Predicting Cascading Failures in Smart Grids

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Grids are reliable but blackouts occur

https://www.npr.org/2013/08/14/210620446/10-years-after-the-blackout-how-has-the-power-grid-changed

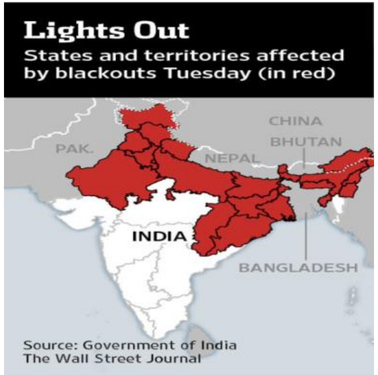
https://blog.cheaperthandirt.com/survive-summer-power-outage/

https://www.buzzfeednews.com/article/gabrielsanchez/2003-blackout-new-york-city-without-power

https://www.amny.com/news/northeast-blackout-2003-1-20432049/

A global problem

2012 India Blackout



wsj.com/articles/SB10000872396390444405804577560413178678898

2014 Bangladesh Blackout

http://theevolutionandpresentdayofbangladesh.blogspot.com/2014/11/blackout-in-entire-country-people-of.html

2015 Ukraine Blackout

https://www.dailykos.com/stories/2018/3/16/1749595/-Ukraine-was-Putin-s-Trial-Run

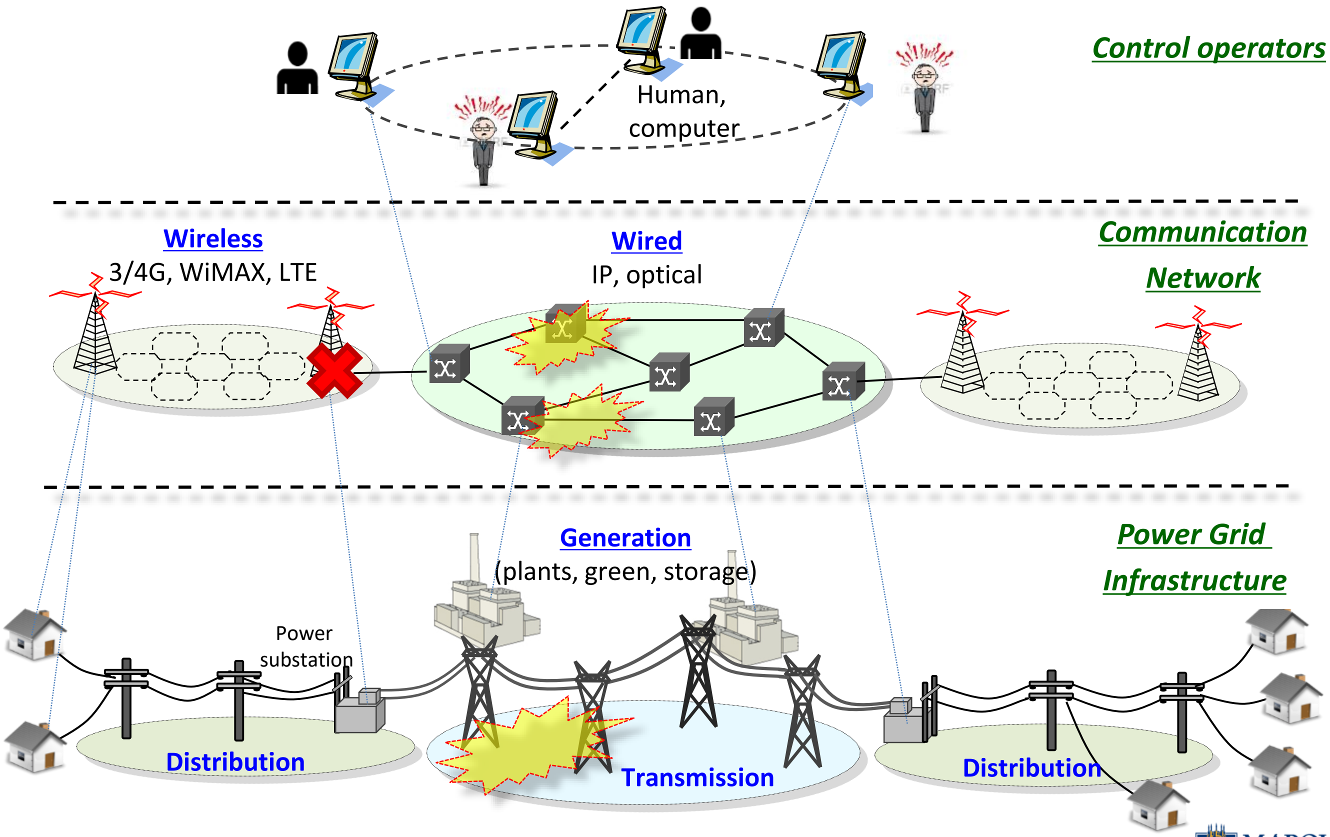
2019 Java Blackout

https://www.nst.com.my/world/2019/08/510124/power-restored-java-after-12-hour-blackout

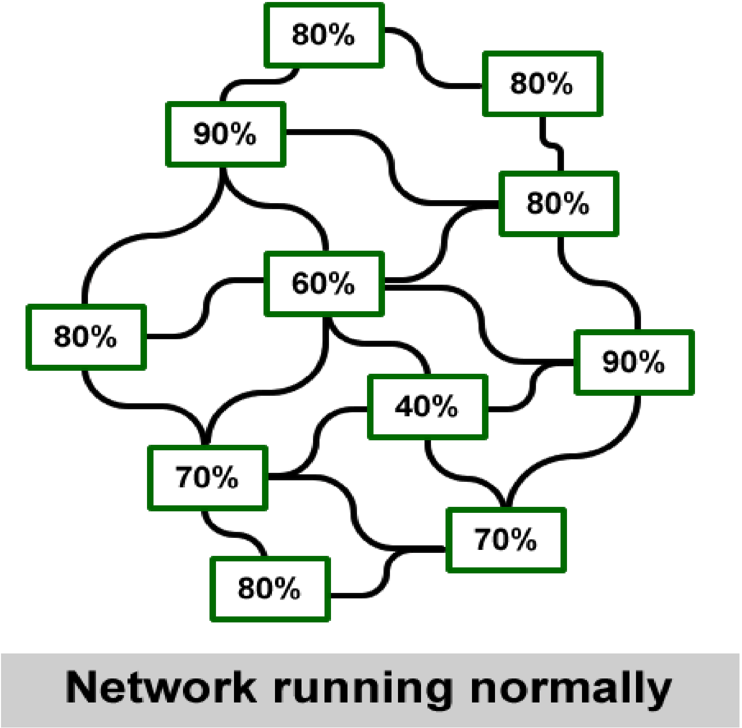
Outline

- Background & motivation for this work
- Data collection and feature engineering
- Data cleaning and visualizations
- Model tuning, discussion and results
- Conclusions and extensions

Interdependent multi-layer view of the smart grid



Cascading failures in power grid : overview

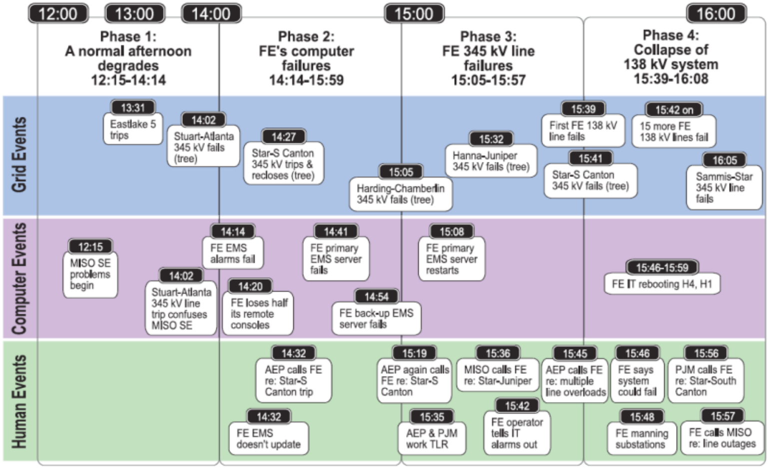


Source: Wikipedia

A few lines/generators trip initially → Loads shifted to nearby elements in the system → Nearby elements are overloaded beyond their capacity → Elements are tripped; load are shifted onto other elements → Cascading chain of failures starts, which can lead to system blackout

Understanding large blackouts: known causes

– **2003 Northeast Blackout**
  - Occurred due to combination of transmission line and communication network failures.
  - Alarm software failed, left human operators unaware of transmission-line outage and resulting confusion and misjudgment led to cascading failures [1].



– **2011 South East Blackout (San Diego and AZ)**

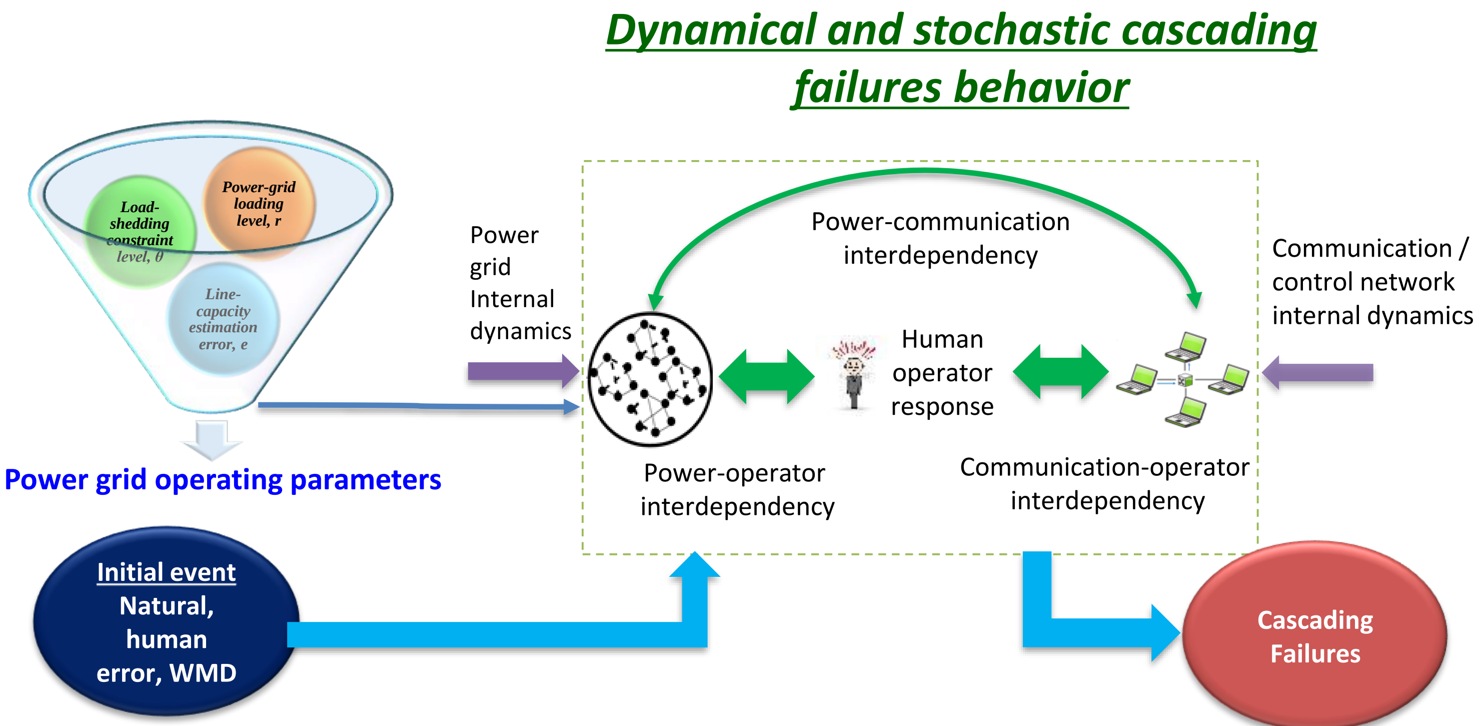
Technician accidentally shut 500-kv transmission line which lead to a blackout affecting 11 million people over 11 hours. Estimated losses in $12-$18M range [3].

– **2015 Ukraine Blackout**

In 2015, cyber attackers gained access to the Ukraine power grid using malware and eventually attacked the grid and did massive outage affecting 0.25 million subscribers.

[1] U.S.-Canada System Outage Task Force, Princeton, NJ, USA, "Final Report on the August 14th Blackout in the United States and Canada 2004
[2] https://www.ferc.gov/legal/staff-reports/04-27-2012-ferc-nerc-report.pdf
[3] D. U. Case, "Analysis of the cyber attack on the Ukrainian power grid, "Electricity Information Sharing and Analysis Center (E-ISAC), 2016.

Overview of cascading failure dynamics



Motivations

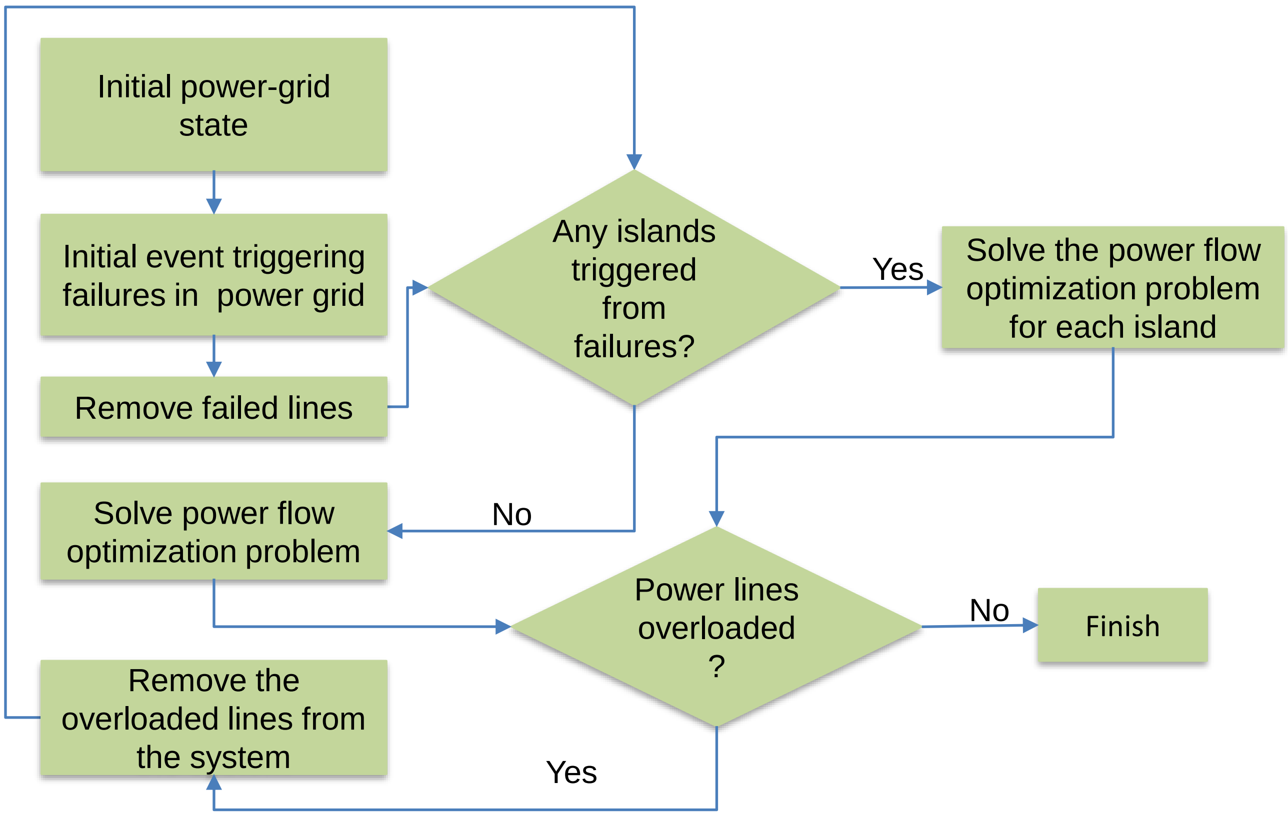
- Limited real-world data
- Generating synthetic cascade data using DC/AC optimal power flow formulations
- Feature engineering

Contributions

- Development of a cascading failure simulation framework
- Classification of cascading failures in power grids
- Predicting cascading failures (from line failures and load-shedding) using regression

- Utilities can use this model to mitigate the risk of cascading failures during planning phase.
- Significantly reduces the computational time.

Data collection: flowchart of the simulation framework



Dataset:

A 66817 X 19 Matrix with 16 features using IEEE 118 bus system (186 lines and max generation of 9966MW).

Target:

Amount of Load-shedding
Total Number of line fail
Cascading effect

Source:

MATLAB using MATPOWER [1] power-flow m-files.

Computation time: 556 hrs.

1. Zimmerman, R. D., Murillo-Sánchez, C. E., & Thomas, R. J. (2011). MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education. *IEEE Transactions on power systems*, *26*(1), 12-19.

Feature selection and engineering

Features	Feature Remarks
Initial number failed lines	Regular feature
Generation	Regular feature
Demand	Regular feature
Served load	Regular feature
Capacity estimation error, alpha	Regular feature (uncertainty of information)
Flow capacity	Regular feature
Islands	Regular feature
Total Number of line fail	Target
Amount of load-shedding	Target

Regular features

- Capacity of the lines
- Generation, demand
- Costs of load-shedding
- Operator attributes
- Topology of the grid
- Total number of line fail, amount of load-shedding

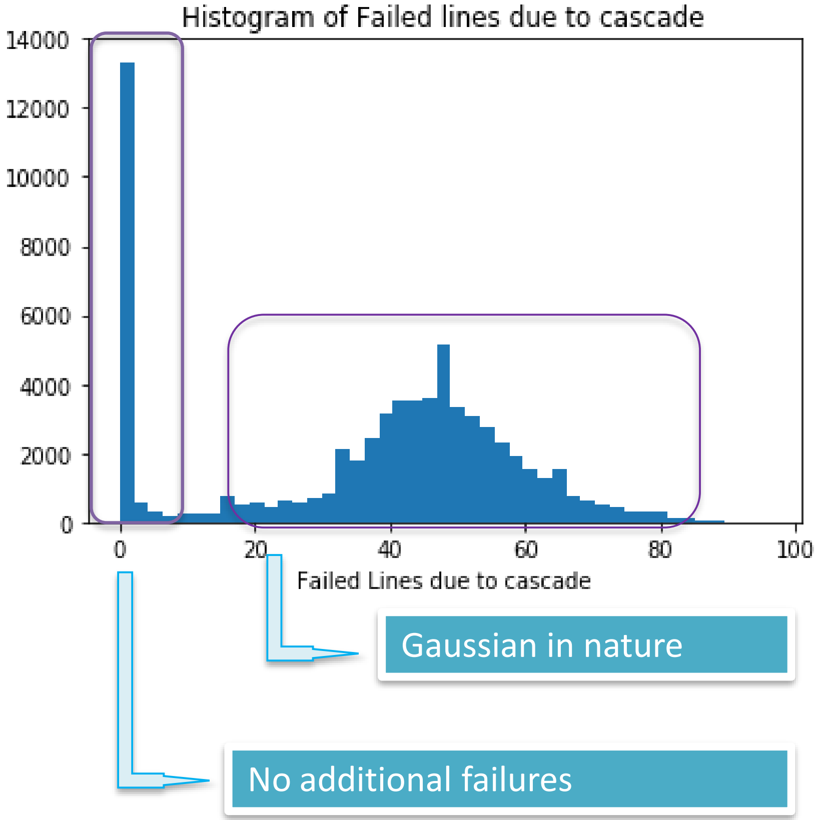
Engineered Features

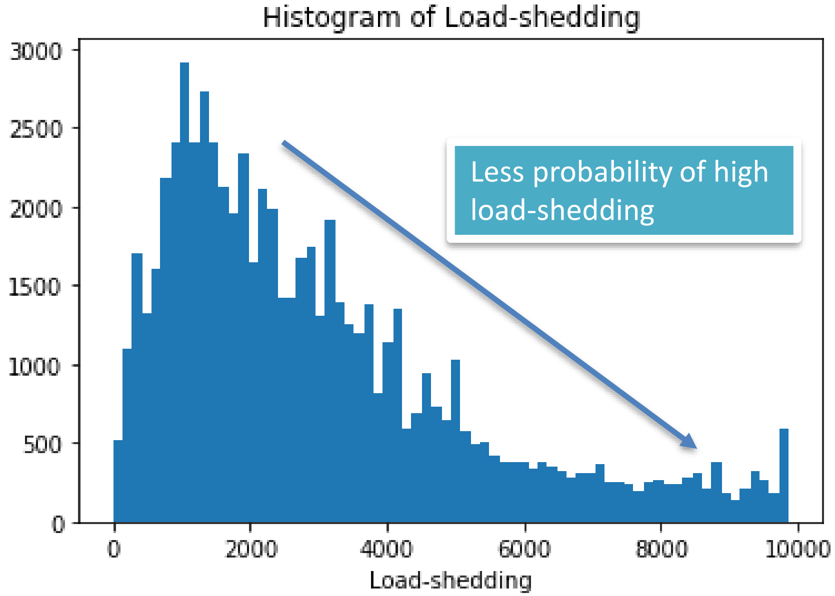
- Total, maximum, minimum capacity of the failed lines
- Ratio between load and maximum generation
- Load-shedding constraint
- Human error Probability
- Average degree, distance
- Cascading effect (linear combination of the target variable after scaling)

Data cleaning

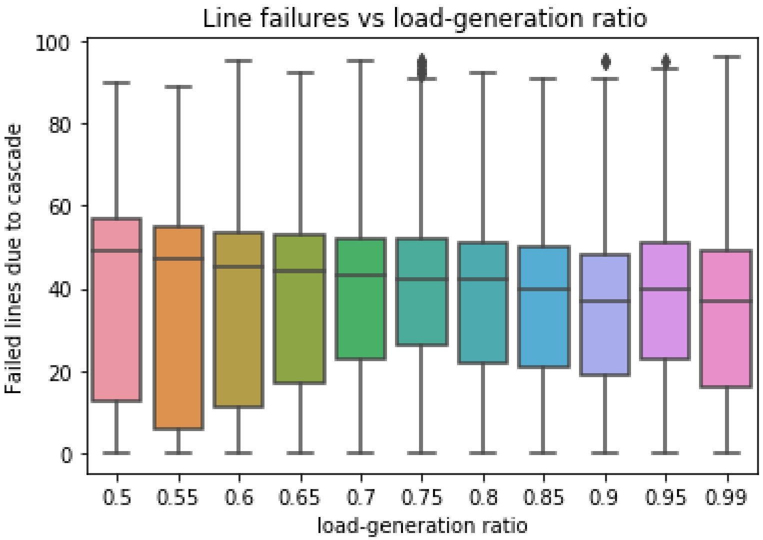
- Duplicate Records – No duplicate records since the dataset is simulated
- Null Values – No null records since the dataset is simulated
- Outliers – No outliers since the dataset is simulated

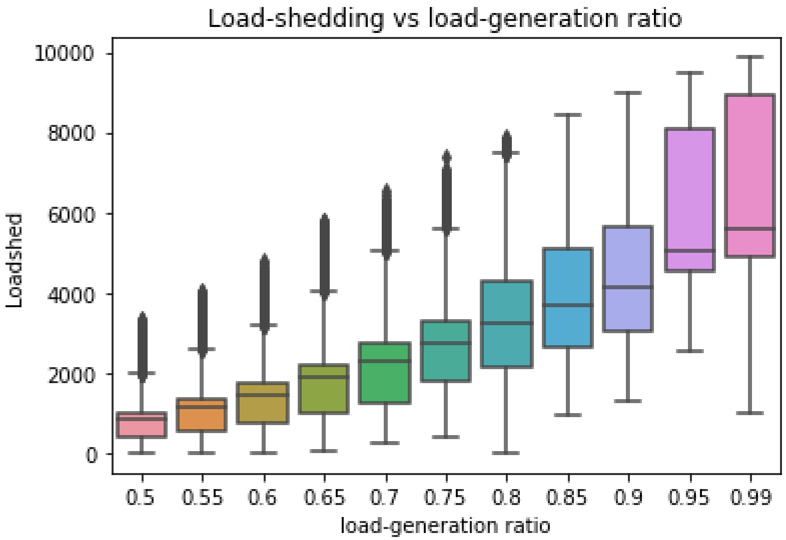
Exploratory data analysis: data visualizations





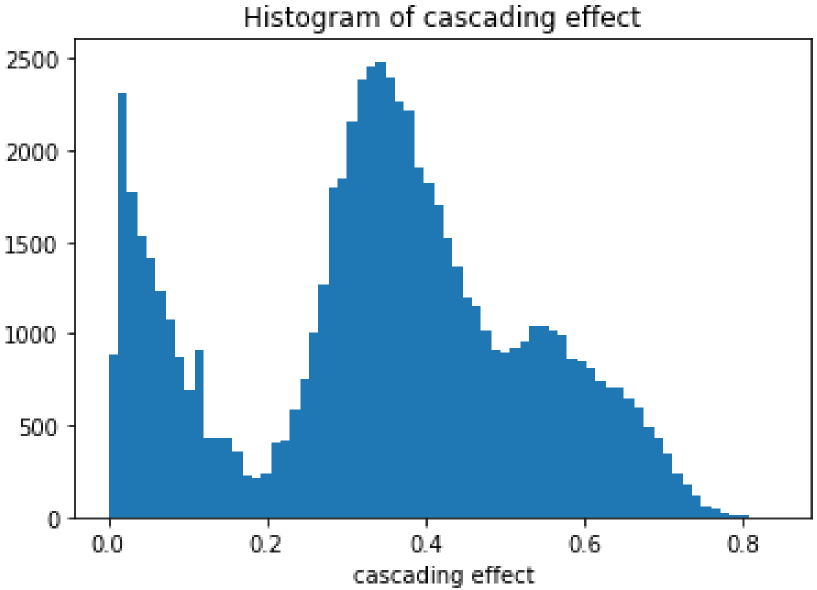
Exploratory data analysis: Data Visualizations





The mean of line failure remains almost the same while the amount of loadshedding increases significantly with higher load-generation ratio.

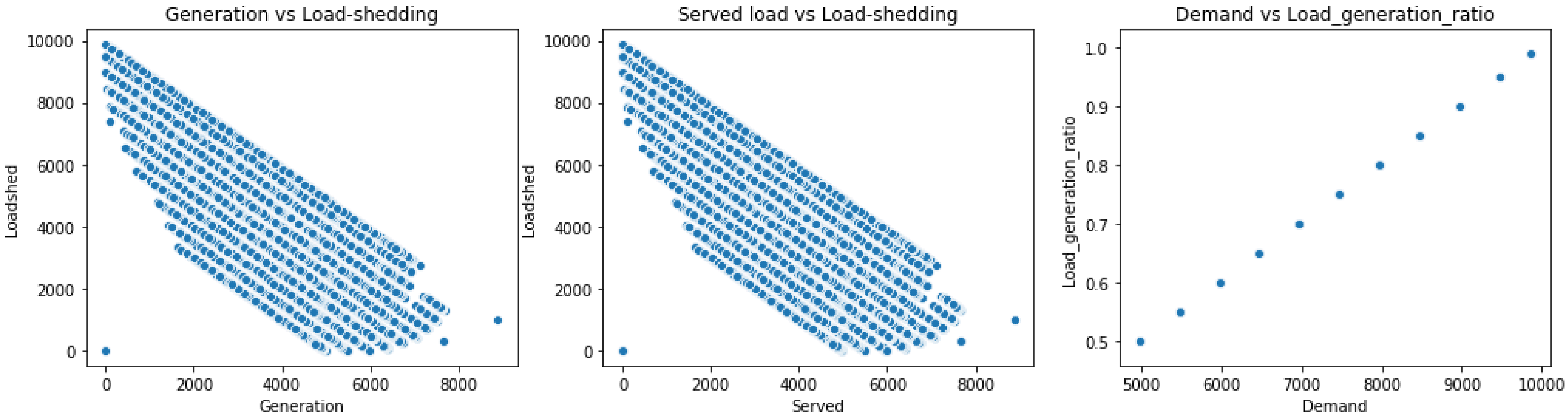
Exploratory data analysis: data visualizations



Histogram of the cascading effect shows bimodal nature. The first peak is due to no line failure scenarios and the second peak captures the average effect of line failures and loadshedding

Exploratory data analysis: pruning features/dimensionality reduction

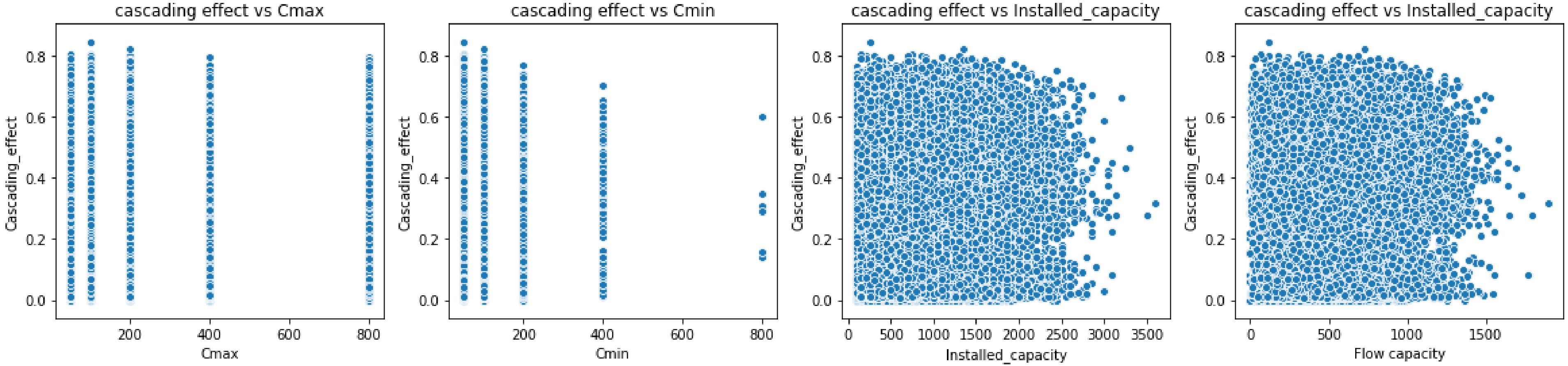
Load features



Decision: Removed generation, served, demand from the dataset to avoid collinearity
Rationale: scatterplot above shows linear correlation.

Exploratory data analysis: pruning features/dimensionality reduction

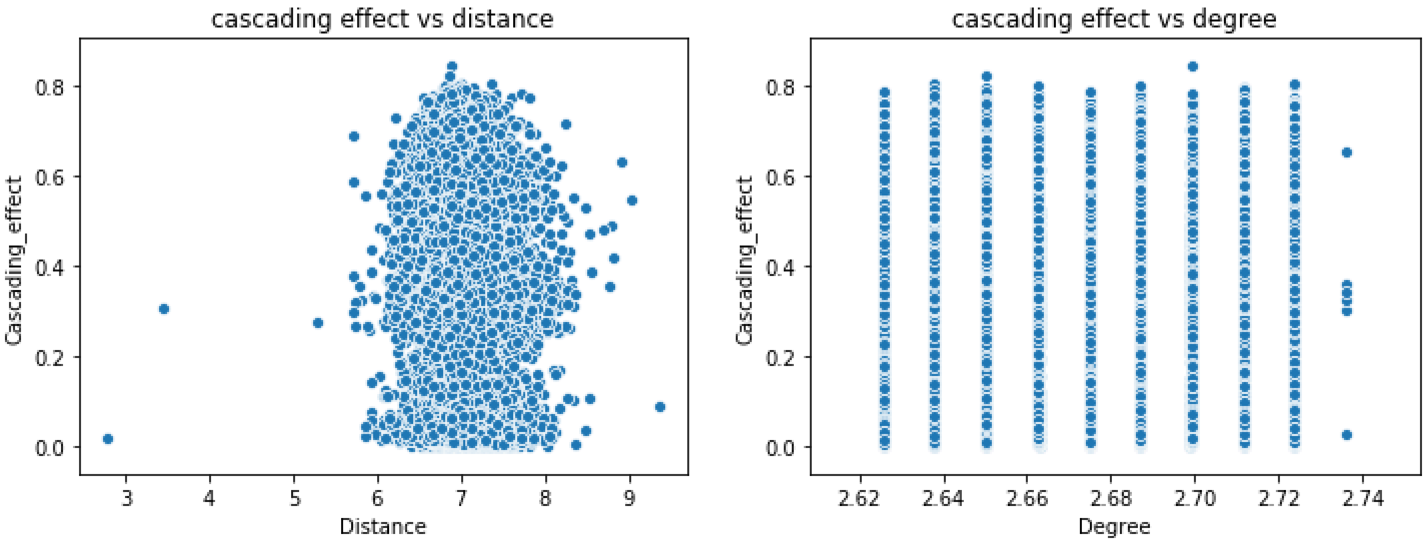
Capacity features



Decision: We can remove this four features from the data set as well. But for now Cmax, Cmin are kept and the other two are deleted. We may delete them later during model tuning.
Rationale: There is no visible patterns between Cmax, Cmin, Installed capacity, Flow capacity with cascading failure.

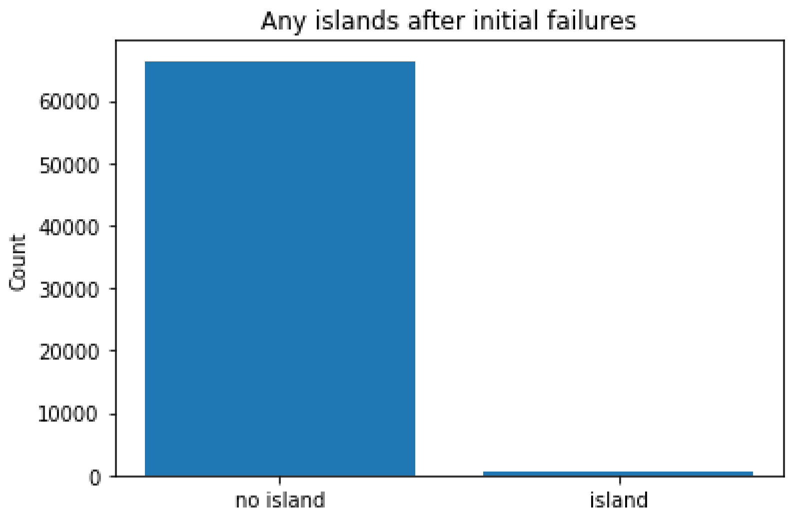
Exploratory data analysis: pruning features/dimensionality reduction

Topological features



Decision: We can remove this two features from the data set as well. But i will keep them for now and may delete them during model tuning.
Rationale: There is no visible patterns between degree and distance with cascading failure.

Exploratory data analysis: pruning features/dimensionality reduction



Finally, removed failed lines after cascade ends and load-shed features since cascading effect is obtained from their linear combinations.

Decision: Removed islands feature From dataset
Rationale: Bar chart above shows no islands formed after initial failures in most cases.

Exploratory data analysis: correlation between features

Strong correlation with cascading effect:

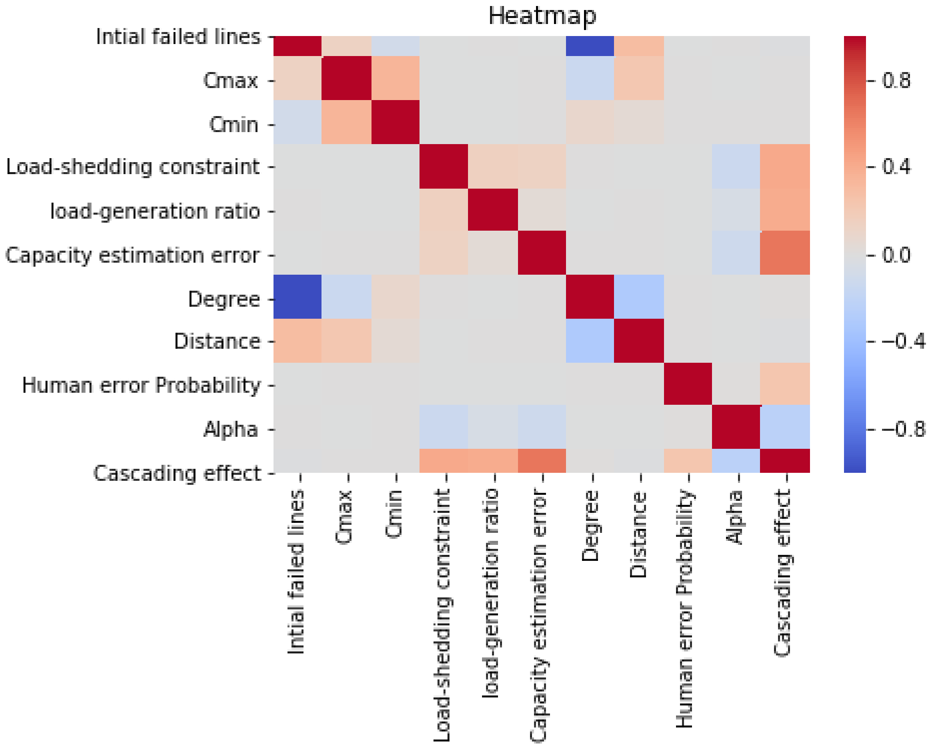
- Capacity estimation error

Moderate correlation with cascading effect:

- Load-generation ratio
- Load-shedding constraint
- Human error probability
- Alpha(negative correlation)

Low/minimal Correlation with cascading effect:

- Cmax, Cmin
- Degree, distance
- Initially failed lines



Modeling : (ML algorithms and modeling steps)

Algorithms for regression:

- Linear regression/ Ridge/Lasso regression
- Random Forest regression
- Support vector regressor

Algorithms for classification:

- Logistic regression
- KNN (k nearest neighbor)
- Random forest
- Decision tree
- Support vector machine
- Adaboost

Regression metric:

- r-squared score.
-mean absolute error
-mean square error

Classification Metric:

- Accuracy
- Precision
- Recall
- F1-score

Steps used for modeling:

Train-test split and separate test data

↓

Use a 2nd train-test split and use 5-fold cross-validation on the training data

↓

Remove the redundant features like Cmax, Cmin and others one after another and compare accuracy

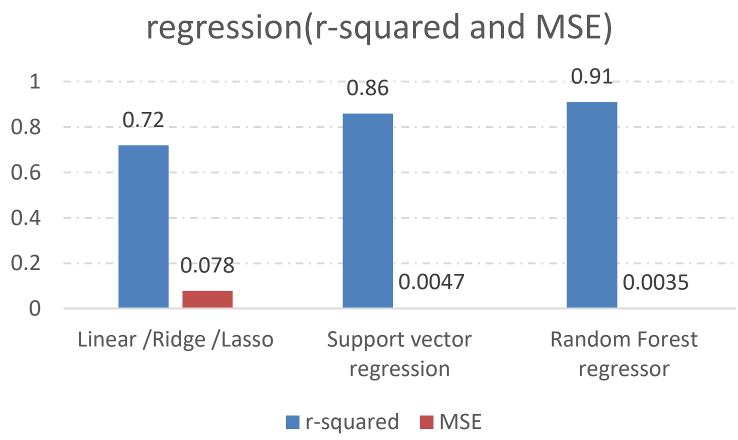
↓

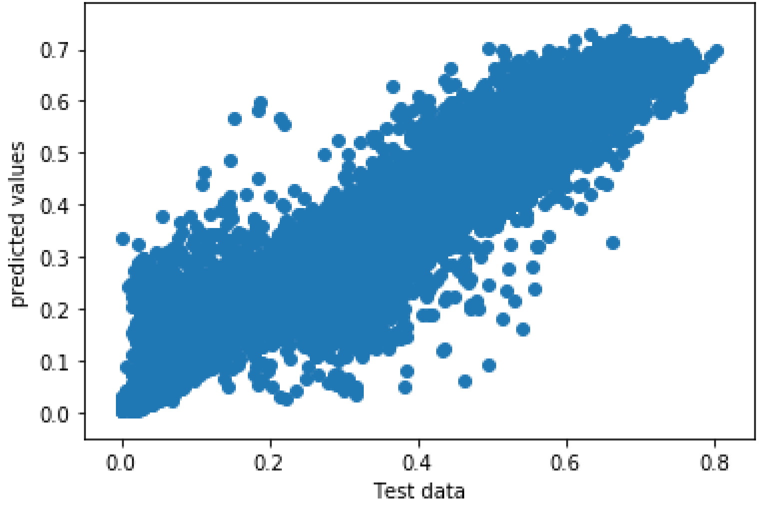
If the accuracy is not affected, then prune that feature; Else keep it.

↓

Update the data set after all the pruning, Fit model using the updated dataset and find final accuracy using the original data

Regression model to predict cascading effect



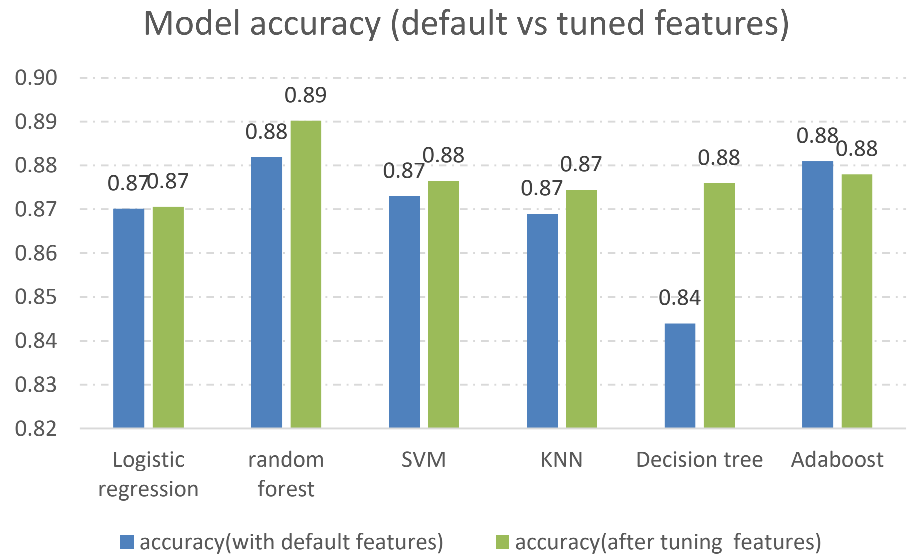


- **Random forest regression worked best.**
- **r-squared of 0.91 found after hyperparameter tuning (n_estimators = 300, min_samples_split=10, min_samples_leaf=10)**

Predicted vs test data showing linear trend (random forest regressor)

Classification of cascading failures

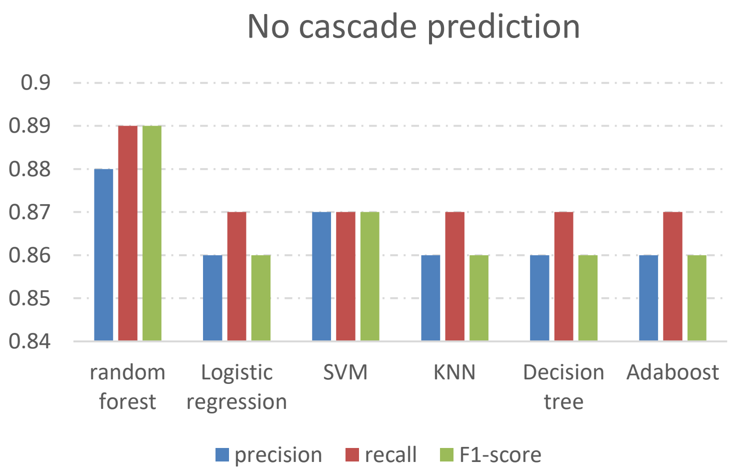
No cascade: cascading effect < mean of cascading effect
Cascade: cascading effect >= mean of cascading effect

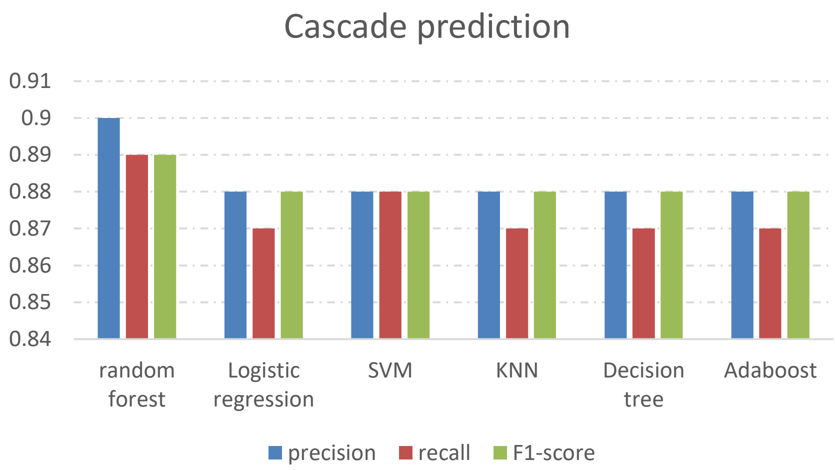


Model	Best hyperparameters
Decision tree	'criterion': 'entropy', 'min_samples_leaf': 10, 'min_samples_split': 5
KNN	'algorithm': 'auto','leaf_size': 1, 'n_neighbors': 10, 'weights': 'distance'
Adaboost	'algorithm': 'SAMME.R', 'learning_rate': 0.5, 'n_estimators': 200
Random forest	'criterion': 'gini', 'min_samples_leaf': 5, 'min_samples_split': 5, 'n_estimators': 50
Logistic regression	C= 10 (penalty ='l2')
SVM	'C': 5, 'kernel': ['rbf']

- **Random forest best accuracy**
- **Decision tree gave the best improvement after feature tuning**

Predicting cascading failures (classification report with tuned features)





- Model could predict the cascade/no cascade classes with high precision and recall.

Summary

- Machine learning algorithms were used to predict cascading failures in smart grids.

- We would use random forest for classification and regression for production because of high accuracy and a wide variety of hyperparameter tuning opportunities.

- Modeling effort reduces computational time.

- Utilities can use this model to mitigate the risk of cascading failures during planning phase.

THANK YOU
QUESTIONS

Outline

Background

Contribution

Data Collection

Feature engineering

Data Cleaning

Exploratory data analysis

Heatmap

Modeling

Regression

Classification

Summary

Annex1: Algorithms for cascading failure simulation

Algorithm 1 Finding maximum overloaded lines probabilistically during cascading failures

Require: e, PF, Capacity
Ensure: FailedIndex

for $i \leftarrow 1$ to M **do**
  $\mathrm{P}_{\mathrm{lf}}(i) \leftarrow \mathrm{abs}(\mathrm{PF}(i))/((1-e) * \mathrm{Capacity}(i))$
ProbTest $\leftarrow 0$
for $i \leftarrow 1$ to M **do**
  if rand $<$ LinkProb(i) **then**
    if (ProbTest $< \mathrm{P}_{\mathrm{lf}}(i)$) **then**
      ProbTest $= \mathrm{P}_{\mathrm{lf}}(i)$);
      FailedIndex $= i$
  return FailedIndex

Algorithm 2 Solving power flow in each islanded grid

Require: mpc, s, c
Ensure: GD, PF

SG = sparse(AdjMatrix)
[s, c] = graphconncomp(G)
for $i \leftarrow 1$ to s **do**
  struct mpc[s] $\leftarrow$ mpc
  [PF, GD] = rundcopf(mpc[s])
  return GD, PF

Algorithms used to find the maximum overloaded line in one iteration and solving power flow in each island.

Annex2: HEP Calculation Using SPAR-H Methodology

Human factor influences transition prob. through human-error probability (HEP)

- HEP is explicit function of performance-shaping factors (PSFs), i.e.,

$$PSF < 3 \rightarrow HEP = NHEP.\prod_{i=1}^{2} PSF_i$$

$$PSF \geq 3 \rightarrow HEP = \frac{NHEP.\prod_{i=1}^{8} PSF_i}{NHEP.(\prod_{i=1}^{8} PSF_i - 1) + 1}$$

SPAR-H PSFs	SPAR-H PSF Levels	Multiplier	Pr.(escalation)
Diagnosis / Action		**0.01/0.001**	
Available time	Inadequate time	1	0.0
	Time available = time required	10	0.9
	Nominal time	1	0.1
	Time available≥ 5x time required	0.1	0.0
	Time available > 50x time required	0.01	0.0
Stress/Stressors	Extreme	5	0.4
	High	2	0.6
	Nominal	1	0.0
Complexity	Highly complex	5	0.4
	Moderately complex	2	0.6
	Nominal	1	0.0
	Obvious diagnosis	0.1	0.0
Experience / Training	Low	10	0.6
	Nominal	1	0.2
	High	0.1	0.3
Procedures	Not available	50	0.0
	Incomplete	20	0.2
	Available, but poor	5	0.1
	Nominal	1	0.7
	Diagnostic/ system oriented	0.5 (Diagnosis only)	0.0
Ergonomics / HMI	Missing/ misleading	50	0.2
	Poor	20	0.0
	Nominal	1	0.8
	Good	0.5	0.0
Fitness for duty	Unfit	p(failure)= 1.00	0.0
	Degraded fitness	5	0.1
	Nominal	1	0.9
Work processes	Poor	2	0.0
	Nominal	1	1
	Good	0.8	0.0

J. M. Abreu, *et al.*, "Modeling Human Reliability in the Power Grid Environment: An Application of the SPAR-H Methodology," International Annual Meeting of the Human Factors and Ergonomics Society, Los Angeles, CA, Oct. 2015

Annex2: Frequency of PSFs (PSF distribution)

Table 3: Frequency of PSFs for 36 events sampled in operator interviews

SPAR-H PSFs	***SPAR-H PSF Levels*** Source: Gertman *et al., 2005*	***Frequency***
NHEP: Diagnosis / Action	**0.01 / 0.001**	**N=36**
Available time	Inadequate time	0.00
	Barely time / time available = time required	0.42
	Nominal time	0.56
	Extra time (between 1 and 2 times nominal time and more than 30 min)	0.03
	Expansive time (more than 2 times nominal time and more than 30 min)	0.00
Stress/Stressors	Extreme	0.03
	High	0.31
	Nominal	0.67
Complexity	Highly complex	0.11
	Moderately complex	0.67
	Nominal	0.14
	Obvious diagnosis	0.08
Experi-	Low	0.11
	Nominal	0.36
	High	0.53
Procedures	Not available	0.06
	Incomplete	0.08
	Available, but poor	0.06
	Nominal	0.81
	Diagnostic/ system oriented	0.00
Ergonomics/HMI	Missing/ misleading	0.36
	Poor	0.17
	Nominal	0.47
	Good	0.00
Fitness for duty	Unfit	0.00
	Degraded fitness	0.00
	Nominal	1.00
Work processes	Poor	0.11
	Nominal	0.69
	Good	0.19

Annex3:

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$\text{F1} = 2 \text{ x } \frac{Precision * Recall}{Precision + Recall}$$

The Formula for R-Squared Is

$$\mathrm{R}^2 = 1 - \frac{\text{Explained Variation}}{\text{Total Variation}}$$