Artificial Intelligence Assisted Power Grid Hardening in Response to Extreme Weather Events

Rozhin Eskandarpour & Amin Khodaei
University of Denver
USA

A. Paaso, N. M. Abdullah
ComEd
USA

Presenter: Hossein Lotfi
University of Denver
USA

Introduction

- Artificial Intelligence (AI) provides the system the ability to learn from historical data and to make predictions without being explicitly programmed.

- Machine learning approaches are utilized in a considerable number of research efforts in the power and energy sector, such as:
  - security assessment
  - load forecasting
  - distribution fault detection
  - and power outage duration prediction

Introduction

- **Hurricanes:**

- Various events have different characteristics and behavior, however, the aftermath of all these events on the power grid is the loss of components and potential power outages.
- Among these events, hurricanes are explored in this paper because:
  - They cause the most widespread and long-lasting outages in the U.S. and
  - Weather forecasting approaches that can predict a hurricane's arrival and characteristics (wind speed, hurricane type, duration, etc.) are optimally advanced to determine the probable impact in a localized region

Introduction

- **Grid Hardening:**

  - Represents the physical and nonphysical improvement to the electricity infrastructure to make it less susceptible to adverse extreme events.

  - Improves grid resilience and enables the grid to withstand the impacts of extreme events with the least possible outages.

- **Two types:**

  - **Physical hardening:** Installing new facilities and modifying the current grid topology (the focus of this paper).

  - **Nonphysical hardening:** Adjustments in consumption, generation, and power flow patterns.

Proposed Model

- An <u>Artificial Intelligence Based Grid Hardening Model </u>is proposed with the objective of improving power grid resilience in response to extreme weather events.

- At first, a machine learning model is proposed to predict the component states (either operational or outage) in response to the extreme event.

- Then, these predictions are fed into a hardening model, which determines strategic locations for placement of distributed generation (DG) units.

Proposed Model

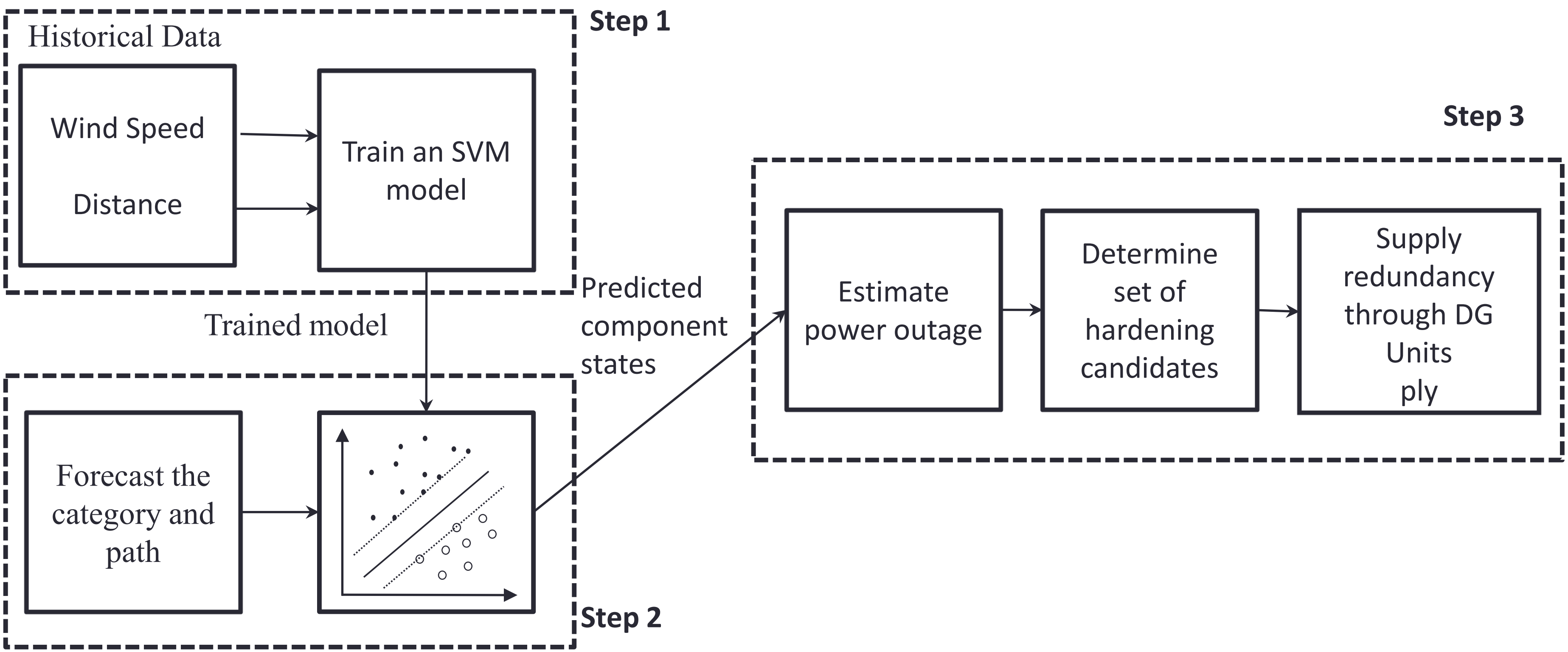
- The problem is solved in three consecutive stages:

a) Training an SVM model to classify the components into two states of damaged (on outage) and operational (in service) based on historical data

b) Forecasting the category and path of the hurricane

c) Grid Hardening Model

Proposed Model



Proposed grid hardening model

Machine Learning

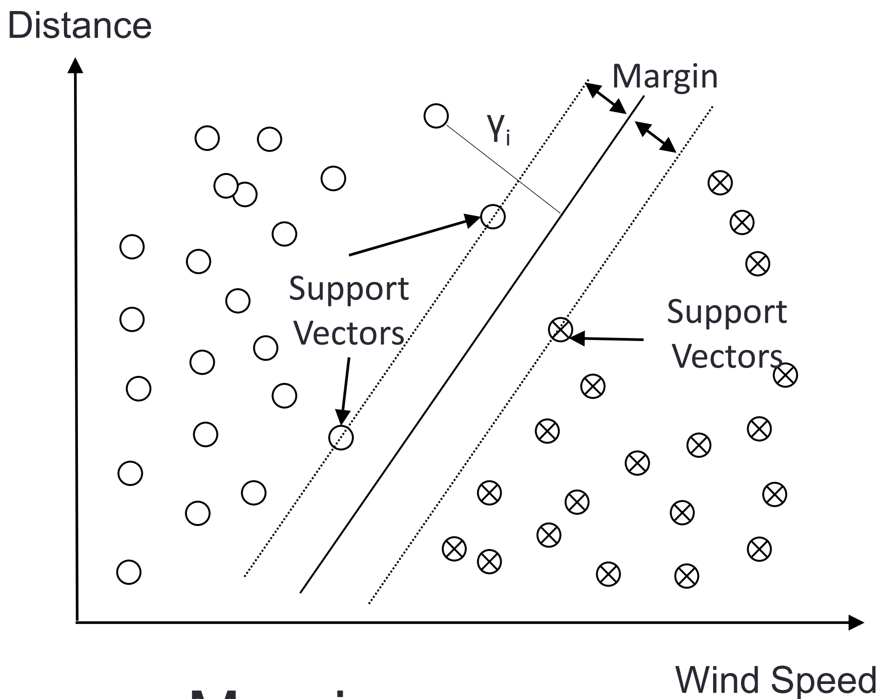
- Machine learning is an application of artificial intelligence (AI) which:
  - Includes data-driven decision-making techniques
  - Explores algorithms that are able to learn from, describe, and make predictions on data.

- 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.

Component Outage Prediction

- A Support Vector Machine 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 or outage (cross)
  - Operational (circle)
- Based on:
  - Distance
  - Wind speed
- Separated by:
  - A decision boundary



Margin

Grid hardening

- The proposed grid hardening model minimizes the total investment cost of the grid hardening candidates as well as system operation costs:
  - The operation cost of all units in normal operation
  - Reliability cost (cost of unserved energy)
  - The investment cost associated with system upgrades by a DG unit

Grid hardening

- The following operational constraints are defined:
  - The nodal load balance (the total injected power to each bus from generation units, supply redundancies through DGs, and line flows is equal to the total consumed load at that bus)
  - Generation unit output capacity
  - Network line capacity and power flow constraints, min on/off time limits, etc.

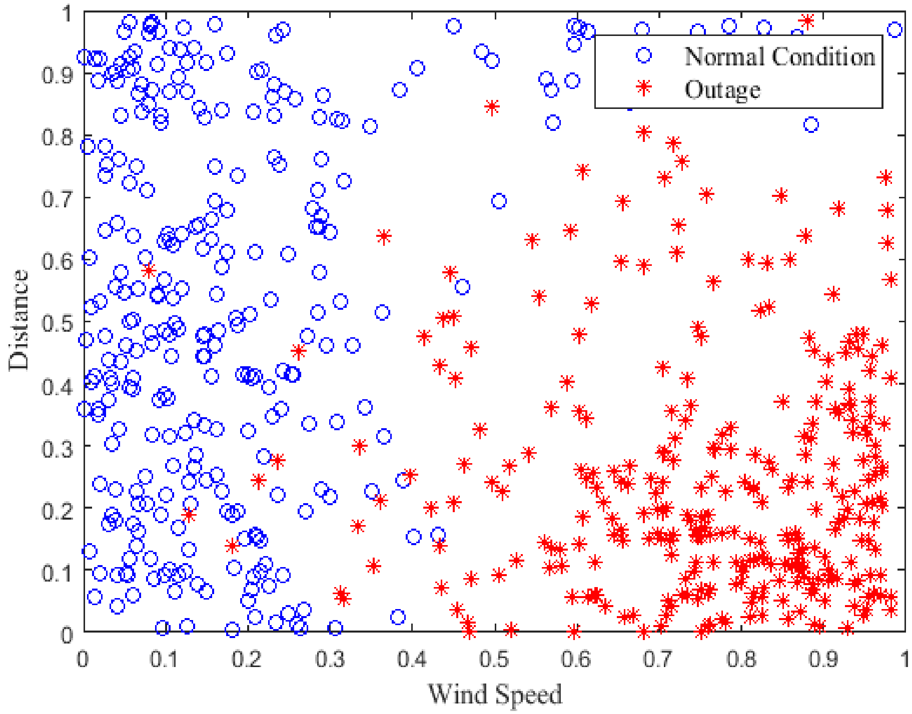
Case Study

- Historical data for the past extreme events at component level are limited.
- We generated 300 samples of each component state (i.e., operational and outage) 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
- To measure the performance of the proposed method:

✓ 20% of the samples (60 samples in outage state and 60 samples in operational state) are randomly selected to test/validate the SVM.

✓ The remaining (80%) are used to train the model.

Case Study

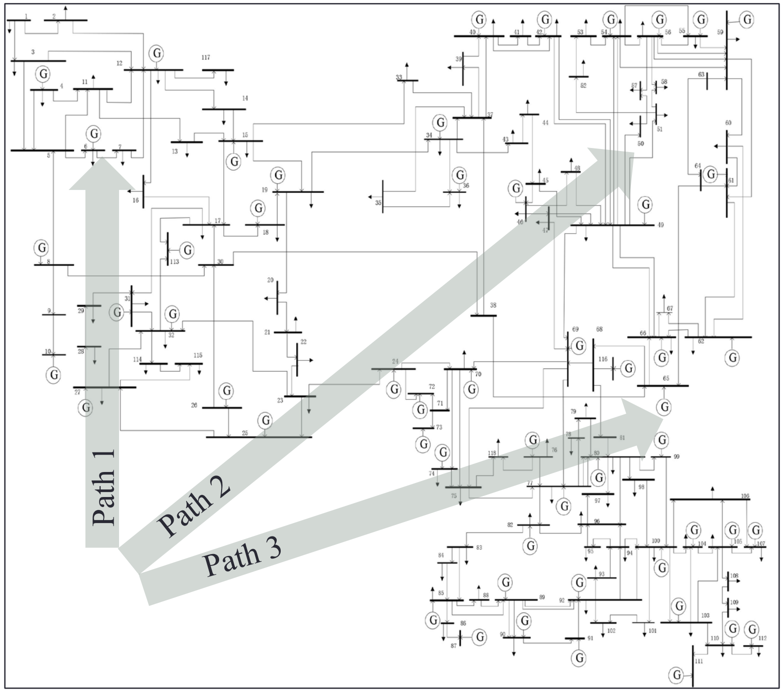


Confusion matrix of classifying system components into two classes of outage and normal during extreme event (number of samples and percentage)

		Predicted	
		Operational	Outage
Actual	Operational	56 (93.33%)	4 (6.66%)
	Outage	5 (8.33%)	55 (91.66%)

Case Study

- The model is applied to the standard IEEE 118-bus test system.
- A hurricane passes through three hypothetical paths.
- The trained SVM model classified 48, 56, and 55 components as outage in paths 1, 2 and 3, respectively.



IEEE 118-bus test system and the forecasted hurricane passing through three hypothetical paths

Case Study

- The proposed hardening model and the optimal scheduling problem is solved for one year (8760 hours).

- The value of lost load is considered $100/MWh at all buses.

- The investment cost associated with installing a DG unit (supply redundancy) at any given bus is assumed to be $50/MW.

Case Study

- **Case 1:** Without hardening
- **Case 2:** Proposed hardening model without constraint on investment budget
- **Case 3:** The effect of system hardening investment budget

Case 1 Results

Operation Cost ($)	Load Curtailment (MWh)			Average Cost of Unserved Energy ($)
	Path 1	Path 2	Path 3	
366,277,300	43338	47143	44393	449,580,000

Case 2 Results

Operation Cost ($)	Load Curtailment (MWh)			Buses with Hardening Options
	Path 1	Path 2	Path 3	
492,307,700	0	0	0	33, 37, 39, 41, 42, 54, 59, and 80

Case Study

Case 3 Results

Budget	Load Curtailment (MWh)			Average Cost of Unserved Energy ($)
	Path 1	Path 2	Path3	
$0M	43,338	47,143	44,393	$449,580,000
$1M	-	22,341	3155	$84,986,666
$10M	-	20,138	2,751	$76,296,666
$100M	-	5294	-	$17,646,666
$126M	-	-	-	$0

Conclusion

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

- These predictions were fed to the proposed hardening model, which took resilience as well as the investment cost associated with system upgrades and decentralized supply of power into consideration.

- The numerical simulations on the standard IEEE 118-bus test system illustrated that the proposed hardening model can produce a robust solution that can protect the system against multiple component outages due to a hurricane.

Thank you

Hossein.lotfi@du.edu