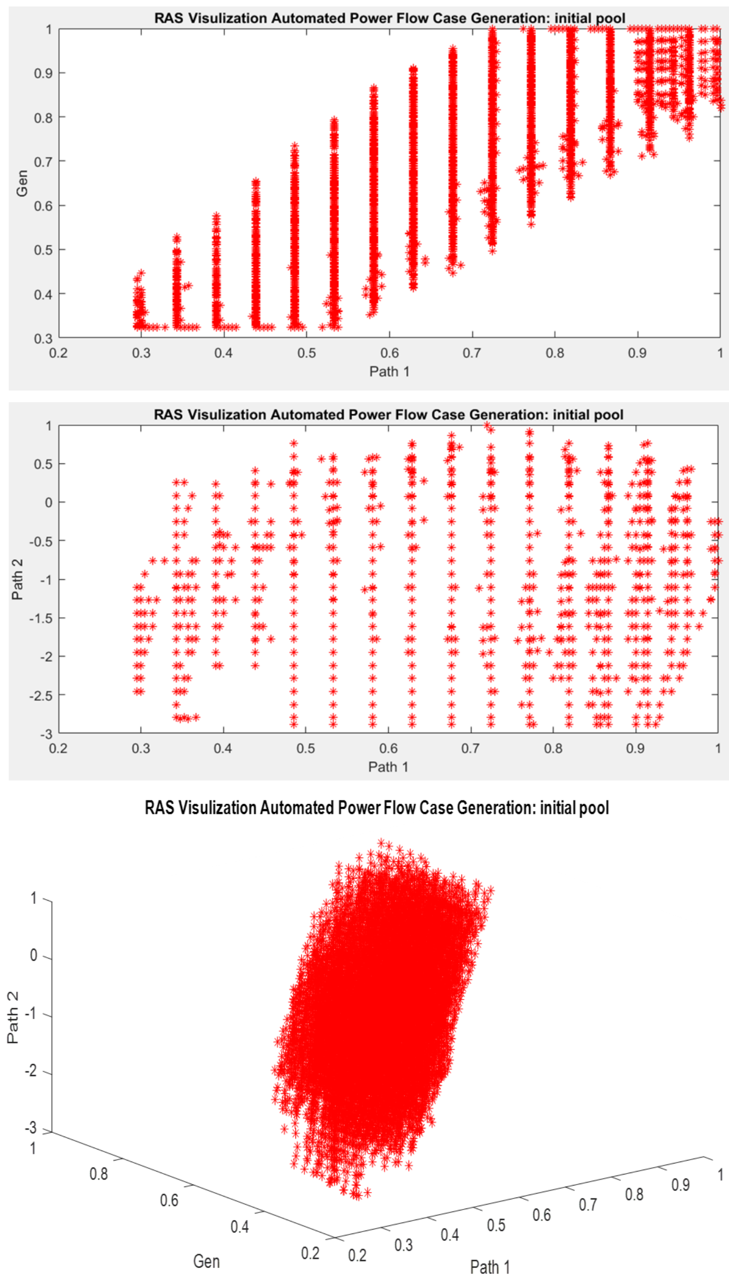

Figure 15 An illustration of initial power flow case pool. The top figure shows the full distribution of one variable with Path1 in the initial power flow case pool, the middle figure shows another variable with Path1 in the initial power flow case pool, the bottom figure shows a 3-D plot for three variables.

From those 11670 power flow cases, TRAST has identified 365 smart sampling candidates based on the 2017 full-year SCADA data. By performing the pairing between the 11670 generated power flow cases and 365 desired power system operation points, 295 seed cases have been identified for next stage in TRAST with a specific threshold (range of 20 MW). Figure 16 shows the 295 identified power flow cases, which show similar trends for the inter-relationship among different variables, compared with the full sample set of Figure 15.

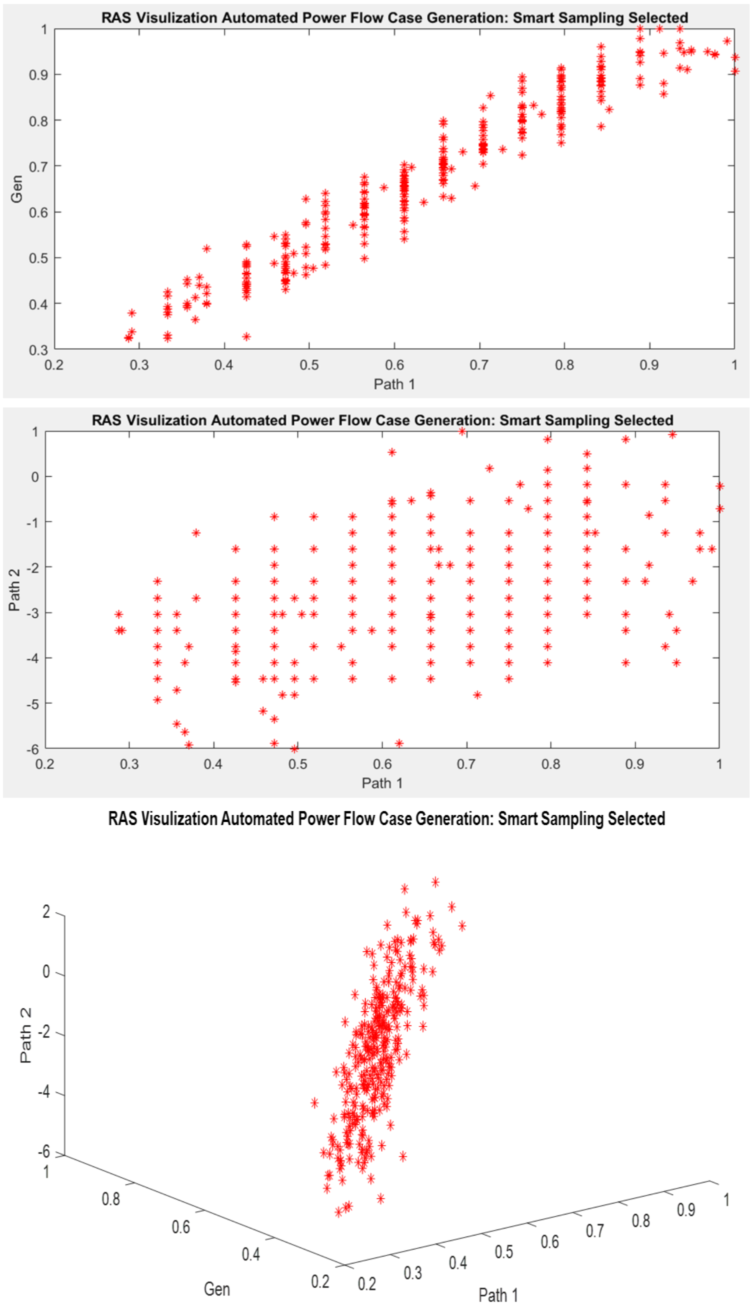

Figure 16 An illustration of the selected smart sampling candidates.

Starting with the 295 smart sampling seed cases, TRAST will create a stressing stream for each seed case by increasing the path flow of Path1 gradually; the step size of active power increase is 20 MW.

For each stream, the new case will be generated until the optimal power flow algorithm that was utilized in the automated case generation process could not achieve feasible solution, the tolerance criteria are formulated given the operational constraints provided by industry collaborators. Figure 17 provides an illustration of the generation power flow stressing streams, each blue dot represents a solvable power flow case, and each horizontal stream represents a series of power flow cases that were created with the same initial power system operation point.

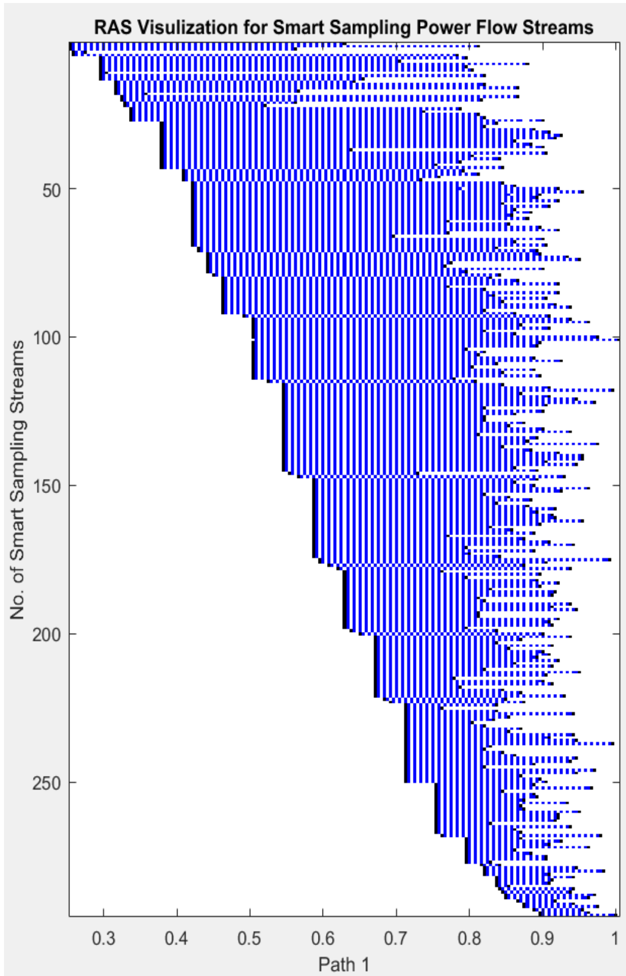

Figure 17 An illustration of 295 stressing streams for further power system transient stability assessment. Blue block indicates a power flow case in the streams, and there is a black block (indicator of stream) before the first case and after the last case for each stream.

3.5 Parallel Computing and Cloud Application for RAS Analysis

To ensure the performance of Jim Bridger RAS under different system operation conditions, the existing design of the Jim Bridger RAS C&D logic considers more than 600 power flow scenarios (S States) in conjunction with 38 active system contingencies (N Events). Moreover, a proper pool of power flow planning cases should be adopted to represent realistic system operation. This leads to a large volume of power system dynamic simulations to be performed in the Jim Bridger RAS analysis. To accommodate this computational burden, the team at PNNL has applied the parallel computing techniques in local computation servers as well as Microsoft Azure Cloud servers. Figure 18 provides an overview of the parallel computing strategy. Figure 19 provides an illustration of the screening results of TRAST for Jim Bridger RAS analysis with the parallel computing techniques applied; the streams have been analyzed in parallel by assigning one stream to one available logical processor.

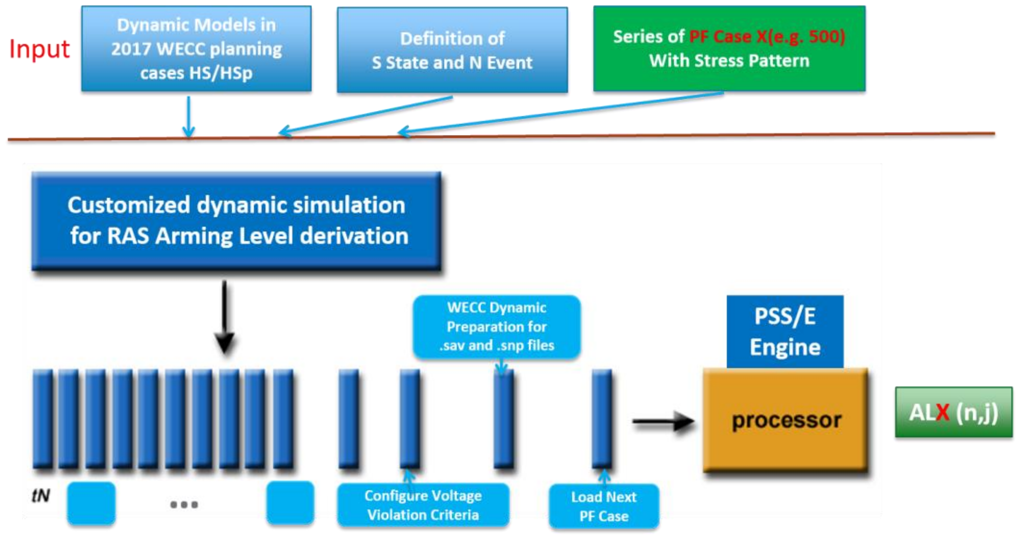

Figure 18 Data deployment to cloud server cluster in TRAST.

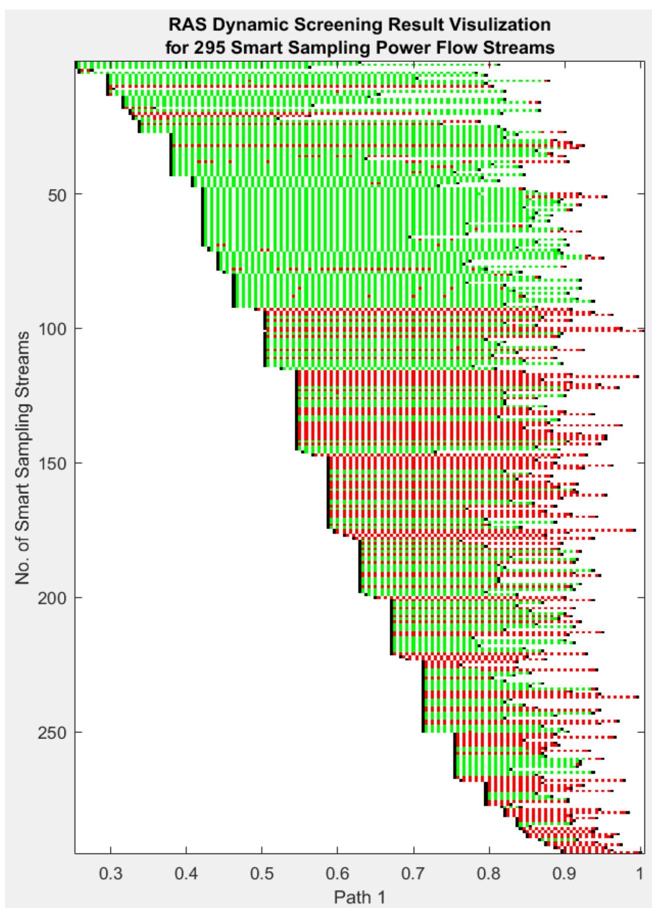

Figure 19 The pre-screening results of dynamic initialization for 295 Smart Sampling stressing streams. Green block indicates a power flow case passed the dynamic screening, and red block indicates a failed power flow case for dynamic simulation initialization. There is a black block (indicator of stream) before the first case and after the last case for each stream.

3.6 Customized Dynamic Simulation for RAS Arming Level Derivation

WECC Transmission Planning Criterion TPL-001-WECC-CRT-3 requires that, following fault clearing, the voltage at each applicable BES bus recover above 80%. Additionally, the voltage at each applicable BES bus serving load must not drop below 70% of pre-contingency voltage for more than 30 cycles, or remain below 80% of pre-contingency voltage for more than 2 seconds [3]. This criterion will be used to evaluate the performance of the Jim Bridger RAS design. Figure 20 provides two different study scenarios that considering the voltage recovery check as well as the voltage dip check.

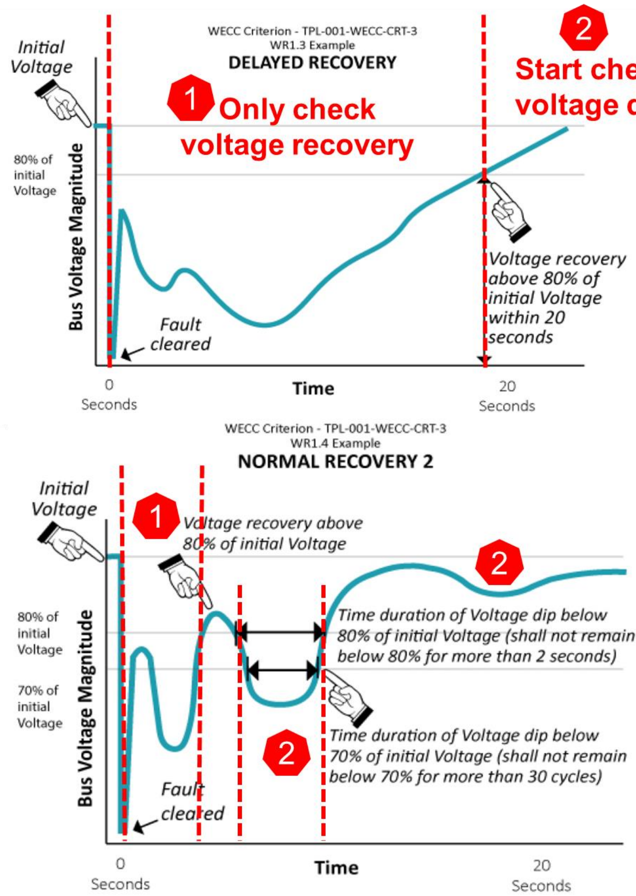

Figure 20 An illustration for WECC CRT-3 Criterion [3].

For the Jim Bridger RAS, it must ensure that the system meets the above-mentioned criterion under all credible contingencies considering various power flow conditions. More specifically, these criteria will be used to evaluate system performance in the large volume power system dynamic simulations and verify the system response in the substations and branches of interest within the footprint of PacifiCorp and Idaho Power Company.

To validate the corresponding functions of TRAST for transient voltage violation check, the PNNL research team also created testing scenarios using the WECC 179-Bus test system. In Figure 21, it can be seen that both voltage recovery criteria (in black) and voltage dip criteria were triggered, and corresponding messages were retrieved from simulation log files and displayed for reference.

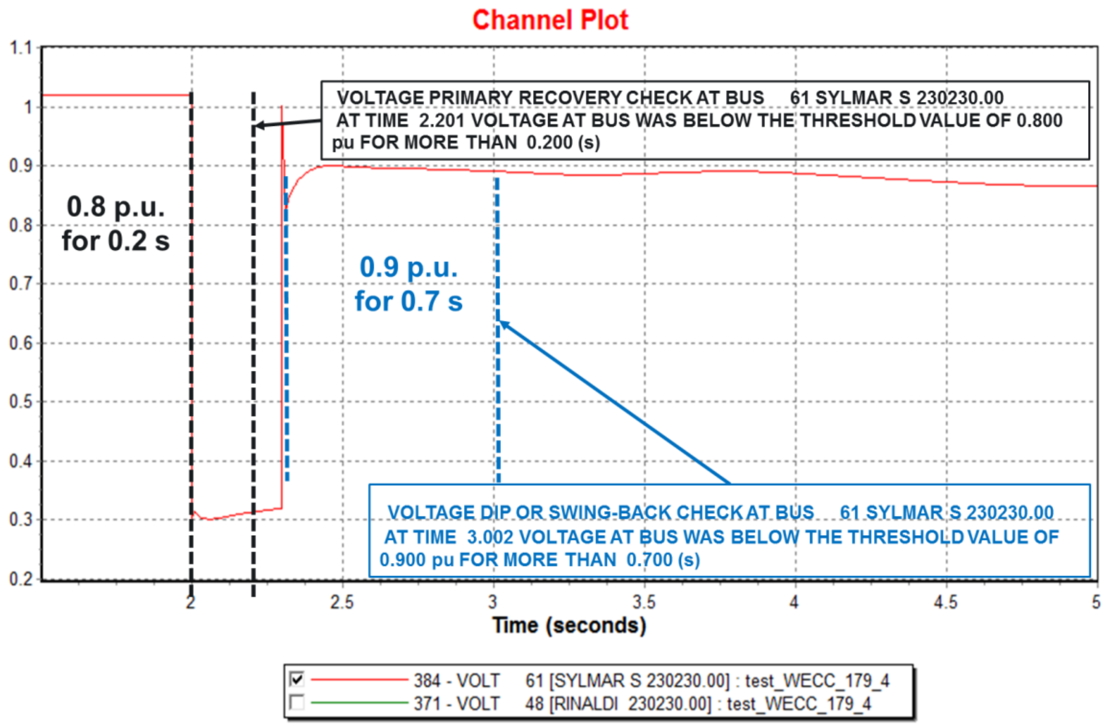

Figure 21 An example for implementing WECC CRT-3 Criterion in TRAST based on PSS/E.

Among all 295 power flow stressing streams, only 116 smart sampling stressing streams were confirmed to be ready for dynamic simulations. TRAST can perform pre-screening of dynamic initialization before launching the 30-second full length simulation, as power system dynamic simulations are usually constrained by the initialization problems.

To address the issues that exists in the remaining stressing streams, the PNNL research team worked closely with industry collaborators to leverage their deep experiences in utility operational analysis and planning study process. Some initialization issues for WECC-size system simulation are due to inaccurate/outdated power system dynamic models in existing WECC planning cases, which are beyond of the scope of this project and the technical projection of TRAST. As a result, the PNNL research team only analyzed the 116 smart sampling stressing streams that were confirmed to be ready for dynamic simulation.

3.7 Machine-Learning-Based RAS Coefficient Prediction

PNNL has constructed a machine learning framework to update the RAS coefficients. Currently, the RAS coefficients in the existing Jim Bridger RAS design are based on engineers’ experience and manual tuning. As a result, the RAS design is very conservative and difficult to maintain. Therefore, a systematic, automated, and data-driven approach is more preferable when applicable, and this has been integrated in TRAST as one of the core functions. Figure 22 illustrates the potential inputs that could be included in this function, and two alternative solutions, namely, neural networks and multiple linear regression, which will be applied to derive the Jim Bridger RAS coefficients.

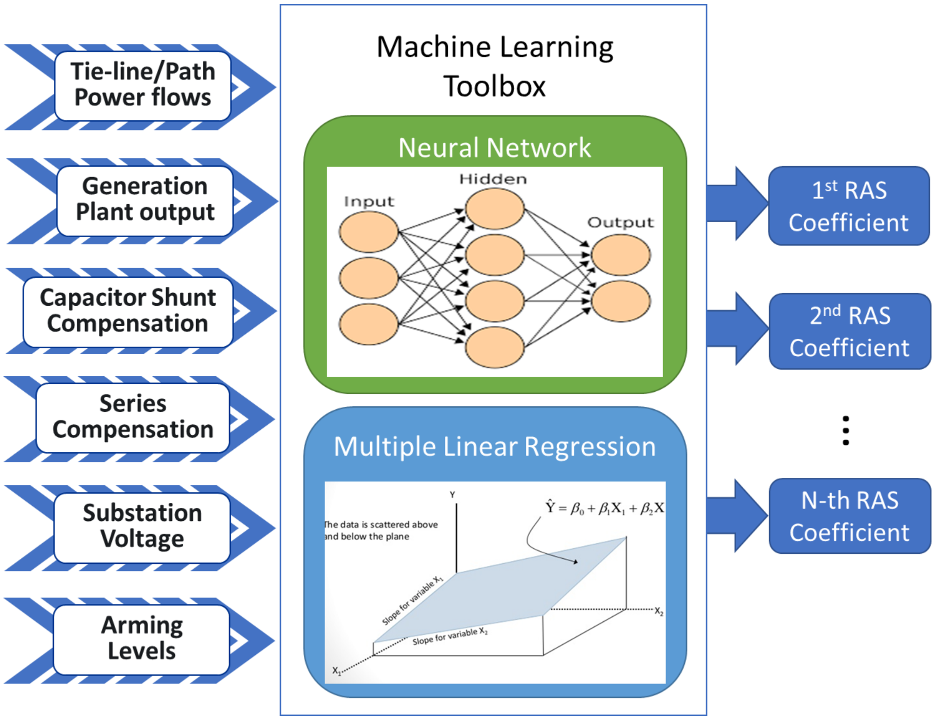

Figure 22. The machine learning framework for Jim Bridger RAS coefficient derivation in TRAST.

For Jim Bridger RAS use case, Table 2 provides a detailed list of the simulated data for RAS coefficient prediction; the data was extracted from the "Limit" case from the dynamic simulation with each stream. An automated data extraction process was developed to identify the necessary data, with users' preference as input. It should be noted that shunt compensation here refers to all the fixed shunts and switchable shunts that in the simulation, the series compensation cannot be properly extracted due to multi-section line modeling in PSS/E.

Table 2 Summary of Dynamic Limit Data for RAS Coefficient Prediction

Dynamic Limit Data	**Number of Selected Points**	**Data Type**	**Total Number of Data**
Path Flow	6	*P* (MW) & *Q* (MVar)	12
Shunt Compensation	8	*Q* (MVar)	8
Synchronous Condenser	3	*P* (MW) & *Q* (MVar)	6
Bus Voltage	37	*Mag.* (PU) & *Phase* (Degree)	74

TRAST utilizes multiple regression and machine learning techniques to derive the RAS coefficients. With the dynamic limit data that is extracted from the power system dynamic simulations for 116 power flow stressing streams, the following steps have been performed for data pre-processing, they are:

1) Review the data quality, identify the continuous and discrete variables according to data properties and groups (four groups as defined), meanwhile exclude no-variance columns (constant or zero);
2) Generate histogram and estimated Gaussian probability density function to derive the knowledge of statistical expression for each variable;
3) Review the pairwise correlation table and check multicollinearity.

Further analyses based on Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) have been performed to evaluate the feature importance, and derive the corresponding coefficients for the RAS Arming Level calculation. It should be noted that due to the limited availability of effective data for this analysis, MLR showed better performance than ANN. At present, there are only 116 WECC-size power flow streams that have been successfully evaluated through power system transient stability analysis; if all 295 WECC-size power flow streams that were created could be properly initialized for dynamic simulation, the performance of both MLR and ANN are expected to be improved.

The following steps are performed for MLR analysis using machine learning library Scikit-learn [8]:

1) Determine the regression target (e.g., Path1_P (MW)). Perform standardization before regression;
2) Determine the features to be used in linear regression;
3) Perform *k*-fold cross validation (*k* = 10) for linear regression model. Plot the prediction using 90% data for training and 10% data for prediction;
4) Save intercept and coefficients of linear regression model using all samples, and save mean and standard deviation values for standardization;
5) Compare the calculated target values using coefficients to sample target values;
6) Get summary report;
7) Review the Relative Feature Importance results from Random Forest, then select features with high importance;
8) Get F scores from univariate linear regression tests. Select features with high scores.
9) Compare the selected feature list from Step 7) and Step 8), finalize the meaningful features for RAS Arming Level calculation.

Figure 23 provides the aggregated Relative Feature Importance for each category calculated from Random Forest. It is evident that with the given 116 dynamic limit data samples, the path flow data and bus voltage magnitude data contribute the most for predicting the Jim Bridger RAS arming level.

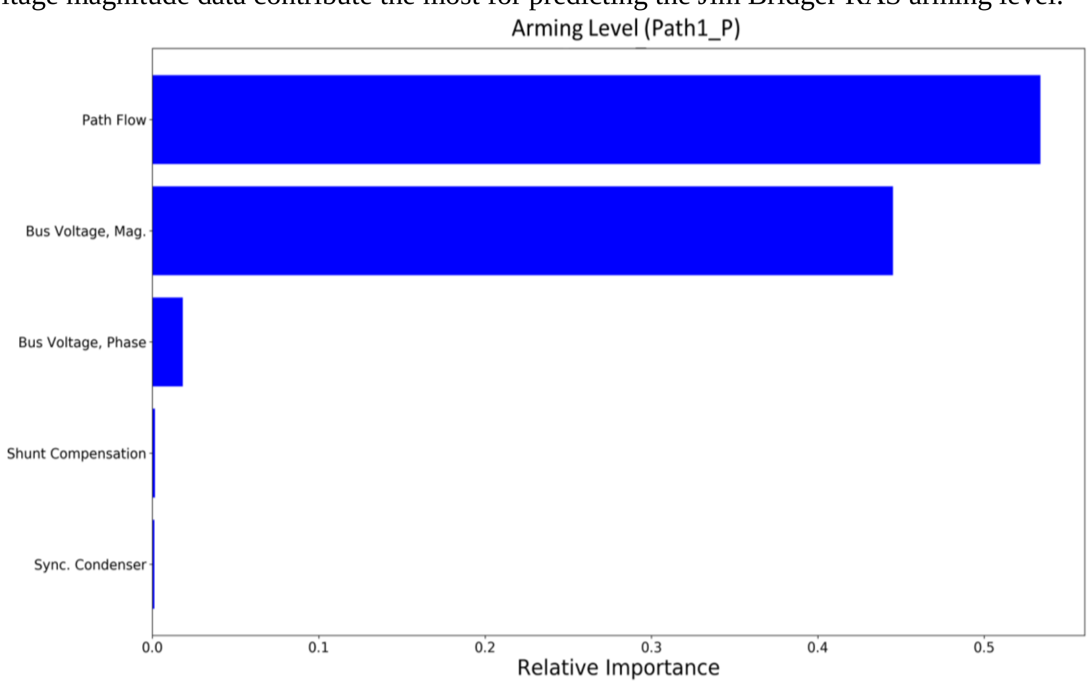

Figure 23 Relative Feature Importance comparison for different categories of features.

One example of the derived RAS coefficients for the considered features is given in Figure 24.

Dep. Variable:	y	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	9.703e+08
Date:	Wed, 11 Dec 2019	Prob (F-statistic):	1.74e-99
Time:	19:53:51	Log-Likelihood:	525.46
No. Observations:	116	AIC:	-864.9
Df Residuals:	23	BIC:	-608.8
Df Model:	92		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1988.0512	0.001	3.65e+06	0.000	1988.050	1988.052
x1	-10.0088	16.497	-0.607	0.550	-44.135	24.117
x2	19.9807	8.276	2.414	0.024	2.861	37.101
x3	-0.3368	1.520	-0.222	0.827	-3.481	2.808
x4	134.4604	24.987	5.381	0.000	82.770	186.151
x5	5.0143	15.703	0.319	0.752	-27.470	37.498
x6	1.4197	8.062	0.176	0.862	-15.257	18.097
x7	12.8221	5.318	2.411	0.024	1.822	23.822
x8	7.7340	4.091	1.891	0.071	-0.729	16.197
x9	-0.0882	0.105	-0.842	0.409	-0.305	0.129
x10	-41.1595	13.420	-3.067	0.005	-68.920	-13.399
x11	-18.5932	5.406	-3.439	0.002	-29.777	-7.409
x12	-0.0003	0.001	-0.186	0.854	-0.003	0.003
x13	-18.1575	5.517	-3.291	0.003	-29.570	-6.745
x14	8.1724	5.522	1.480	0.152	-3.250	19.595
x15	-0.0871	0.065	-1.350	0.190	-0.220	0.046
x16	-3.4700	1.747	-1.986	0.059	-7.084	0.144
x17	4.7763	53.252	0.090	0.929	-105.383	114.936
x18	131.6896	175.720	0.749	0.461	-231.815	495.194
x19	-62.8099	25.836	-2.431	0.023	-116.256	-9.364
x20	57.6388	21.375	2.697	0.013	13.421	101.857
x21	5.3360	1.530	3.488	0.002	2.171	8.501
x22	-47.3287	14.121	-3.352	0.003	-76.541	-18.117
x23	-22.0915	8.151	-2.710	0.012	-38.953	-5.230
x24	23.6555	6.373	3.712	0.001	10.471	36.840
x25	-0.0978	0.095	-1.029	0.314	-0.295	0.099
x26	6.3468	7.348	0.864	0.397	-8.853	21.547
x27	2.1781	1.360	1.601	0.123	-0.636	4.992
x28	-5.6256	1.624	-3.465	0.002	-8.984	-2.267
x29	-1.2513	4.238	-0.295	0.770	-10.018	7.515
x30	0.6035	1.852	0.326	0.747	-3.227	4.434
x31	-10.5200	6.621	-1.589	0.126	-24.217	3.177
x32	7.8692	7.379	1.066	0.297	-7.396	23.134
x33	38.3286	10.429	3.675	0.001	16.754	59.903
x34	0.0494	0.128	0.385	0.704	-0.216	0.315
x35	-50.3558	13.463	-3.740	0.001	-78.205	-22.507
x36	74.1362	16.598	4.467	0.000	39.800	108.472
x37	27.4682	8.119	3.383	0.003	10.672	44.264
x38	-11.0934	4.262	-2.603	0.016	-19.911	-2.276
x39	-3.2811	2.026	-1.620	0.119	-7.471	0.909
x40	-19.8675	21.210	-0.937	0.359	-63.744	24.009
x41	-7.8581	66.913	-0.117	0.908	-146.278	130.562
x42	0.0243	0.408	0.060	0.953	-0.819	0.867
x43	-19.5188	9.698	-2.013	0.056	-39.581	0.543
x44	0.1182	0.236	0.502	0.621	-0.369	0.606
x45	-0.1484	0.160	-0.927	0.363	-0.479	0.183
x46	0.7164	0.564	1.270	0.217	-0.451	1.884
x47	0.0252	0.317	0.080	0.937	-0.631	0.682
x48	0.3411	0.295	1.155	0.260	-0.270	0.952
x49	0.1458	0.090	1.620	0.119	-0.040	0.332
x50	-2.1463	0.852	-2.518	0.019	-3.910	-0.383
x51	-0.0410	0.325	-0.126	0.901	-0.714	0.632
x52	70.1522	23.472	2.989	0.007	21.597	118.708
x53	10.7744	9.166	1.175	0.252	-8.187	29.736
x54	131.8226	175.722	0.750	0.461	-231.686	495.331
x55	-3.5788	1.510	-2.370	0.027	-6.702	-0.455
x56	742.3609	927.538	0.800	0.432	-1176.397	2661.119
x57	-482.3309	676.771	-0.713	0.483	-1882.339	917.677
x58	-105.2678	62.751	-1.678	0.107	-235.077	24.542
x59	-864.9620	1040.886	-0.831	0.415	-3018.198	1288.274
x60	1007.1966	1759.300	0.572	0.573	-2632.193	4646.586
x61	-728.2477	1318.449	-0.552	0.586	-3455.666	1999.171
x62	-7.1500	21.362	-0.335	0.741	-51.340	37.040
x63	113.7100	335.596	0.339	0.738	-580.522	807.942
x64	-53.2111	63.664	-0.836	0.412	-184.909	78.487
x65	96.7665	56.750	1.705	0.102	-20.630	214.163
x66	-12.9288	24.129	-0.536	0.597	-62.843	36.985
x67	396.3638	162.088	2.445	0.023	61.058	731.669
x68	343.3265	119.301	2.878	0.008	96.534	590.119
x69	-6762.0851	1.52e+04	-0.445	0.661	-3.82e+04	2.47e+04
x70	-1021.4008	294.699	-3.466	0.002	-1631.033	-411.769
x71	2520.7372	659.392	3.823	0.001	1156.681	3884.793
x72	-671.7605	165.002	-4.071	0.000	-1013.093	-330.428
x73	-370.5609	136.980	-2.705	0.013	-653.926	-87.196
x74	-528.5957	136.610	-3.869	0.001	-811.194	-245.997
x75	-583.4207	145.543	-4.009	0.001	-884.499	-282.342
x76	12.3020	25.794	0.477	0.638	-41.057	65.661
x77	213.3816	358.366	0.595	0.557	-527.956	954.719
x78	-29.1598	151.352	-0.193	0.849	-342.256	283.936
x79	-0.8864	6.053	-0.146	0.885	-13.409	11.636
x80	-352.6909	142.288	-2.479	0.021	-647.035	-58.347
x81	-10.9732	10.922	-1.005	0.326	-33.568	11.622
x82	-6.0701	6.760	-0.898	0.379	-20.054	7.914
x83	-14.0901	29.076	-0.485	0.633	-74.239	46.059
x84	-20.9832	15.415	-1.361	0.187	-52.871	10.904
x85	-14.5025	11.621	-1.248	0.225	-38.542	9.537
x86	3.9631	3.817	1.038	0.310	-3.933	11.859
x87	-11.4169	9.007	-1.268	0.218	-30.049	7.216
x88	24.1603	18.084	1.336	0.195	-13.249	61.569
x89	36.0648	556.220	0.065	0.949	-1114.563	1186.693
x90	7112.2720	1.52e+04	0.466	0.645	-2.44e+04	3.87e+04
x91	4.6299	5.039	0.919	0.368	-5.795	15.054
x92	50.8865	50.772	1.002	0.327	-54.142	155.915

Omnibus:	5.263	Durbin-Watson:	2.222
Prob(Omnibus):	0.072	Jarque-Bera (JB):	7.757
Skew:	-0.016	Prob(JB):	0.0207
Kurtosis:	4.266	Cond. No.	2.50e+08

Figure 24 One example of the calculated Jim Bridger RAS coefficients.

Moreover, the calculated RAS coefficients were evaluated through the prediction against observed values. Based on the MLR model, there were 12 randomly selected samples being validated, the comparison between the predicted values and the observed simulation values is given in **Figure 25**.

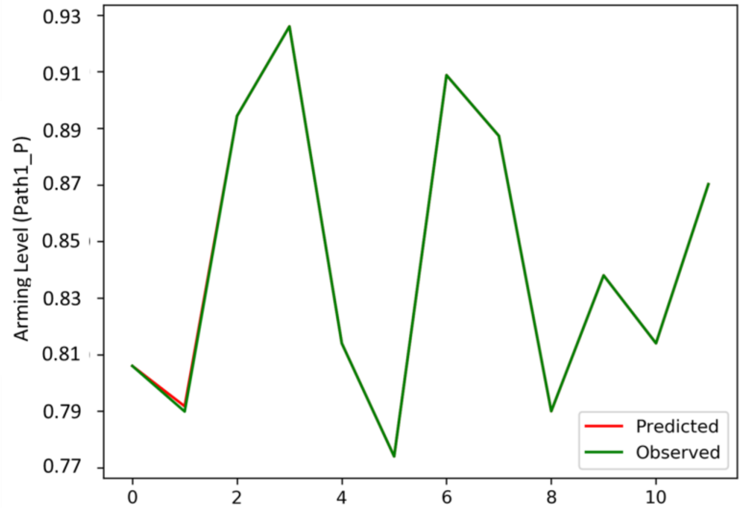

Figure 25 The comparison between the MLR prediction and the observation from simulations.

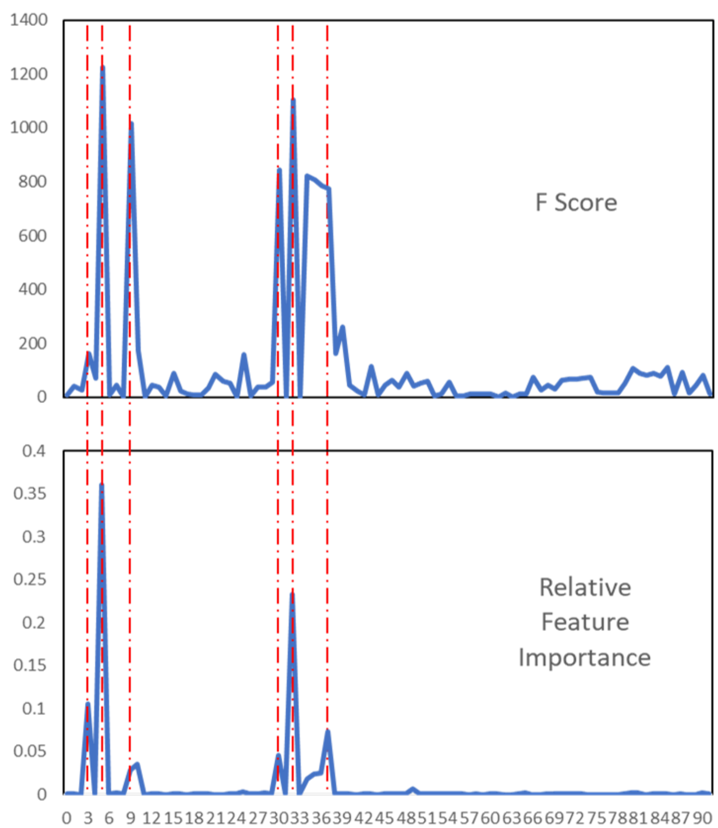

Figure 26 The comparison between Relative Feature Importance and F Score.

The feature importance scores from Random Forest analysis and the F scores from ANOVA (Analysis of Variance) are aligned, as shown in Figure 26, to assist the final selection of RAS features. Feature selection/ranking is used to reduce the feature number and reduce overfitting. In addition, it will help to obtain a better understating of features and their relationship to the target. F scores are calculated from univariate linear regression tests for feature selection. It is converted from cross correlation between each feature and target, and it examines each feature individually. A test statistical significance, "p-value", is calculated for each feature, which is shown in Column 5 in Figure 24; a small "p-value" indicates high significance of feature [8].

Another commonly-used and easy-to-use method is feature importance, which is an in-built class from tree-based learning models. In random forest model, feature importance is calculated as the decrease in node impurity weighted by the probability of reaching that node.

For each specific case, the performance of feature selection should be validated through model performance by using independent features with high scores by defining the selected features in Step 5. It has been observed that strong multicollinearity exists in the current selected RAS features. In the future, principle component analysis (PCA) can be utilized to identify and remove any correlated input features. The feature selection step should be repeated after reducing multicollinearity.

3.8 RAS Coefficient Comparison and Validation

One important function of TRAST is to provide a transparent and reliable RAS validation and evaluation process. This can provide an objective way to not only validate the derived RAS coefficients, but also to evaluate the performance of the updated RAS. The team at PNNL has been working closely with industry on how to validate the derived RAS coefficients for Jim Bridger RAS with TRAST. It has been confirmed that a simulation-based method is still favored for the Jim Bridger RAS, as there is no way to perform online testing in the production environment without another standalone RAS for offline testing. In this case, an effective validation and evaluation process will be simulation-based, but with test cases that consider extreme operation conditions with randomly-selected power flow planning cases. Figure 27 illustrates the data interface for RAS validation and evaluation in TRAST.

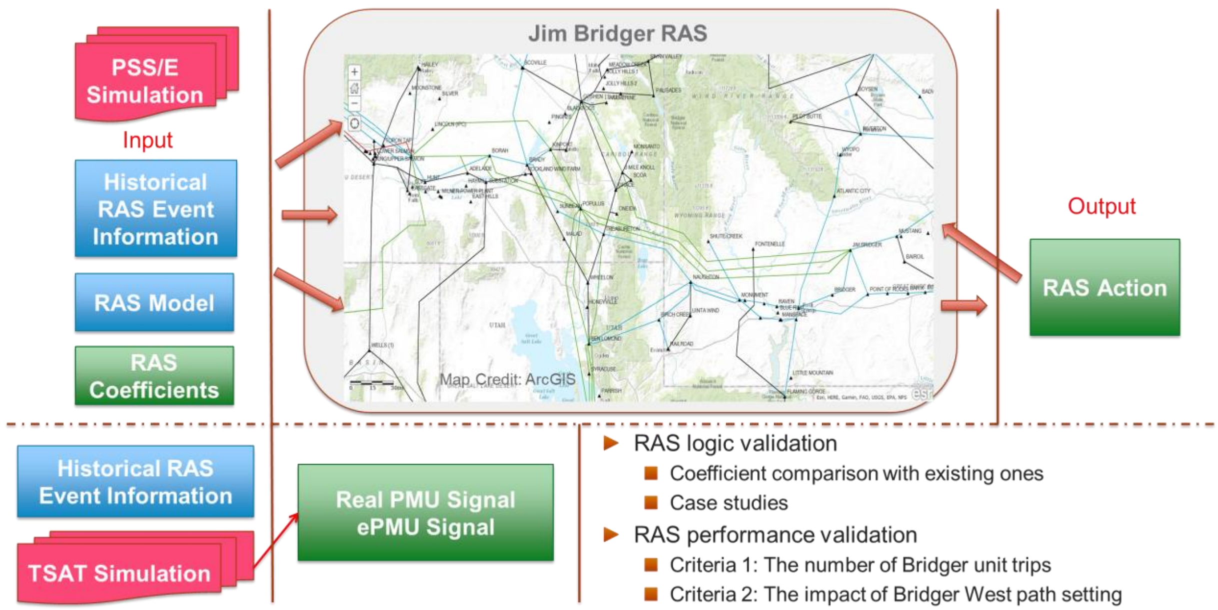

Figure 27. Data interface for RAS validation and evaluation in TRAST.

It should be noted that there is no existing standard and regulation regarding RAS validation, which is still a challenging process. Moreover, as the U.S. power industry starts to embrace the disturbance-based power plant model validation, and push forward the system-level model validation, the proposed methodology for RAS can be leveraged and integrated in such process.

For the Jim Bridger RAS use case, the team at PNNL worked with PacifiCorp to identify historical RAS events, then the team from Peak Reliability used TSAT (Transient Stability Assessment Tool) to simulate those events and general pseudo PMU signals. More details about the ePMU signal generation process can be found in [5].

3.9 Prototype Demonstration in PNNL Electricity Infrastructure Operations Center (EIOC)

In September 2018, the PNNL research team had set up a testing server in PNNL Electricity Infrastructure Operations Center (EIOC). The testing server is configured with comprehensive software environment for hosting TRAST and corresponding industry demonstration. The functions and scripts in TRAST were deployed to this EIOC server, and tested by Mr. Song Wang from PacifiCorp and Dr. Orlando Ciniglio from Idaho Power Company through a secure and authorized remote access. In this way, PNNL team had a secure, convenient and effective way to interact with our industry collaborators.

4.0 Summary

The goal of this project is to develop innovative methods for adaptively setting RAS (or SPS) parameters based on realistic and near real-time operational conditions to improve power grid reliability and grid asset utilization. The PNNL team successfully completed the prototype design of TRAST and its implementation. This report describes the various features and components of TRAST, with a use case to illustrate how TRAST was utilized in the Jim Bridger RAS updated design.

5.0 Next Step

The project team has developed a prototype of the Transformative Remedial Action Scheme Tool (TRAST). It has been accomplished in collaboration with three Western utility companies: PacifiCorp, Idaho Power Company, and Peak Reliability (Western Interconnection Reliability Coordinator).

In future, TRAST will be continuously validated and improved by developing more use cases considering complex grid-operation scenarios. The capability of data-driven analysis and machine-learning-assisted feature exploration for RAS design and evaluation will be fully investigated in those scenarios. Two potential candidate scenarios are given as follows:

1) Considering high-penetration of renewable energy, especially how the stochastic behavior of large-scale wind farms in Southern Wyoming influence the operation of Jim Bridger RAS, as well as the coal-fired Jim Bridger Power Plant.

2) Considering a major system topology change, especially how to bridge the gap between new transmission line planning and critical RAS operation without interruption.

Moreover, the project team at PNNL would like to select another Western Interconnection RAS for consideration. This will improve the extensibility and compatibility of TRAST, and demonstrate that the whole procedure can be extended to a set of interconnection RAS without loss of generality. Such a successful demonstration would prompt work with WECC and NERC to promote a holistic RAS design standard and evaluation procedure using TRAST.

This project aligns well with WECC Near-Term Priorities (2019-2021), in which WECC would like to explore and evaluate the impacts of the Changing Resource Mix on 1) Existing path ratings, 2) Remedial Action Scheme (RAS) effectiveness, etc. The WECC statement is published and board approved on June 20th, 2018. This will also provide the opportunity for PNNL to further develop an innovative and transformative approach to RAS design and maintenance that could significantly advance the industry’s ability to efficiently and effectively improve, test, and validate RAS system settings throughout the Western Interconnect and with the potential to extend to across the North American electric grid.

Lastly, the research prototype TRAST developed at PNNL is available for licensing, with a commercialization flyer attached in Appendix A. The interested parties can also view TRAST [9] and other aspects of PNNL’s intellectual property, with many designed to help power grid operators and utility planning engineers [10].

6.0 References

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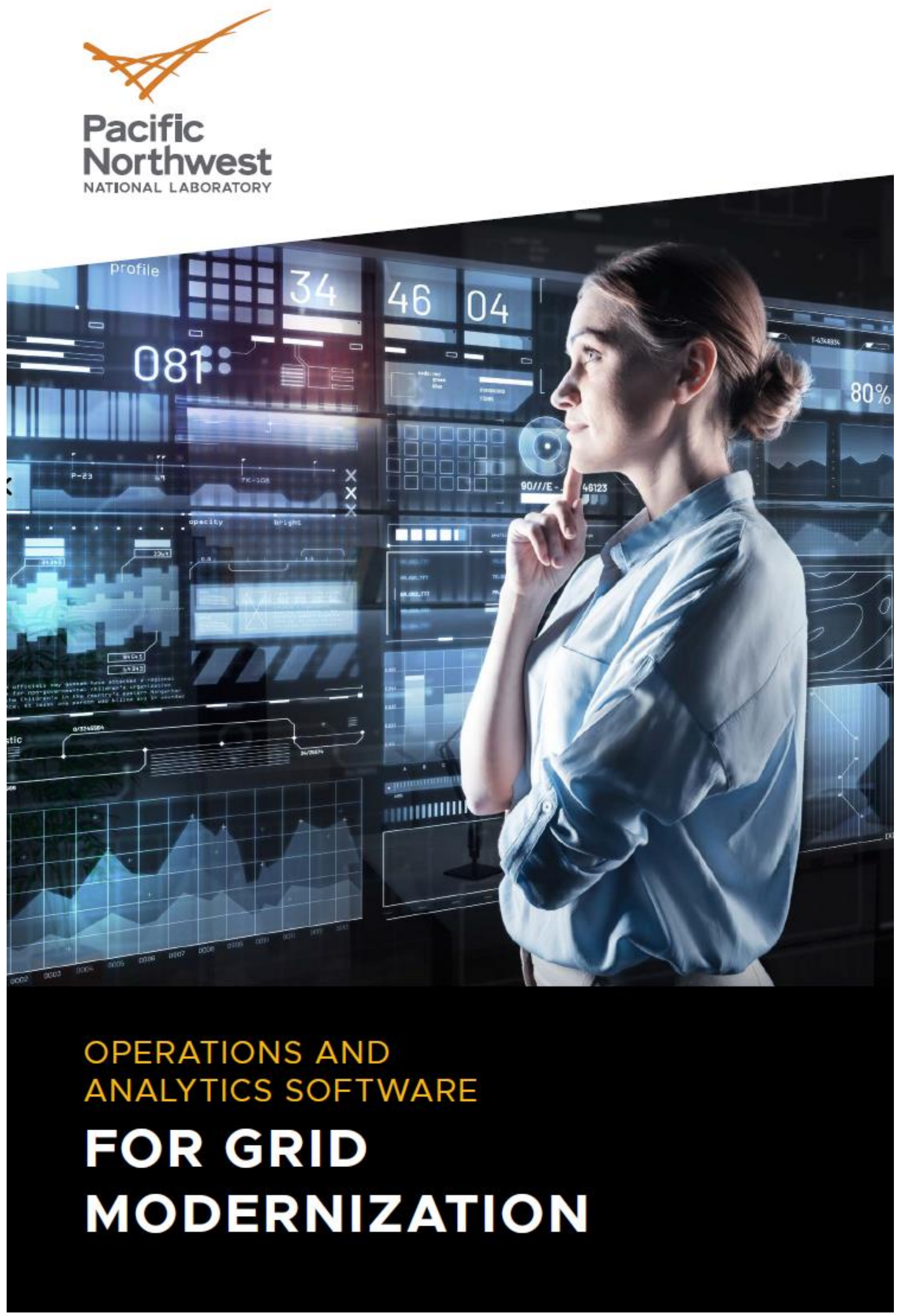
[8] Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011.

[9] The official PNNL project website: https://www.pnnl.gov/projects/adaptive-rassps-system-settings-improving-grid-reliability-and-asset-utilization-through

[10] Available Technologies at PNNL: https://availabletechnologies.pnnl.gov/Default.aspx

Appendix A: Commercialization Flyer for Transformative Remedial Action Scheme Tool (TRAST)



TECHNOLOGY HIGHLIGHT

Transformative Remedial Action Scheme Tool (TRAST) | 31349, 31490

Cost-effectively enhances grid reliability and resilience

Remedial action schemes hold promise for ensuring grid reliability, but they only determine the worst operating conditions and may miss critical contingencies, result in under-utilization of assets, and cause the very reliability issues they seek to solve. TRAST has been tested in the Western Interconnect to validate and improve a manually created remedial action scheme based on realistic and near-real-time operational conditions, thus improving power grid reliability and grid asset utilization. The tool provides advanced statistical data analysis, customized dynamic simulation, a prediction based on machine learning, and a reliable validation strategy on multiple commercial platforms. The automatic/semi-automatic functionalities in TRAST could significantly simplify and shorten the remedial action scheme design and study process, from end to end.

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