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Artificial Intelligence for Predictive Maintenance of Photovoltaic Panels.

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ABSTRACT

We apply convolutional neural networks (CNN) for monitoring the operation of photovoltaic panels. In particular, we predict the daily electrical power curve of a photovoltaic panel based on the power curves of neighboring panels. An exceptionally large deviation between predicted and actual (observed) power curve can be used to indicate a malfunctioning panel. The problem is quite challenging because the power curve depends on many factors such as weatherconditions and the surrounding objects (causing shadows with a regular time pattern). We demonstrate, by means of numerical experiments, that the proposed method is able to predict accurately thepower curve of a functioning panel. Moreover, the proposed approach outperforms the existing approaches that are based on simple interpolation filters.

1.INTRODUCTION

The deployment of photovoltaic (PV) power plants has increasedsignificantly in recent years. The growth of number and size of PVpower plants also raises the importance of predictive maintenance.Optimal power production requires monitoring of each individual PV panel. A typical monitoring system consists of sensors connected to each PV panels measuring the electrical power production of each panel as function of time, i.e. the power curve. The power measurements are collected by a wireless sensor network (WSN) and then analyzed using data mining tools. PV monitoring systems havebeen studied during the past decade and also commercial systems exist.The ultimate goal of predictive maintenance is to identify malfunctioning PV panels. However, the current monitoring systems focus merely on collecting and visualizing operational data. We introduce an algorithm which detects a malfunctioning PV panel based on the power measurement history data (time-series of the power measurements) of the target panel and the neighboring panels. The problem is challenging because of the large dynamic variation in the power measurements of functioning panels. These variations throughout "normal" or functioning operations are due to several factors, e.g.F1 The power generated at a certain time is proportional to the solar irradiance received by the panel. The irradiance varies due to seasons and daytime depending on the geographical location and precise position (orientation) of the panel. However, these variations can in principle be calculated explicitly. Moreover, these factors are strongly correlated for panels of the same type and which are located close to each other. The maximum power on a sunny day can be close to the maximum nominal power of the panel while the maximum power on cloudy day may be less than 20% of the nominal power. Weather predictions are not accurate enough to predict the output power of a single PV panel in each moment of time.This causes large and somewhat unpredictable variations especially in geographical areas where partly cloudy days are common. F3 Normally the power curves of close-by panels are very close to each other in a fully cloudy weather, or in sunshine without shadows. However, nearby objects (trees, buildings, etc.) may cause shadows to fall on the panels individually. This causes large differences between adjacent panels and it occurs regularly at certain daytimes (due to the position of the sun). F4 Malfunctioning panels may cause gradual or fast drops for the amount of generated power.We illustrate the power curves obtained for three similar adjacent panels where factors F1-F3 are present.

2.Problem Statement

We consider predictive maintenance as a classification problem, i.e., we classify each panel as 'functioning' or 'malfunctioning'. The classification is based on the measured power curves. What hinders a naive application of standard classifiers (e.g., naive Bayes or logistic regression) is the lack of large amounts of training data from malfunctioning panels since panel faults are rare. Instead, we follow the approach described in and do anomaly detection by comparing the actual power curve measured at a particular panel with the predicted power curve based on the neighboring panels. A large deviation between actual and predicted power curves indicates a malfunctioning panel. Our problem then becomes to find the best predictor for the power of the target panel using the power values of the neighboring panels. In this study, all our data is from fully functional panels and we aim at constructing a reliable predictor. The actual measurements of the target panel are known and can be used as training and test data for the predictor. In this paper we focus on neural network based estimators [18]. The power measurements of one panel form a time series P(t, d, s), where t is time of the day (in minutes), d corresponds to the date and s is the spatial location of the panel. Such sequential data is usually processed with Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) Networks. However, those methods have challenges with long-term dependencies.the gradient values tend to disappear or explode. This is relevant also in our case, because we have long time-dependencies (due to the regular daily pattern of the power curves). Additionally, these methods do not consider absolute time but only treat time relative to the current instance of time. In our application, however, the signal is very much dependent on absolute time: the daily power curve has a quite regular daily shape - from sunrise to sunset - as referred in factor F1 mentioned in Section 1. Thus, instead of single power measurements, we take the daily power curve as our input. The input data can be considered as 2-dimensional signal, one dimension representing the time of the day t and a second dimension representing the spatial location of the panel.

3. CNN BASED PREDICTIVE MAINTENANCE

Convolutional Neural Networks (CNN) have been successful in finding patterns in 2-dimensional signals. Since our input data (cf. (1)) is actually 2-dimensional, we focus in this paper in the derivatives of CNNs in solving our target problem. The next step is to select the architecture to be used, i.e. the num-ber and type of the layers to be used in the CNN. Because we only have a limited amount of available real-life data, we try to keep the amount of model parameters reasonable to avoid overfitting. On the other hand, we need to have an architecture which has enough power to model the complexity of the function to be estimated. As a com-promise between these requirements, we limit our considerations in this paper to two-layer CNN architectures. The design choice for the types of layers can be split into two parts:

1. How to calculate the local interpolators (based on the input values in the close time-space neighborhood) for the target panel? The problem suggests the use of convolutional layer for the first layer as also used.

2. How to combine the local interpolators in the second layer? A standard method is to use convolutional layer with parame-ter sharing, which means that the combining is done the same way at all times of the day - i.e. our system is time-invariant. However, in this application we have phenomena depending on absolute time of the day; e.g. regular shadows falling on a panel e.g. every day between 10 am and 12 am. A con-volutional layer without parameter sharing can learn to take this into account; i.e. to do the combination differently on different time of the day. This approach is sometimes called unshared convolution.

4.CONCLUSION

According to our results, the application of CNN based methods has potential for predictive maintenance for PV systems. Our results also open several possibilities for further study; e.g. considering larger real-life datasets. Probably the performance of both the algorithms can be improved by fine-tuning the hyperparameter values. CUC al-gorithm can clearly predict the regular shadows and get performance gain from that. It was also the overall winner with the real-life data.On the other hand also CC algorithm seemed to be able to learn some patterns of the training data with a smaller amount of parameters. More research would be needed to understand, where this performance gain comes from; i.e. what are the features of the data it can learn and utilize in the prediction. An interesting option would also be to try to combine CC and CUC algorithms into a hybrid model having best properties of both approaches.

5.REFERENCES

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