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eeh power systems laboratory

Constrained Support Vector Machines for PV In-Feed Prediction

IEEE Conference on Technologies for Sustainability 2013 (Sustech), Portland, OR

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Agenda

- Renewable In-Feed in Germany
- Characteristics of PV
- Constraint SVM
- Concluding remarks

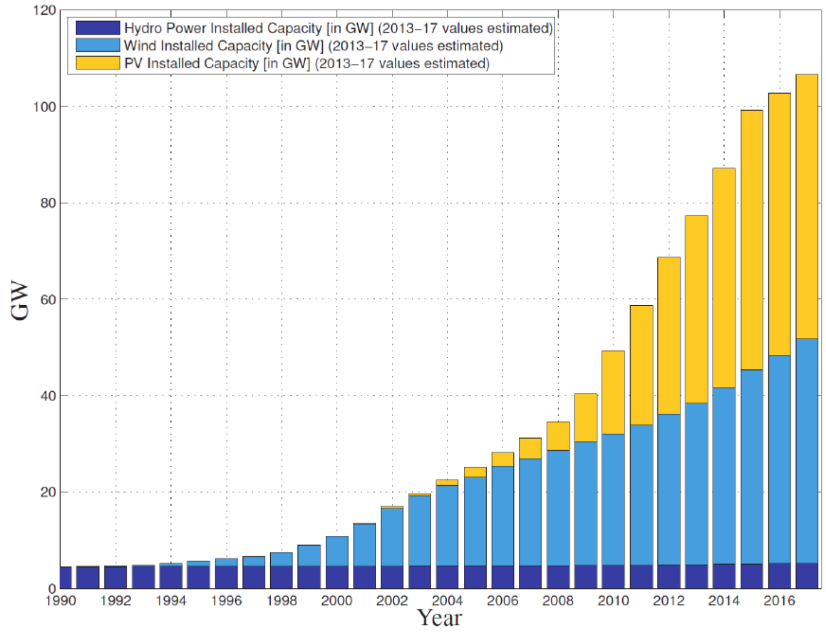
Motivation: Why PV

- Strong support schemes for PV and wind in Germany
- As a result, we see a large increase wind and PV
- Political decision
  - Goal is the increase of in-feed, no technical problems matter
  - A lot of open and hidden support schemes are in place

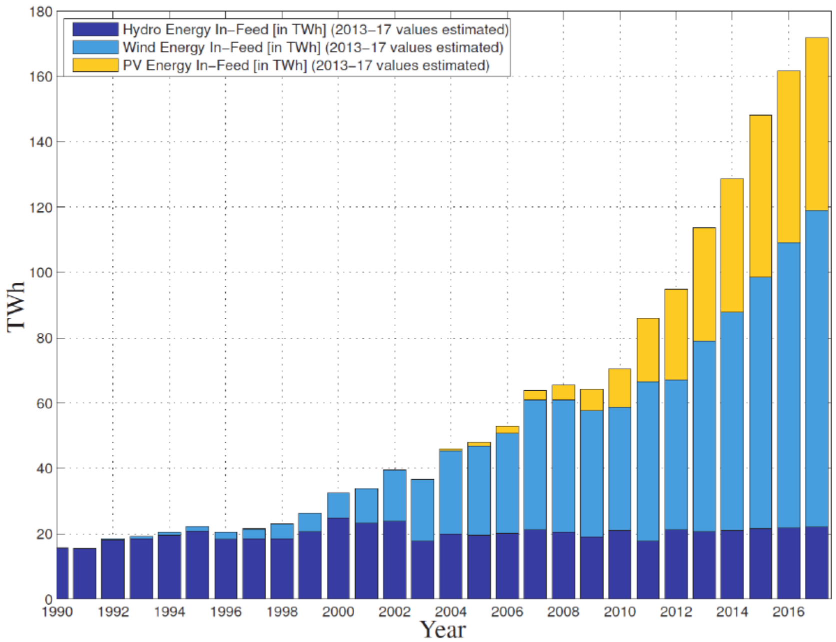
Support Schemes

- **In-feed tariffs for wind and PV**
  - Prices are independent of market prices
  - Tariff is coupled to a technology
- **The do not have to cover the forecast error**
  - Additional cost for grid operation occur
  - Increase of grid tariffs
- **Duration of In-feed tariffs is 20 years**
  - What will happen after the end of the tariffs?

The result of the support schemes:



Installed capacity



Yearly in-feed

- Increase of more than 20% of PV each year

Source: Revisiting the Merit-Order Effect of Renewable Energy Sources, Marcus Hildmann, Andreas Ulbig, Göran Andersson; Working paper http://arxiv.org/abs/1307.0444

Problems

- **Consumer Perspective**
  - High costs because of in-feed tariffs
  - Additional hidden costs

We need good forecasts!

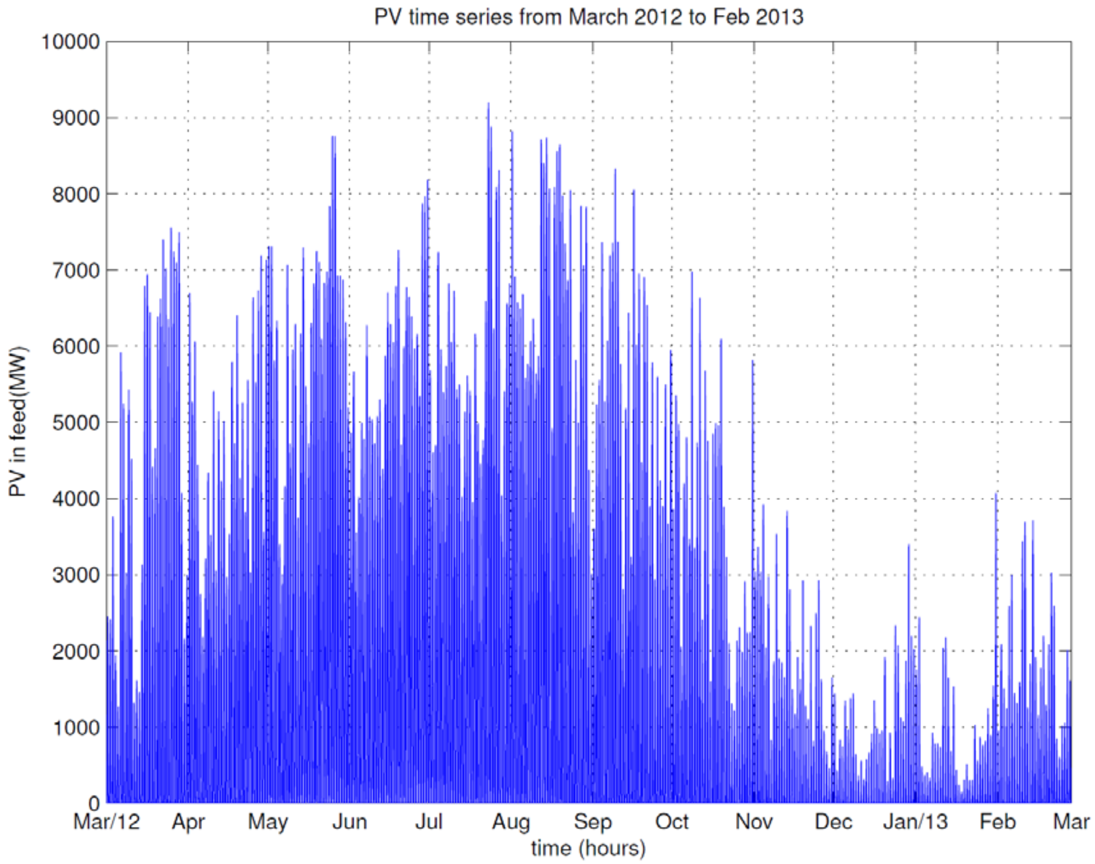
- **Producer Perspective**
  - Flexible power plants are necessary to fill the wholes and forecast errors

- **Grid Perspective**
  - Grid has problems to handle the decentralized production
  - Higher amount of ancillary services are necessary

Characteristics of PV In-feed

- Seasonal pattern
  - Day-/night pattern
  - Yearly seasonality
- Dependencies
  - Auto dependency
  - Cross dependency
- Weather dependency
  - Cloud coverage
  - Other minor effects

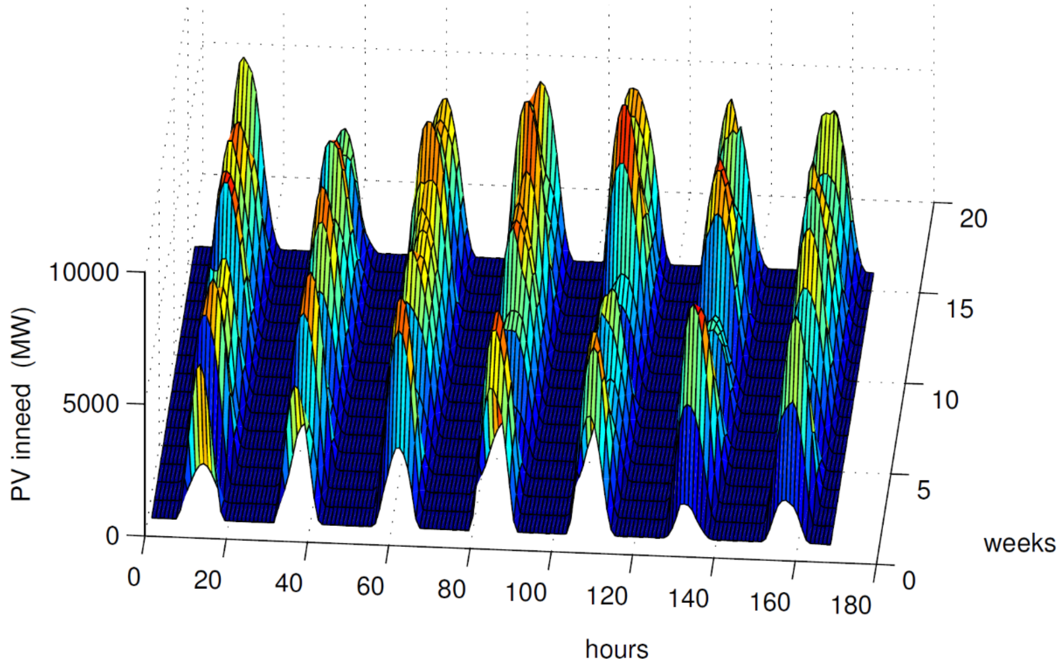
PV time series



Source: European Energy Exchange Transparency Platform http://www.transparency.eex.com/de/

Seasonality of PV

- Plot of PV in-feed on hourly basis



Source: Constrained Support Vector Machines for PV In-Feed Prediction, Marcus Hildmann, Abhishek Rohatgi, Göran Andersson; IEEE Conference on Technologies for Sustainability 2013 (Sustech) 2013, Portland, OR

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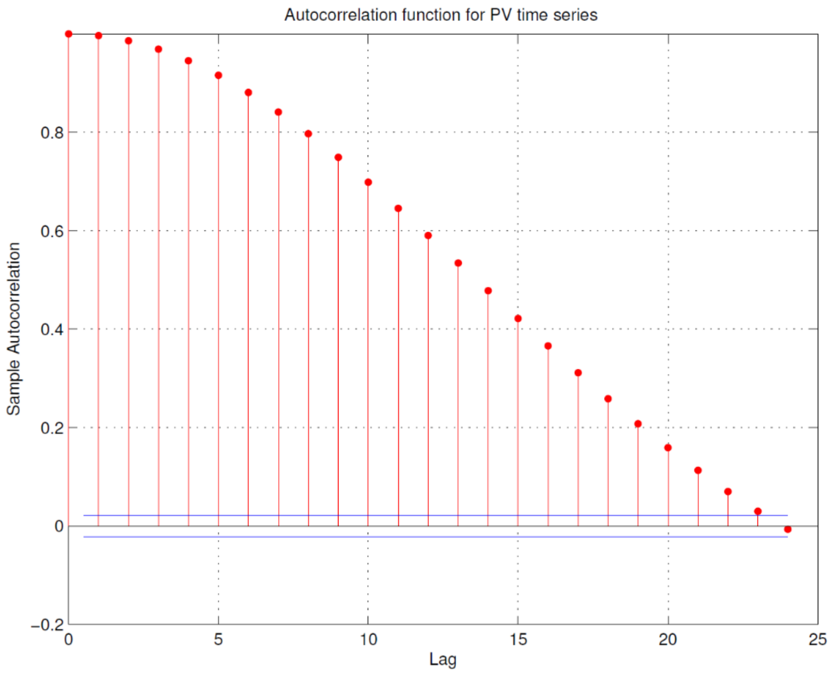
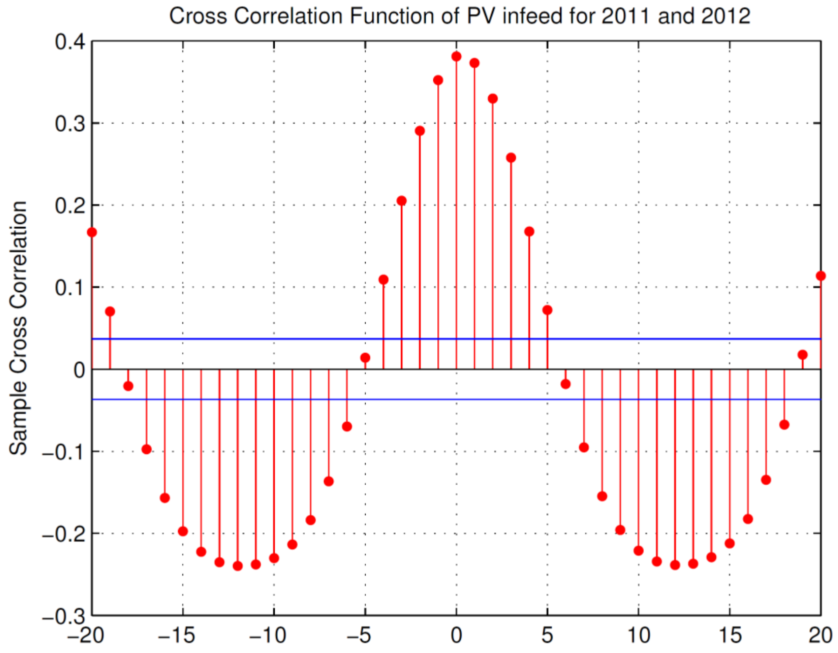
Auto- and cross-dependency

- Strong auto-correlation and cross-correlation patterns





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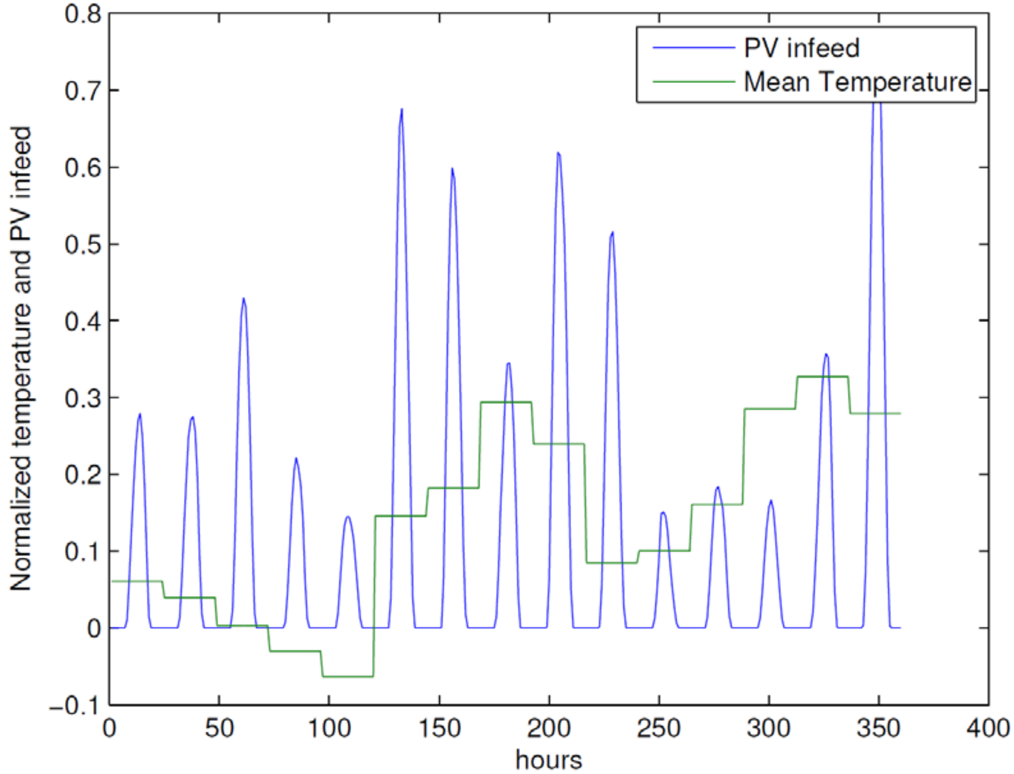
Dependency on Weather

- The dependency on mean temperature is not strong



Source: Constrained Support Vector Machines for PV In-Feed Prediction, Marcus Hildmann, Abhishek Rohatgi, Göran Andersson; IEEE Conference on Technologies for Sustainability 2013 (Sustech) 2013, Portland, OR

Estimation Methods

- Linear estimation methods
  - OLS
  - LAD
  - quantile regression
- Nonlinear regression methods
  - Artificial Neuronal Networks (ANN)
  - Support Vector Machines (SVN)
- Bayesian methods
  - *Bayesian tracking (Kalman Filtering, Particle Filtering)*
  - *Markov-Chain Monte Carlo*

Why SVM

- External effects
  - Cloud cover, temperature, ..
- Statistical effects
  - Dependencies
- Model questions
  - Unknown model
  - Parameter estimation
- Assumption of normality
  - Natural process, errors are normal distributed

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Why constraint methods

- Reduce the chance of over-fitting
- Increase physical boundaries
  - Minimum in-feed
  - Maximum in-feed
- Integration of prediction in the estimation step

Constrained SVM

- Classic SVM

$$
\begin{aligned}
\min_{w,b,\xi,\xi_\star} \quad & J_p(w) = \frac{1}{2}w^T w + c\sum_{k=1}^{N}(\xi_k + \xi_k^\star) \\
\text{s.t.} \quad & y_k - w^T\phi(x_k) - b \leq \epsilon + \xi_k, k = 1, \ldots, N \\
& w^T\phi(x_k) + b - y_k \leq \epsilon + \xi_k^\star, k = 1, \ldots, N \\
& \xi_k, \xi_k^\star \geq 0, k = 1, \ldots, N
\end{aligned}
$$

- Constrained SVM

$$
\begin{aligned}
\min_{w,b,\xi,\xi^\star} \quad & J_p(w,\xi,\xi^\star) = \frac{1}{2}w^T w + c\sum_{k=1}^{N}(\xi_k + \xi_k^\star) \\
\text{s.t:} \quad & y_k - w^T\phi(x_k) - b \leq \epsilon + \xi_k, k = 1, \ldots, N \\
& w^T\phi(x_k) + b - y_k \leq \epsilon + \xi_k^\star, k = 1, \ldots, N \\
& \xi_k, \xi_k^\star \geq 0, k = 1, \ldots, N \\
& \underline{w^T\phi(x_\tau) + b \leq \psi, \tau \in \mathbb{S}, \mathbb{S} \subseteq [N+1, \ldots, M]}
\end{aligned}
$$

Results: Testing Framework

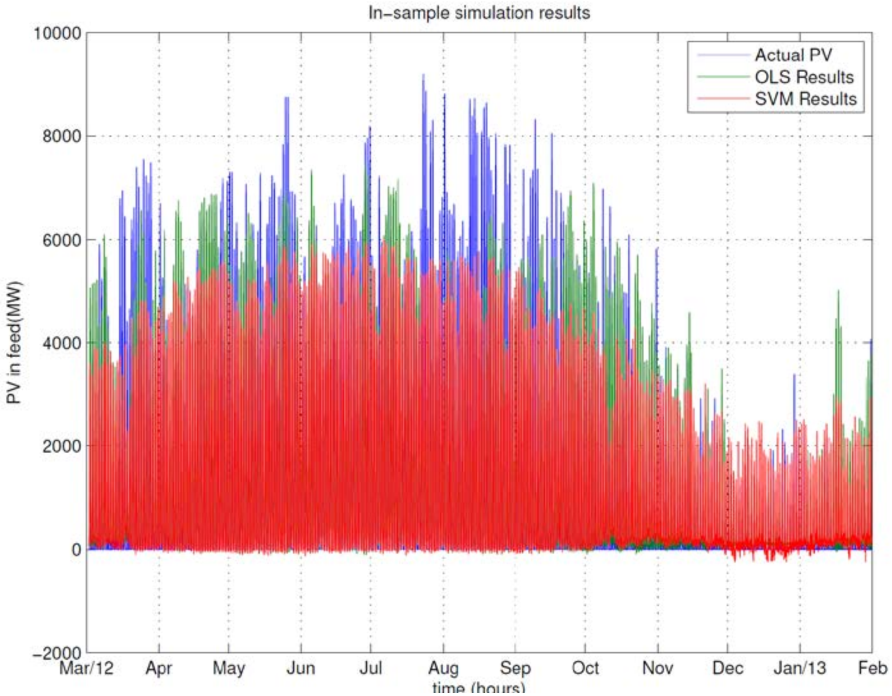
- Data set learning
  - German PV data from March 2012 until February 2013
  - Weather data on daily basis

- Data set prediction
  - German PV March 2013 for comparison
  - Norm weather based on 30 years average on daily basis

- Benchmark
  - Constraint OLS

- Measures
  - Mean absolute prediction error (MAPE)
  - Mean square error (MSE)

In-sample learning



- No constraints on the learning sets
- Statistics both show better performance of SVN (what is not surprising in-sample)

IN-SAMPLE STATISTICAL MEASURES

Measure	OLS	SVM
MAPE	0.61	0.5
MSE	343	279

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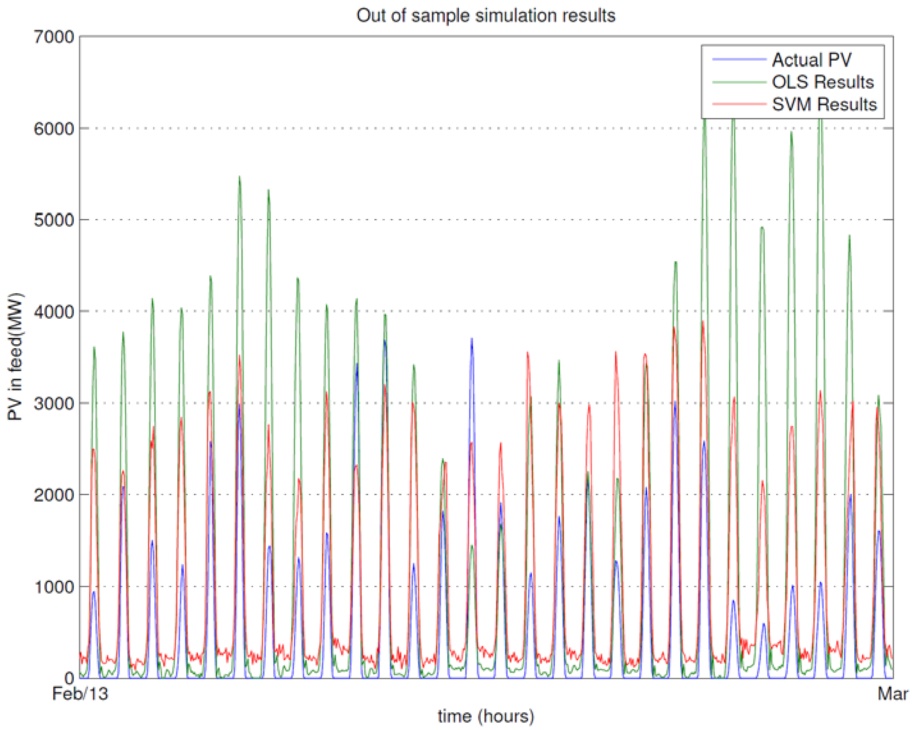
In-sample learning



- Constraints min in-feed zero
- Statistics both show better performance of SVN out-of-sample
- Small estimation problems during the night

OUT-OF-SAMPLE STATISTICAL MEASURES

Measure	OLS	SVM
MAPE	0.85	0.82
MSE	516	393

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Conclusion

- Constrained SVM prediction on PV works
- The algorithm outperforms the constrained OLS by around 20%
- Estimation during night must be improved

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