Load Curtailment Estimation in Response to Extreme Events

Rozhin Eskandarpour & Amin Khodaei
University of Denver
USA

Ali Arab
Protiviti Inc.
USA
Introduction

• Hurricanes:
  • Cause significant economic, social, and physical disruptions
  • Result in considerable inconvenience for residents living in disaster areas
  • One of the most recurring events in the United States

• Power System Resilience:
  • Rate and speed of a system in bouncing back to its normal operating condition after an external shock.

• Prediction of Power System Component Outages:
  • An exact prediction of power component outages plays a significant role in restoration, recovery, and improving power system resilience.
Hurricane Irma
Proposed Model

• The problem is solved in three consecutive stages:
  a) Forecasting:
      • The category and the path of an upcoming hurricane
  b) Component Outage Prediction:
      • Using Machine Learning method
  c) Load Curtailment Estimation:
      • Optimization using mixed integer programming
Machine Learning

- Machine learning is an application of artificial intelligence (AI):
  - Includes data-driven decision-making techniques
  - Explores algorithms that are able to learn from, describe, and make predictions on data.

- Machine learning algorithms are often categorized as:
  - **Supervised machine learning**: algorithms can apply what has been learned in the past to new data using labeled examples to predict future events.
  - **Unsupervised machine learning**: algorithms are used when the information used to train is neither classified nor labeled.
Support Vector Machine

• Support Vector Machines (SVM)
  • Supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.

• Linear Classifier:
  • The goal is a dimensional hyperplane.

• Best Hyperplane:
  • Represents the largest margin, between the two classes
  • If such a hyperplane exists,
  • It is known as the maximum-margin hyperplane
Component Outage Prediction

- An SVM method is used and trained to determine the decision boundary;
  - Subsequently, power grid component outages in response to upcoming hurricanes can be effectively predicted.

- Classify the components into two states of:
  - Damaged (cross)
  - Operational (circle)

- Based on:
  - Distance
  - Wind speed

- Separated by:
  - A decision boundary
Evaluation

• To evaluate the performance of the classifier, usually a subset of historical data is reserved as the validation/test set.

• The $F_1$-Score is a common and reliable measure of classification performance:

\[
P = \frac{\text{number of correctly predicted outages}}{\text{total number of predicted outages}}
\]

\[
R = \frac{\text{number of correctly predicted outages}}{\text{total number of actual outages}}
\]
Load Curtailment Estimation

• The objective of the minimum load curtailment problem is defined as the value-weighted cost of load curtailment in the system:

• Includes the generation cost, and the cost of unserved energy during contingency scenarios.

• Subject to:
  • Operational constraints
  • Load balance
  • Generation unit output capacity
  • Network line capacity and power flow constraints, Min on/off time limits, etc.
Case Study

- Historical data for the past extreme events at component level are limited
- We generated 300 samples of each component state
  - Following a normal distribution function with a small Gaussian noise.
- The samples belong to two classes of components
  1. High probability of failure
  2. Components that can survive the extreme event.
- The features are normalized to \([0, 1]\) based on the maximum considered values of wind speed and distance.
Role of Hyper-parameters and Kernel Shape

• Table 1 shows the accuracy of SVM with aforementioned combinations of penalty parameters and kernels.
• The polynomial kernel SVM with $c=1$ outperforms other models in terms of classification accuracy.
• The margin size of the SVM with polynomial kernel is 0.1131, and the average ε (regularization weight) is 0.4558.

Table 1. Accuracy (%) of SVM with various penalty-parameters and kernels

<table>
<thead>
<tr>
<th>Kernel</th>
<th>$c=0.1$</th>
<th>$c=1$</th>
<th>$c=10$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>91.0</td>
<td>91.4</td>
<td>91.2</td>
</tr>
<tr>
<td>Quadratic</td>
<td>91.3</td>
<td>91.2</td>
<td>91.2</td>
</tr>
<tr>
<td>Polynomial</td>
<td>92.3</td>
<td>92.8</td>
<td>92.7</td>
</tr>
<tr>
<td>Gaussian</td>
<td>91.3</td>
<td>91.2</td>
<td>91.8</td>
</tr>
</tbody>
</table>
Visualizing the Decision Boundary

- This Figure shows the decision boundary of the polynomial kernel with penalty parameter $c=1$, separating outage from operational components based on wind speed and distance from the center of the hurricane.

- The instances are not linearly separable.

- A nonlinear kernel is necessary to better classify the components.
SVM Performance

- Table 2 shows the confusion matrix of this classification.
- The proposed method can effectively classify the components into outage and operational classes.

Table 2. Confusion Matrix of classifying system components

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Normal</td>
</tr>
<tr>
<td>Normal</td>
<td>91.7%</td>
</tr>
<tr>
<td>Outage</td>
<td>6.0%</td>
</tr>
</tbody>
</table>
Load Curtailment Estimation

- Table 3 shows the load curtailment of each contingency scenario based on the predicted outages.

Table 3. Load Curtailment of Bus Outages along three Hurricane Paths

<table>
<thead>
<tr>
<th>Bus number</th>
<th>Total Load (MW)</th>
<th>LC Scenario 1 (MW)</th>
<th>LC Scenario 2 (MW)</th>
<th>LC Scenario 3 (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>423.08</td>
<td>0</td>
<td>0</td>
<td>4.91</td>
</tr>
<tr>
<td>3</td>
<td>46.79</td>
<td>44.95</td>
<td>0</td>
<td>1.62</td>
</tr>
<tr>
<td>15</td>
<td>159.87</td>
<td>0</td>
<td>0</td>
<td>0.37</td>
</tr>
<tr>
<td>18</td>
<td>62.39</td>
<td>0</td>
<td>59.94</td>
<td>2.10</td>
</tr>
<tr>
<td>19</td>
<td>185.22</td>
<td>0</td>
<td>177.95</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>42.89</td>
<td>0</td>
<td>41.21</td>
<td>0</td>
</tr>
<tr>
<td>23</td>
<td>62.39</td>
<td>0</td>
<td>0</td>
<td>9.92</td>
</tr>
<tr>
<td>24</td>
<td>169.62</td>
<td>0</td>
<td>0</td>
<td>162.97</td>
</tr>
<tr>
<td>29</td>
<td>46.79</td>
<td>0</td>
<td>0</td>
<td>0.31</td>
</tr>
</tbody>
</table>
Conclusion

• An SVM model was trained to predict the outage state of power grid components due to an imminent hurricane strike.

• A minimum load curtailment problem was formulated to estimate the amount of load curtailment considering the predicted outage states from a Support Vector Machine method.

• This model provides a practical forward-looking framework for utilities, local governments, and policy makers for a risk-informed operations management, emergency response planning, humanitarian logistics, and restoration of the life-line power grid infrastructure in both strategic level and real-time basis.
Thank you
rozhin.eskandarpour@du.edu