Prediction of PV Power Production with Neural ODEs on the base of Weather data

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1 Introduction

Predicting energy production from photovoltaics (PV) is crucial for efficient energy management. In order to be able to apply different operating strategies, it is necessary to be able to predict the expected amounts of PV energy. The operating strategies are typically optimized with regard to economic or technical goals or a combination of both. Within this work, we show a possibility to predict PV power production using local weather data. Based on the measured values from the PV system and an associated weather station, our model is trained and validated with regard to PV production. The measurement data come from the PV system of the former Campus North of Offenburg University of Applied Sciences from the years 2017-2021. The PV system consisted of 3 strings with a nominal output of 2.16 kWp each. The strings have a collector inclination of 30° and 40° and an orientation of 18° south.
We will use Neural Ordinary Differential Equations (NODEs) [1] for the prediction of the PV power production. NODEs can be understood as a Residual Neural Networks, given by
$x_{t+1} = h\,f(x_t) + x_t$ where $h = \Delta t$,
where the discretization h goes to zero and the function changes from discrete to continuous
$\frac{dx}{dt} = f(x)$ or $x_{t+1} = \int_t^{t+1} f(x)\,dt + xt$
where the Neural Network f(x) represents the continuous change of the hidden state x(t). Or in other words Residual Neural Networks are the Euler discretization of NODEs [3,4,5].
In contrast to traditional neural network architectures with discrete layers, NODEs model the continuous evolution of hidden states with ordinary differential equations. More concrete, the input features don't pass through a fixed number of layers, the hidden states evolve over a time interval by using a solver. The differential equations themselves are represented by Neural Networks and describe the rate of change of the hidden states over time. The Neural Network is then integrated with a solver to obtain the trajectory of the hidden states over the time. In the context of solving ordinary differential equations, the input features can be interpreted as initial values for the hidden states. Despite the initial values of the PV power production at time t0, we will use furthermore the weather data (actual and predicted) as additional input features to predict the PV power production at time t1 in the future. For the training of the NODEs we are using the so-called discretize-then-optimize approach where we backpropagate through the internal operation of the ode solver to obtain the gradients [2].
Because of the mentioned properties, NODEs are very well suited for the modeling of time series. For the same reasons NODEs are also well suited for the modeling of physical systems that can be expressed as differential equations.

The article will be organized as follows. In the Introduction we will give an overview of the state of the art for PV power prediction and the use of Neural ODEs for modeling of physical systems. In the second chapter we give a short introduction to Neural ODEs for the prediction of time series. After that, we present the data and will describe the data preparation steps. The data preparation includes the resampling to a half hourly base. We also applied Principal Component Analysis and Fourier Transform to the data. After the preparation of the data we will discuss the hyper parameter tuning for the NODE. In the next step we present the training and validation results of the NODE for the PV power prediction. We will conclude the article with a conclusion and discussion.

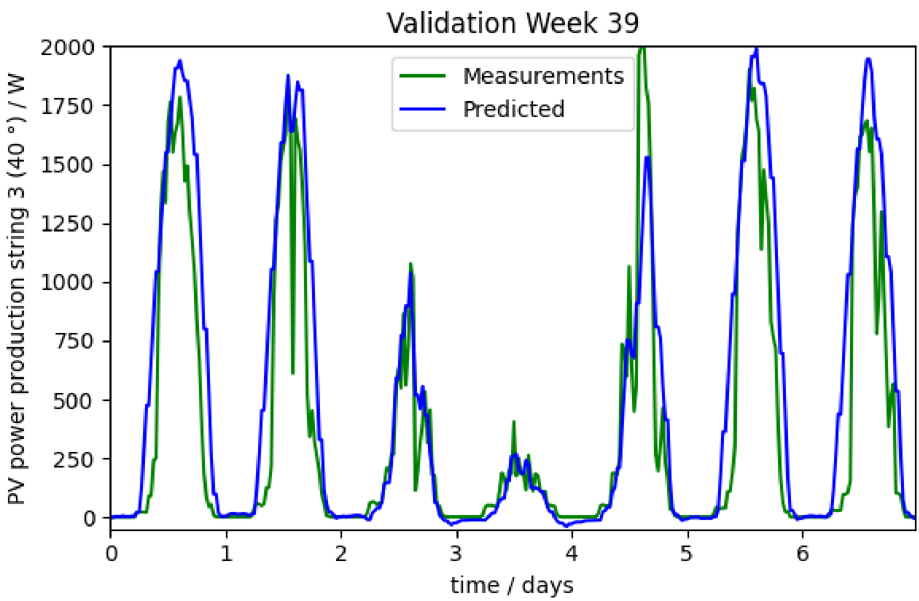

Fig. 1. Comparison of predicted and measured PV power production of string 3 with a collector inclination of 40°.

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