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# Load Curtailment Estimation in Response to Extreme Events

**R. ESKANDARPOUR, A. KHODAEI**
**University of Denver**
**USA**

**A. ARAB**
**Protiviti Inc.**
**USA**

## SUMMARY

In this paper, we propose a machine learning model to estimate the potential nodal load curtailments due to an upcoming extreme weather event. This task is performed through prediction of the grid components that are expected to fail due to such extreme event, and the subsequent power supply interruptions in parts of the power system. A Support Vector Machine (SVM) is adopted to model the outage prediction of the components in the system. The proposed model uses the category and the path of historical hurricanes in the feature vector to train the SVM model. The trained model is capable of classifying the grid components into two categories, i.e., *outage* and *operational*. Consequently, the predicted component outages are plugged into a load curtailment minimization model to estimate the nodal load curtailments in the system. The standard IEEE 30-bus system with a combination of hurricane path and intensity scenarios are used to study the model. The results demonstrate that the proposed modelling framework is capable to effectively capture the dynamics of load curtailment estimation in response to extreme events.

## KEYWORDS

Extreme weather events, load curtailment, power systems resilience, supervised machine learning.

Rozhin.Eskandarpour@du.edu

## 1. INTRODUCTION

Resilience is defined as the rate and speed of a system in bouncing back to its normal operating condition after an external shock [1]. Among all types of extreme events, hurricanes are notably recognized as one of the most recurring events in the United States, mostly occurred by the Atlantic Ocean throughout Gulf of Mexico, from Maine to Texas [3]. An accurate forecast of the component outage and load curtailment in response to this extreme event is an essential task in pre-event and post-event planning and recovery of power systems. Improving resilience in power systems is extensively discussed in the literature including research work on system modelling, resource allocation, and optimal scheduling for enhancing grid resilience, among others. In [3] a proactive resource allocation method is proposed to recover power grid components after an extreme event. A proactive recovery framework of the components and a deterministic recovery model are proposed in [4] and [5] to manage the available resources prior and post an extreme event. In [6], a restoration model is proposed by considering the AC power flow constraints and incorporating the macroeconomic concept of the value of lost load (VOLL) in an optimal scheduling problem in order to find the minimum economic loss in case of load interruptions.

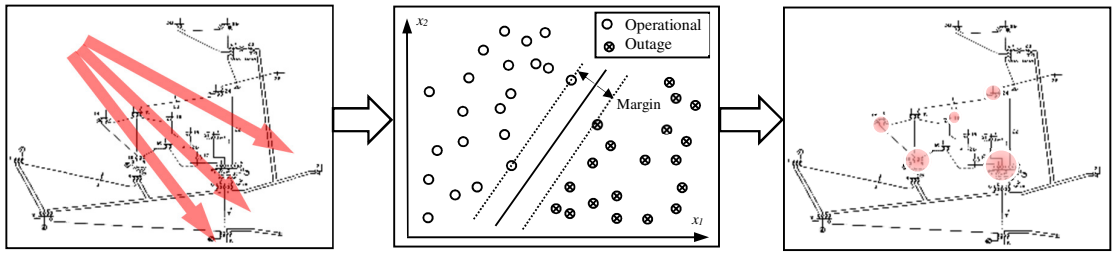
A proper formulation with a closed-form solution for many of the emerging power system problems is not readily available. Machine learning algorithms are however capable to learn and forecast from historical data and address this challenge. The historical data can be categorized by a supervised learning classifiers, unsupervised learning (e.g., clustering), or conventional linear statistical models (e.g. regression modelling) [7]. In power and energy research, a wide range of machine learning methods are utilized to solve various problems [8]. The application of machine learning in power grids includes but is not limited to risk analysis using regression models and artificial neural networks (ANNs) [9], and distribution fault detection using ANNs and SVMs [10], to name a few. There are also few machine learning works to estimate component outages in response to extreme events. In [11], a logistic regression model is applied considering the wind speed and the distance of the each component from the center of the hurricane as two major features to find the state of the each component after an extreme event.

In this paper, the SVM method is adopted to predict the state of each component in the aftermath of an imminent hurricane. The predictions are integrated into a minimum load curtailment model to estimate the potential nodal load curtailments—which are of utmost importance for grid operators in order to identify critical and prone-to-curtailment areas to proactively mobilize the restoration resources. The rest of the paper is organized as follows: Section 2 presents the problem statement and proposes two models for outage prediction and load curtailment estimation. Section 3 presents a case study on the proposed SVM model and estimating the nodal load curtailment using IEEE 30-bus test system. Finally, Section 4 concludes the paper.

## 2. LOAD CURTAILMENT ESTIMATION

The problem is solved in three consecutive stages as illustrated in Fig. 1. First, the category and the path of an upcoming hurricane are predicted, as shown in Fig. 1(a). The category and path are used to identify the intensity of the hurricane and the potentially impacted regions, respectively. These data are obtained from weather forecasting agencies. Next, the speed of the hurricane, and the distance of each power grid component from the center of the hurricane—denoted by $x_1$ and $x_2$, respectively—are used to predict the state of a component, as shown in

Fig. 1(b). A SVM method is used in this stage to classify the components into two states of damaged (on outage) and operational (in service). The SVM model is trained on historical data. Finally, a minimum load curtailment problem considering the predicted state of each component to estimate the potential nodal load curtailments is solve, as shown in Fig. 1(c).




(a) Forecasting (b) Component Outage Prediction (c) Load Curtailment Estimation

Fig. 1 The schematic view of the proposed model

### 2.1. Component Outage Prediction

Fig. 1(b) illustrates a schematic of the damaged (cross) and operational (circle) components based on distance and wind speed (intensity of the hurricane), separated by a decision boundary. First, a machine learning method is used and trained to determine the decision boundary; subsequently, power grid component outages in response to upcoming hurricanes can be effectively predicted. A SVM method [12] is adopted to classify the component states using a decision boundary into two classes (i.e., *operational* and *outage*) based on the wind speed ($x_1$) and the distance of each component from the center of the hurricane ($x_2$), Fig. 1(b) illustrates the obtained support vectors and optimal hyperplane separating two classes.

A SVM is a binary classifier that separates training examples of one class from the other by defining a proper hyperplane. The best hyperplane is defined as the hyperplane with the widest margin, obtained by solving a quadratic programming problem, as follows:

$$\begin{aligned} &\min \ \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{m}\varepsilon_i \ , \\ &s.t. \\ &y^{(i)}\left(w^t x^{(i)} + b\right) \geq 1, -\varepsilon_i, \qquad i = 1,.....,m \\ &\varepsilon_i \geq 0, \qquad i = 1,.....,m \end{aligned} \tag{1}$$

where $y^{(i)}$ represents the class labels of the training examples (i.e., -1 and +1 in case of a binary classification problem), $x^{(i)}$ is the feature vector of each training example, $w$ is the normal vector to the hyperplane separating training examples, and $|b|/||w||$ is the perpendicular distance from the hyperplane to the origin. This quadratic programming problem can be solved by a Lagrange dual problem.

The quadratic programming problem (1) is developed based on the assumption that classes are linearly separable. In a case that the training data cannot be separated by a linear hyperplane (which is common), SVM can use a soft margin. The soft margin classification is solved by introducing a penalty parameter $c$ and a regularization (often L1 or L2). $\varepsilon_i$ is the regularization weight of the samples in the margin (support vectors). In other words, if an example has functional margin 1-$\varepsilon_i$ (with $\varepsilon_i$ >0), the objective function is penalized by $c\varepsilon_i$.

Another approach for applying SVM to nonlinear data is the kernel method [12]. The idea of a kernel method (or as sometimes called kernel trick) is to map the input feature vector into a higher-dimension space where the classes are linearly separable. Kernel trick simply states that inner product of $x_1$ and $x_2$ in the input space can be replaced by a certain function $K(x_1,x_2)$. For example, a polynomial kernel of degree $d$ can be defined as: $K(x_1,x_2) = (x_1,x_2)^d$. Finding a proper value of penalty parameter $c$ and the best kernel depends on the shape of classes, which are often unknown. Therefore, $c$ and the kernel function are often found via a search method to minimize the error on a test set.

### 2.2. Load Curtailment Estimation

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

$$\min \sum_t \sum_s \sum_b VOLL_b \times LC_{bts} \tag{2}$$

where $VOLL_b$ is the Value of Lost Load at bus $b$, and $LC_{bts}$ is the amount of load curtailment at bus $b$ at time $t$ during contingency scenarios $s$. The Value of Lost Load represents the average cost that each customer is willing to pay in order to avoid any load interruptions [13]. Assuming $UX_{its}$ as the outage state of unit $i$ at time $t$ in scenario $s$ (where *operational* state equals to 1 and *outage* state equals to 0) and $UY_{lts}$ as the outage state of line $l$ at time $t$ in scenario $s$, the proposed objective function is subject to the following physical constraints:

$$\sum_{i \in B_b} P_{its} + \sum_{l \in B_b} PL_{lts} + LC_{bts} = D_{bt} \qquad \forall b, \forall s, \forall t \tag{3}$$

$$P_i^{\min} I_{it} UX_{its} \le P_{its} \le P_i^{\max} I_{it} UX_{its} \qquad \forall i, \forall s, \forall t \tag{4}$$

$$\left| P_{it0} - P_{its} \right| \in \Delta_i \qquad \forall i, \forall s, \forall t \tag{5}$$

$$-PL_l^{\max} UY_{lts} \le PL_{lts} \le PL_l^{\max} UY_{lts} \qquad \forall l, \forall s, \forall t \tag{6}$$

$$\left| PL_{lts} - \frac{\sum_b a_{lb} \theta_{bts}}{x_l} \right| \le M\left(1 - UY_{lts}\right) \qquad \forall l, \forall s, \forall t \tag{7}$$

where $b$, $i$, and $l$ are the indices for buses, generation units, and lines, respectively; $B_b$ is the set of components connected to bus $b$, $s$ is index for scenarios, and $t$ is index for time; $P_i^{\max}$ and $P_i^{\min}$ represent the maximum and minimum generation capacity of unit $i$, respectively; $PL_{lts}$ is the real power flow of line $l$ at time $t$ in scenario $s$, $\theta_{bts}$ is the phase angle of bus $b$ at time $t$ in scenario $s$, and $M$ is a large positive constant. The parameter $a_{lb}$ is the element of line $l$ and bus $b$ at line-bus incidence matrix, and $D_{bt}$ is the load at bus $b$ at time $t$.

The total injected power to each bus from generation units and line flows is equal to the nodal load which can be ensured by load balance equation (3). Load curtailment variable ($LC_{bts}$) ensures a feasible solution in case of component outages when there is not sufficient generation and/or transmission capacity to supply loads. Generation unit output power is limited to its capacity limit and will be set to zero depending on its commitment and outage states (4). The change in unit generation is further limited by the maximum permissible limit between normal and contingency scenarios (5). Transmission line capacity and power flow constraints are modeled by (6) and (7), respectively, where the outage state variable is effectively incorporated in order to model the line outages in contingency scenarios.

## 3. CASE STUDY

Due to the scarcity of structured historical data at components level from the recent hurricanes, a set of synthetic data is generated to train the SVM model. The data includes 300 samples in *outage* state and 300 samples in the *operational* state. To define the synthetic data, Saffir-Simpson Hurricane Scale [14] is used to generate wind speed features of the synthetic data. These generated scenarios are used in the pre-process stage for training the proposed machine learning model, ensuring relevant outage scenario generation. A subset of data (80%) is sampled for training purpose, and the remaining 20% is held out to validate the model. The output of this model (i.e., the outage state of the power grid components) can be used as an input not only for load curtailment estimation application of this study, but also to enhance the accuracy of the scenarios and reduction of *model risk* in other applications such as those presented in [3], [4].

In our previous work, a linear SVM was applied to classify the data into two classes. Although the model was adequately accurate for its purpose, but in general, the linear models are not sufficiently adequate to classify the more complex and intertwined instances. In this paper, in order to find the best kernel and its penalty parameters, a set of linear, polynomial quadratic, and Gaussian kernels with different ranges of penalty parameter (i.e., $c$ = 0.01, 0.1, 1, 10) are also examined in training process. Table 1 shows the accuracy of SVM with aforementioned combinations of penalty parameters and kernels. As shown, 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 $\varepsilon$ (regularization weight) is 0.4558.

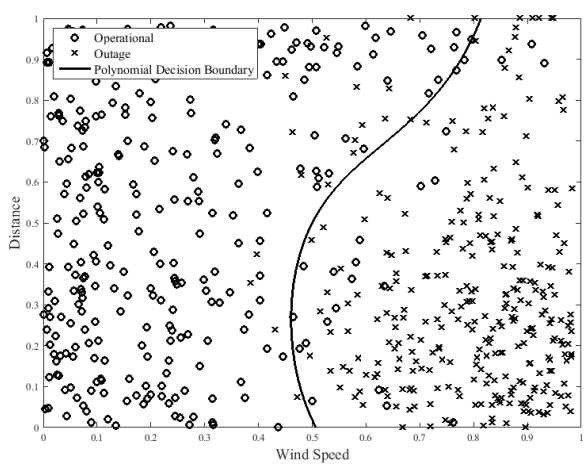



Fig. 2. Decision boundary of the polynomial kernel with penalty parameter $c$=1

Fig. 2 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. As shown, the instances are not linearly separable, and a nonlinear kernel is necessary to better classify the components. Table 2 shows the confusion matrix of this classification. As shown, the proposed method can effectively classify the components into *outage* and *operational* classes.

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

| Kernel | $c$=0.1 | $c$=1 | $c$=10 |
|---|---|---|---|
| Linear | 91.0 | 91.4 | 91.2 |
| Quadratic | 91.3 | 91.2 | 91.2 |
| Polynomial | 92.3 | **92.8** | 92.7 |
| Gaussian | 91.3 | 91.2 | 91.8 |

Table 2. Confusion Matrix of classifying system components

| Actual | Predicted | |
|---|---|---|
| | Normal | Outage |
| Normal | 91.7% | 8.3% |
| Outage | 6.0% | 94.0% |

The proposed minimum load curtailment model is applied to the standard IEEE 30-bus test system. A hurricane passes through three hypothetical paths with different intensities. Particularly, based on the available hurricane data and the estimated distance from the center of the hurricane, the state of each component in the system is predicted using the trained SVM model. This study estimates how much load curtailment is expected to occur due to an imminent hurricane. Table 3 shows the load curtailment of each contingency scenario based on the predicted outages. As shown, buses 3 and 18 are shown to be the most sensitive buses, since in both Scenarios 2 and 3 these two buses are predicted to be in *outage* state. In addition, buses 18, 19, and 20 are the most critical buses as more than 95% of the total load curtailments are expected to take place in these buses. The predicted outages and load curtailment estimation are of crucial for utilities to effectively mobilize their restoration resources in prior- and post-hurricane phases.

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

| Bus number | Total Load (MWh) | LC Scenario 1 (MWh) | LC Scenario 2 (MWh) | LC Scenario 3 (MWh) |
|---|---|---|---|---|
| 2 | 423.08 | 0 | 0 | 4.91 |
| 3 | 46.79 | 44.95 | 0 | 1.62 |
| 15 | 159.87 | 0 | 0 | 0.37 |
| 18 | 62.39 | 0 | 59.94 | 2.10 |
| 19 | 185.22 | 0 | 177.95 | 0 |
| 20 | 42.89 | 0 | 41.21 | 0 |
| 23 | 62.39 | 0 | 0 | 9.92 |
| 24 | 169.62 | 0 | 0 | 162.97 |
| 29 | 46.79 | 0 | 0 | 0.31 |

## 4. CONCLUSION

A SVM model was trained to predict the outage state of power grid components due to an imminent hurricane strike. The results demonstrated the effectiveness of the proposed SVM model in classifying the *operational* and *outage* classes by using a feature vector consisting of the wind speed and the distance from the center of the hurricane. A minimum load curtailment problem was formulated to estimate the amount of load curtailment considering the predicted outage states from SVM. The proposed framework enables one to effectively identify the critical components in the power system, and prioritize the limited restoration resources. Given the crucial importance of accurate power grid outage prediction, 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.

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