PV FAULT DETECTION USING A FEEDBACK ENHANCED POSITIVE UNLABELED LEARNING METHOD

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***Abstract* – As solar panels become more ubiquitous, the need for automatic array management and PV fault detection becomes ever more important. PV array faults often create inefficiencies and can be hazardous. Traditional machine learning approaches to this problem require large amounts of labeled data from each panel array location. This data can be noisy, resource intensive, and expensive to obtain. Our approach uses new positive unlabeled learning techniques to dramatically reduce the amount of labeled training data required, while making use of readily available unlabeled data. Our method uses minimal training and achieves similar or better performance compared to fully supervised techniques. In this paper, we use a customized positive unlabeled learning algorithm called MLRf to demonstrate effective fault detection on the PVWatts dataset when only a small percentage of the labels are known.**

***Index Terms*—machine learning, positive unlabeled learning, solar arrays, solar fault detection, photovoltaic**

1. INTRODUCTION

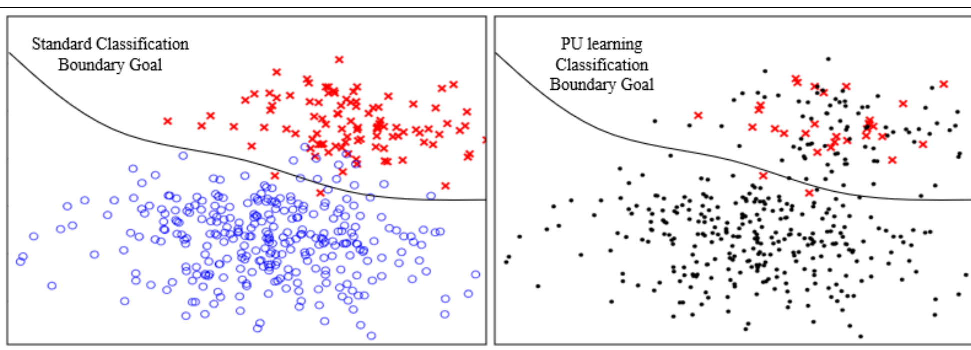
Despite substantial improvements in solar array efficiency in recent years, accurate fault detection and diagnosis remains an open problem as undetected faults can cause substantial power loss or even fire and electrocution. [1] Solar panel arrays can experience several types of faults of varying severity. Some faults, such as those associated with soiled or dirty solar panels and shaded solar panels simply reduce the efficiency of the PV array. These can be corrected by identifying and then cleaning the array or removing objects causing shading when possible. Another type of fault is caused by degradation of panels after extended usage, especially under extreme weather conditions. Solar panels can also experience short-circuit and ground leakage faults which can be quite hazardous by causing fires, shock, and maintenance staff electrocution.

Various machine learning (ML) and signal processing techniques have been developed for solar fault detection and identification in utility scale PV arrays. However, these algorithms generally need large amounts of labeled training data that is difficult and expensive to obtain. Additionally, these algorithms are generally not fault-specific and generally do not distinguish among different types of faults. There is a need for an effective solution that can detect and accurately classify PV faults with a much smaller amount of labeled data.

A unique and powerful type of semi-supervised learning called Positive unlabeled learning (PU learning) effectively classifies data when only unlabeled data and a small amount of labeled training data from the class of interest is available. For PV fault detection, it is possible to obtain a small number of fault examples of one or more types. A large amount of unlabeled PV data of unknown fault status can be automatically generated during day-to-day solar generation. With a small amount of labeled data and large quantity of unlabeled data, this problem is well defined as a PU learning problem. This is much less expensive than identifying the large training set required for traditional supervised learning algorithms.

In this paper, we describe the development of a customized PU learning algorithm which is tailored specifically for solar fault detection and similar small feature-set classification problems. The feature space available for solar fault data is generally small – limited to a dozen or less sensor features and typically historical data. A feedback process using advanced pre-processing and feature engineering techniques has been developed. This algorithm is called MLRf and uses a customized feedback version of a Modified Logistic Regression (MLR) [2] method.

The MLRf algorithm is optimized to effectively detect solar faults in real time even when very little labeled data is



(a) Supervised classification learning problem with all labels known.

(b) Positive Unlabeled learning problem with only a percentage of positive labels known and all others unknown.

Figure 1: Illustration of the Positive and Unlabeled binary classification problem.

available. We will demonstrate that using this algorithm, we can obtain similar or even better accuracy than other documented ML methods [3]–[5], even those with all labels present.

This paper is broken into the following sections. We start by describing prior work on PV fault detection using machine learning in section 2. In section 3, we described the datasets we used in this work – both real and simulated – along with the features used and some basic feature analysis. Section 4 introduces the positive and unlabeled learning problem (PU learning) including motivation as to why it is a good fit for this type of application. Section 5 describes our customized MLRf_solar algorithm in detail. In section 6 we provide results and comparisons between fully supervised fault detection and the MLRf_solar semi-supervised PU learning fault detection approach described in this paper. Finally, we present concluding remarks in section 7.

2. PRIOR WORK

To enable smart and efficient fault detection systems for solar PV arrays, machine learning techniques have been integrated in the PV control system for specific fault cases. Using various sensors to detect weather and solar-specific conditions has encouraged a combination of traditional signal processing approaches to solar array monitoring [6] and machine learning [4] for solar fault detection. Recent work in the area of graph signal processing for PV fault detection by [7] is spanning both of these areas.

An outlier detection method solely based on the measurement data to identify the faulty panel based on the current measurements is presented in [8]. This technique does not account for the environmental factors such as shading, soiling, and requires large amounts of data for efficient detection. In [9], to eliminate the protection blind spot caused by OCPD, a statistical outlier detection method is developed, by only considering the PV-string current measurements.

Authors in [10], train an artificial neural network (ANN) to monitor the health of a PV system and to manage maintenance schedules based on degradation of PV modules. A review of neural networks (ANNs) based PV monitoring methods and power prediction algorithms is presented in [11]. More complex neural networks involving deep learning along with dropout and pruned neural networks is described in [12] and [13] respectively.

Several papers, [14]–[17], propose statistical fault detection methods and neural network classifiers by identifying the outliers in the data as faults based on the measurement data for specific PV conditions. Recent work by [1] has looked at fault detection and multi-class classification using the same feature set using a novel graph technique with good results. Other graph and graph topology algorithms have been recently described by [18], [19].

3. DATASET

We use the PVWatts dataset [20] which originally spans a period of one year, from January to December, 2006. All time data has been stripped from this dataset, resulting in 21,485 individual measurements and their feature values. The dataset

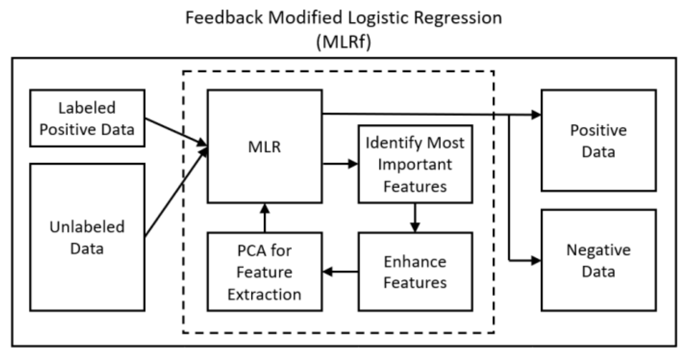


Figure 2: Feedback enhanced Modified Logistic Regression (MLRf)

includes clean, "no fault" data labeled Standard Test Conditions (STC) and four commonly occurring faults: shaded, soiled, degraded modules, and short circuits.

We obtain 4297 measurements per class giving us 21,485 data samples total. Each measurement has a total of ten features: the DC output, the VOC, ISC, VMP, IMP, fill factor, temperature, irradiance, gamma ratio and maximum power. These features are derived from the Sandia model and are commonly used in fault detection experiments [9], [21], though they are not always available in many real-world datasets.

In addition to the real data from the PVWatts dataset, we generated a similar simulated set with the same characteristics using MATLAB Simulink for further testing.

4. POSITIVE UNLABELED LEARNING

Positive and unlabeled learning is a relatively new and powerful type of semi-supervised binary classification. PU learning with classes commonly referred to as positive and negative. [22] In solar panel array fault detection and classification, the positive class would be the fault type of interest (or all faults collectively) and the negative class would contain data from which no fault occurred, referred to above as STC. When only some labeled data from the positive (or faulty) class is available, while all other data are unlabeled, this is referred to as the PU learning scenario. An illustration of this is shown in figure 1. As with supervised learning algorithms, the goal is to identify a decision boundary that separates the positive and negative data distributions. Modern PU learning algorithms such as the MLR algorithm can attain accuracy and f-score levels similar to those where all data is known, and supervised learning methods are used.

The MLR (modified logistic regression) algorithm used in this research learns a non-traditional classifier to identify the probability of a sample being labeled, not of being positive.

$$p(x\ is\ labeled\ |\bar{x}\ ) = \frac{1}{1 + b^2 + e^{-\bar{w}\cdot\bar{x}}}$$

The b variable in the denominator is learned during training. From b, we can estimate the probability that a positive sample is labeled positive $c = p(x\ is\ labeled\ |\ x\ is\ positive)$. This is related to, though not identical, to the class prior $\alpha = p(x\ is\ positive)$ that is commonly used in other PU papers.

$$\hat{c} = \frac{1}{1 + b^2}$$

As [2] describes, once these values are known, we can estimate our final classifier as

$$p(x\ is\ positive|x) = \frac{p(x\ is\ labeled|x)}{\hat{c}}.$$

The derivation for this is also provided in [23].

5. THE MLRf ALGORITHM

Photovoltaic fault detection and classification is different from the average classification problem as the maximum feature set is usually quite small, while vast quantities of unlabeled data can be generated automatically. As described in section 3, our dataset has thousands of measurements but only 10 features, and some of those features such as the gamma ratio are calculated as combinations of other features.

Because our feature set is so small, we introduce a unique feedback loop to enhance the feature set in MLRf as shown in figure 2. The MLR algorithm by itself includes no feature enhancement or engineering and is analogous to standard classification algorithms such as logistic regression or support vector machines.

The MLRf first learns an initial classification model using the original MLR algorithm. This initial model is a weighted combination of features. As the original feature data was mean normalized before training as part of the MLR algorithm, the most influential features are those with the highest magnitude weights. What is unique and new in MLRf are: a) the most significant or influential features are identified from the first pass of the MLR algorithm, b) the selection of some hyperparameter tuned percentage of these most influential features, c) the general enhancement of all features, and finally d) the final reduction of the feature space using principal component analysis (PCA) to isolate the most effective of the enhanced features. These new components of the MLRf algorithm greatly extend the number of hyperparameters required for effective tuning but provide a substantially more flexible algorithm that can be used with even a small feature space such as with solar fault detection.

The MLRf algorithm chooses some percentage of the most influential features to be maximally enhanced. All other features are minimally enhanced. The percentage and levels of enhancement are hyperparameters chosen by the user. This enhancement itself is performed by adding polynomial combinations of the chosen features. For example, a second-degree polynomial enhancement of two original features x_1 and x_2 would return the enhanced feature space $x_1,\ x_1^2,\ x_2,\ x_2^2,\ x_1 \cdot x_2$. A third-degree polynomial enhancement would include cubic values and combinations, and so forth. The greater the size of the initial feature set, the larger the set of expanded features.

Once the feature space has been expanded using polynomial features, additional feature manipulation can be performed using the PCA algorithm to capture the dimensionality of the enhanced feature set that incorporates more than 95-99% of the variability of the space. This will eliminate any enhanced features that do not substantially contribute to the final classification.

Once this feedback modified feature set is created, it is sent back through the MLR algorithm for final classification.

6. RESULTS

As described in section 3, we used both results from a PV array site and synthetic results to evaluate the effectiveness of the MLRf algorithm on PV solar fault data.

To test our model, we compared each fault type (soiled, degraded, shaded, and short circuit) individually against all other data, including the other fault data and the non-fault STC data. We also grouped all fault data together into a single "fault" class that we compared against non-fault STC data. This latter is equivalent to a general fault detection, while the former enables specific fault classification. For each

c	Number of Labeled Pts.	All Faults vs None	Shaded vs Rest	Degraded vs Rest	Soiled vs Rest	SC vs Rest
2%	85	0.883	0.684	0.957	0.4	0.433
4%	171	0.907	0.709	0.776	0.571	0.457
6%	257	0.902	0.7107	0.979	0.911	0.463
8%	343	0.897	0.71	0.999	0.915	0.476
10%	429	0.903	0.714	0.993	0.914	0.474
30%	1289	0.92	0.725	1	0.92	0.478
50%	2148	0.919	0.733	1	0.922	0.481
70%	3007	0.919	0.741	1	0.936	0.481
90%	3867	0.919	0.692	1	0.937	0.481
Oracle	21,485	0.92	0.64	1	0.92	0.0005

Table 1: MLRf F-scores for each type of fault detection and classification for each value of c, rounded to two decimals with three enhanced features. The Oracle's performance, with all labels known, is shown in final row.

of these five scenarios, we then randomly selected a variety of different c values – the percentage of true fault samples that were labeled positive – between 10% and 90% of the original 4297. To demonstrate at what point the model "broke", we also tested values under 10%, though for some fault types, this was still enough for good classification demonstrating the robustness of our algorithm. In addition to showing the c value, the second column of Table 1 provides the absolute number of labeled samples that correspond to that c value for each run. The remaining data out of the original 21,485 samples was unlabeled.

This simulated PU dataset was then classified by the new MLRf algorithm, the original MLR algorithm, and a traditional or standard logistic regression algorithm (SLR). To compare results against supervised learning techniques where all labels are known, we also created a simple "oracle" that also uses a standard logistic regression, but this time over fully labeled data. In all algorithms, a standard stochastic gradient ascent solver algorithm was used to fit the data. It is possible that other algorithms or other more advanced solvers would improve the performance of these algorithms, but we wanted to compare the MLRf results to other algorithms using the same solver.

The five hyperparameters associated with the MLRf algorithm: the learning rate, the number of epochs, the percentage of most important features to heavily enhance, and the levels of enhancement for both the most important features and the remaining features. We performed hyperparameter tuning and found that a learning rate of 0.01 and 1000 epochs generally provided the best results. Not surprisingly, adding too many enhanced features resulted in slightly poorer results due to overfitting. We found that a good balance was between 30 to 60% of the features being maximally enhanced with a polynomial enhancement of order 3. Enhancing the remaining features did not appear to be helpful in this application. Because the class sizes are skewed, we used the F-score (also called the f1-score) to evaluate each experiment as the accuracy metric is misleading when the class sizes are not similar.

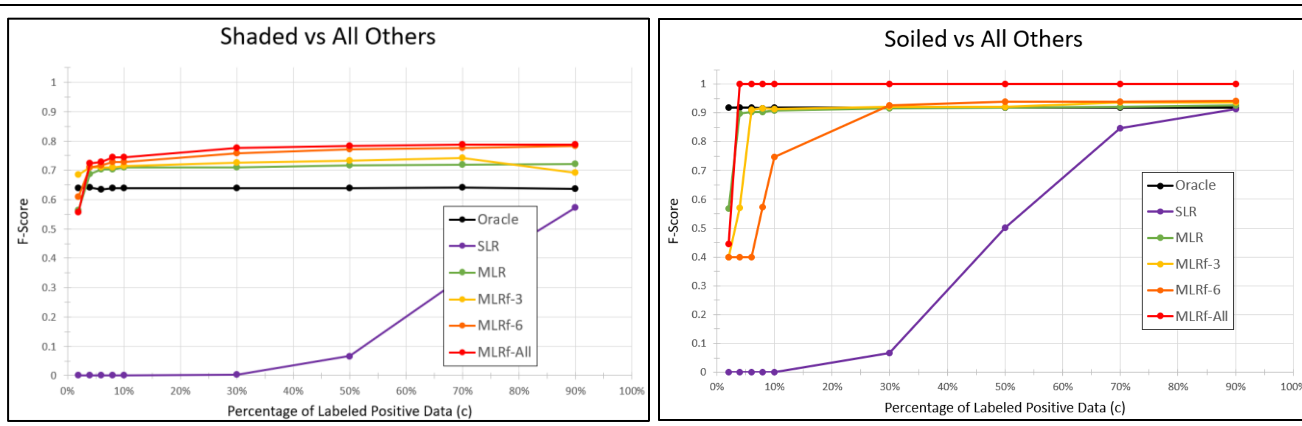
For each fault type and c value, the MLRf algorithm was run three times and mean value was chosen as the F-score shown in Table 1. This was intended to reduce variance, though we found that the variance per run was minimal when c was greater than $10-20\%$. This is not unexpected as with small c values, the random selection of the labeled samples can substantially affect the outcomes.

As can be seen in Table 1, the MLRf algorithm is extremely effective and robust on the simulated positive and unlabeled solar fault datasets. In fact, the MLRf performed as well as the oracle or better when only very small percentages of the labeled positive data were available. This can be seen visually in Figure 3, where the MLRf algorithm performs as well or better than the oracle even when only 6% of the soiled data is labeled. That is, when a random selection of less than 300 datapoints is selected out of over 21,000 datapoints, the MLRf algorithm achieves the same classification performance as when all 21,000+ datapoints are labeled. This indicates that those 300 datapoints can effectively represent the soiled distribution. These results can be visualized in figure 3 where despite having only 6% (257) of the soiled labels known, and the remaining 21,228 labels unknown, the MLRf algorithm performs as well as the oracle. Notice the performance of a standard classifier, in this case logistic algorithm (SLR) on the poorly labeled data.

7. CONCLUSION

In this paper, we presented a new algorithm developed for PU learning with application on fault detection of PV arrays. The algorithm encompasses several unique components including, feedback, feature enhancement, and feature pruning. These components significantly increase the flexibility of the algorithm, though they do require additional hyperparameter tuning.

Extensive simulations were performed for both PU labeled fault detection and classification for a variety of different c values representing the percentage of known labels



(a) (b)

Figure 3: The MLRf algorithm can classify shaded data (a) and soiled data (b) as well or better than the oracle with only a very small percentage of labels known.

for the class of interest. The new MLRf algorithm provides in extremely robust results, equaling or surpassing an oracle algorithm with all labels known even when less than 10% of labels from the class of interest were available. These resulse demonstrate the effectiveness and robustness of the MLRf algorithm on poorly labeled positive and unlabeled solar fault data. Even with only a very small number of labeled positive samples, this algorithm is capable of solar fault classification.

8. ACKNOWLEDGEMENTS

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