EE5121 Project

SD using QSS: Why this problem matters?

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Motivation

- **Decomposition of a time series signal into components**: an age-old problem, solved using statistical and heuristic methods
- Existing methods - involve optimization of an objective function
- **Motivation for SD-QSS**: Lack of useful, practical tools for **solar data**
- **Industry**: Use PV output time-series plus + time series measuring local weather conditions (irradiance, temperature, wind speed) + system parameters (location, mounting, and orientation), but difficult to do!

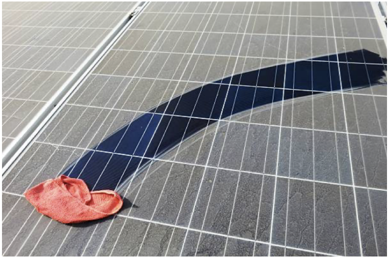


Figure: PV Soiling (described next)

How do we tackle this?

- **Data:** Use **only** PV output time series, and leverage the power of signal decomposition - focus on practical solutions more than theory
- **Signal Decomposition:** Given time series y (possibly with missing data), decompose as: $y = x^1 + x^2 \ldots\ x^K$ where each component x^i has known characteristics (smooth, periodic, nonnegative, nonincreasing, sparse..)
- As discussed in the poster, our goal is to:

$$\min \phi_1(x^1) + \phi_2(x^2) \ldots \phi_K(x^K)$$

with some prior information on signal entries

The proposed method

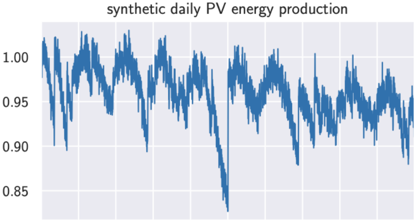
- **SD-QSS**: a framework that unifies many existing approaches, where components are described by their loss functions
- guaranteed to find the globally optimal decomposition when the loss functions are all convex, and is a good heuristic when they are not

Advantages of the method

- **Handles missing data well:** obtains an estimate of missing entries using known entries with good accuracy (check out our Recovery Error result)
- **Expressivity and interpretability:** describes well-known loss functions as specific cases, and enables the design of newer loss functions
- **Simplicity:** solution via ADMM algorithm only requires $prox_g$, easy to compute
- **Generalizable:** this method has been shown to work on various testcases that we have generated, along with applications to real-life practicality data
- **Applications specific to Solar Cells:**
  - **Outage detection in a PV box**
  - **Shade Loss in PV cells**
  - **Clear Sky Detection for PV cells**
  - **PV Soiling Data**

Application to PV Soiling
Our initial goal

- **Soiling**: build-up of material on the surface of PV surfaces over time
- causes large yield (output power) reduction, as high as -3% per day
- soiling is hard to predict as it varies with weather and system parameters
- an important problem the PV industry is trying to solve, with entire tracks dedicated to it in PVSC/PVRW (conferences, workshops)



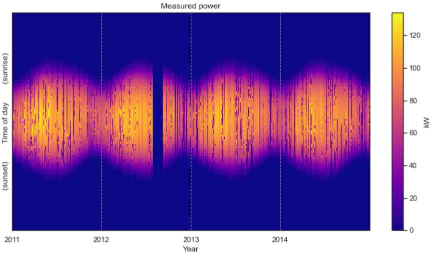


Figure: Left side shows PV data generated using NREL's soiling model over 10 years, right figure is the measured power from 2011-2015

Approach

- Component losses are multiplicative, so applying *log* $\implies$ additive model
- Soiling loss is decomposed as shown:
  $\ell_{\text{soil}}(x) = \ell_1(x) + \ell_2(x) + \ell_3(x) + \ell_4(x)$

	soiling loss term	description
ℓ_1	$\mathcal{I}(x \leq 0)$	non-positive
ℓ_2	$\lambda_a \|\|x\|\|_1$	sparse
ℓ_3	$\lambda_b \sum_{t=1}^{T-1} \left[\frac{1}{2}\left\|(D_1 x)_t\right\| + \frac{2}{5}(D_1 x)_t\right]$	asymmetric 1^{st} diff.
ℓ_4	$\lambda_c \left\|\|D_2 x\right\|\|_1$	piecewise affine

- actual soiling values are known based on NREL's model, so comparing we get

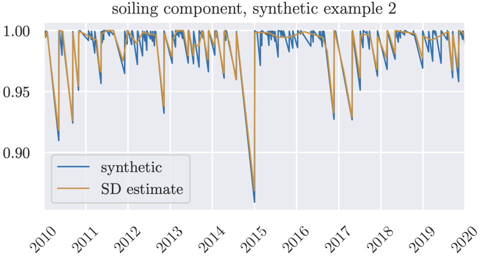


Figure: Result using SD-QSS

Thanks for your listening