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Reactive Power Estimation For Large-Scale Customers Using Machine Learning



## **Contributors**

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## Introduction

- Active (or "real") power P (measured in watts; W)
- Reactive power Q (volt-ampere-reactive; VAR)
- Apparent power S (volt-ampers VA)
- *PF* (power factor)=  $P / \sqrt{P2+Q2}$



### Data

- Active power (P) for large-scale customers for ~86,000 customers
- Reactive power (Q) for a set of 3,264 customers
- Reactive power measurements as a monthly total are available for ~30,000 customers
- Metadata about the customers

\*\*\*Relation between Q and P can varies between customers and/or over time and does not correspond to a constant power factor.\*\*\*



Fig 1. For 12 random large customers for 12 months P vs Q.

### Results

#### Model 1:

Assume constant power factor

PF = 0.95

#### Model 2:

Fit optimal constant power factor PF ~= 0.98

#### Model 3:

Constant estimate of Q for each month Set the value to match the monthly total measurements ci

#### Table 1 comparison of MAE and RMSE for each method

Model	MAE (kVAr)	RMSE (kVAr)	Explanation
1	16.86	41.67	PF=0.95
2	12.52	27.87	PF~0.98
3	6.8	9.95	Constant monthly Q to match monthly sums
4	4.10	7.77	Constant monthly PF to match monthly sums

\*MAE: Mean Absolute Error \*RMSE: Root Mean Square Error

#### Model 4:

Monthly optimal PF Defined by monthly measurements c i  $\Sigma$  t  $\epsilon$  month\_i Q(t) = c i Q(t) = P(t) \* ( $\Sigma$  t  $\epsilon$  month Q(t)) / ( $\Sigma$  t  $\epsilon$  month P(t))



## **GBM (Gradient Boosting Machine)**

- Related to random forests; uses decision trees as weak learning
- Iteratively attemps to correct errors in prediction

Model	MAE	RMSE	Explanation
	(kVAr)	(kVAr)	
Light-	3.56	4.94	(after re-scaling and combination with
GBM			baseline method)



Figure shows how well the LightGBM model can predict Q/P for every fifteen-minutes. SHAP values evaluates the impact of every input feature and what we then see is that it's very much based on this monthly Q / P value.



## Conclusion

- Traditional assumption of a fixed power factor does not hold for the subset of Dutch large customers in this study.
- By employing different approaches, a fourfold reduction in estimation error compared to standard methods was achieved.
- With a model using LightGBM the mean absolute error decreases 13% further. Machine learning approaches offer valuable insights in what drives the reactive power and make more reliable predictions with fewer large errors.
- Direct measurements of Q provide still the most accurate and reliable results, allowing for more efficient system operation.

# Thanks for your attention!





