Load Forecasting Analysis in Power Distribution Networks and usefulness for Electricity Market

Dr. Nils Jakob Johannesen

June 29, 2023

Associate Professor, Electrical Engineering, IT and Cybernetics at University of South-Eastern Norway

Overview

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- Ph.D from University of Agder
  Machine Learning in Load Forecasting

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- Guest Lecturer:
  at University in Tromsø
  University of Agder

Introducing Data Science to the Power Engineer

Bachelor Power Engineering

<table>
<tr><th>Autumn’23</th><th>Spring’24</th><th>Autumn’24</th><th>Spring’25</th><th>Autumn ’25</th><th>Spring’26</th></tr>
<tr><td>Digital Systems</td><td>Math1</td><td>Math2</td><td>Statistics</td><td>Electrical Machines</td><td>Project</td></tr>
<tr><td>Electronics1</td><td>Physics1</td><td>Physics2</td><td>Chemistry</td><td>HVAC</td><td rowspan="4">Thesis</td></tr>
<tr><td colspan="2">Low Voltage</td><td>PLS</td><td>Hydro Power</td><td>HVDC</td></tr>
<tr><td colspan="2">OOP</td><td>Electric security</td><td>Electric Power System</td><td>Math3</td></tr>
<tr><td>Python</td><td>Electronics2</td><td></td><td></td><td></td></tr>
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Subjects containing programming

Introduction: Research Area

Research Area: Machine Learning in Smart Systems

Research Area: Machine Learning in Smart Systems

i)
Urban Area Load Forecasting

Research Area: Machine Learning in Smart Systems

i)
Urban Area Load Forecasting

ii)
Network Capacity Planning

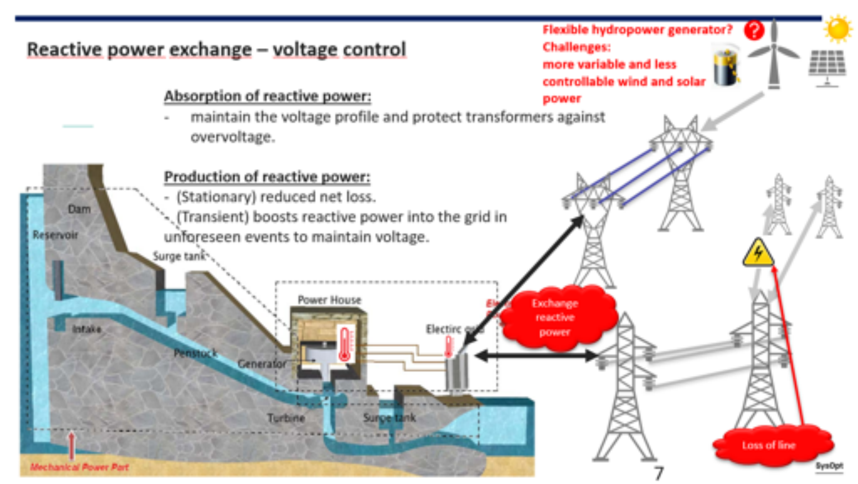
Research Area: Machine Learning in Smart Systems

i)
Urban Area Load Forecasting

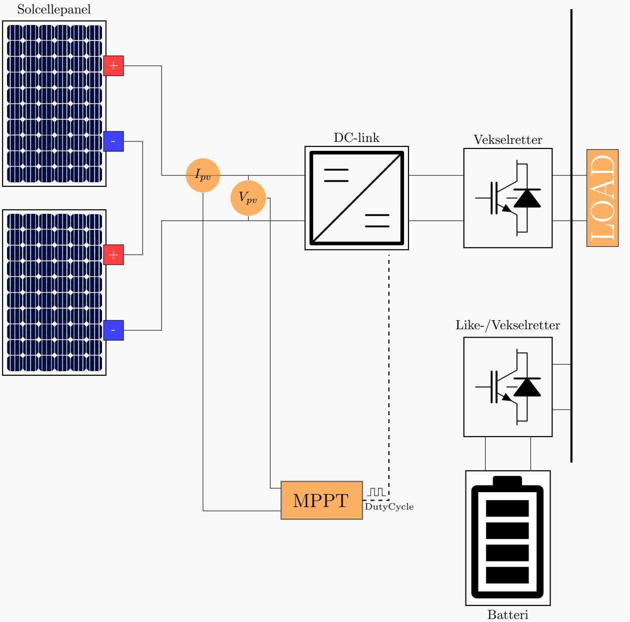
ii)
Network Capacity Planning

iii)
Demand Side Management and Electricity Markets

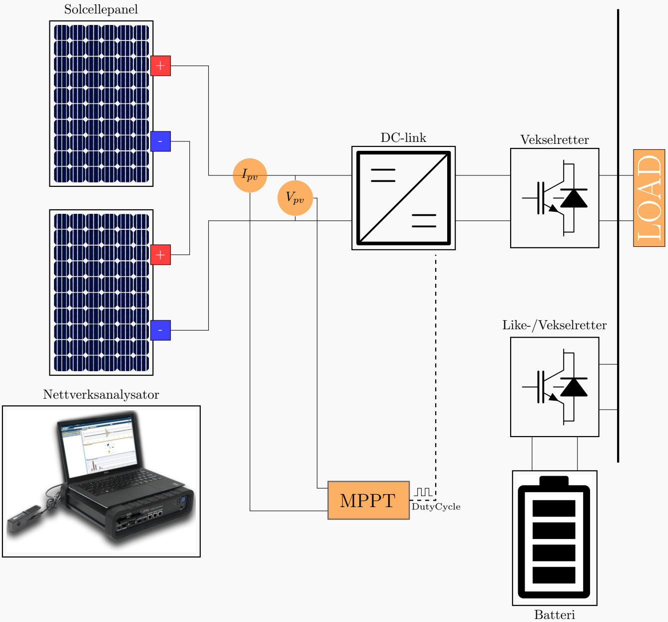
Current Research - SysOpt

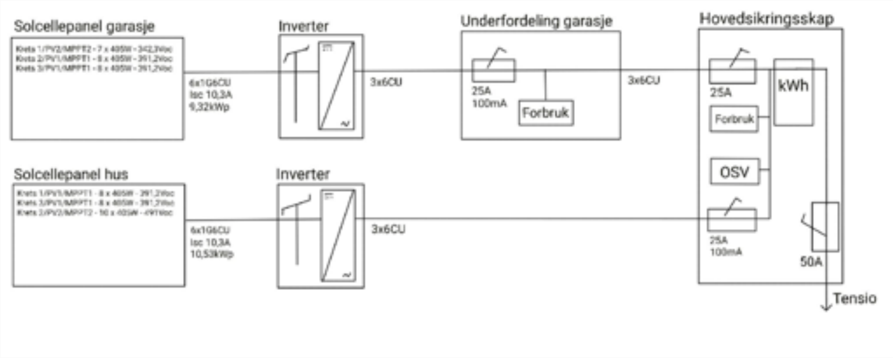


Next-Step Lab



Next-Step Lab

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6x1G6CU
Isc 10,3A
9,32kWp
Inverter
3x6CU
Underfordeling garasje
25A
100mA
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3x6CU
Hovedsikringsskap
25A
kWh
Forbruk
OSV
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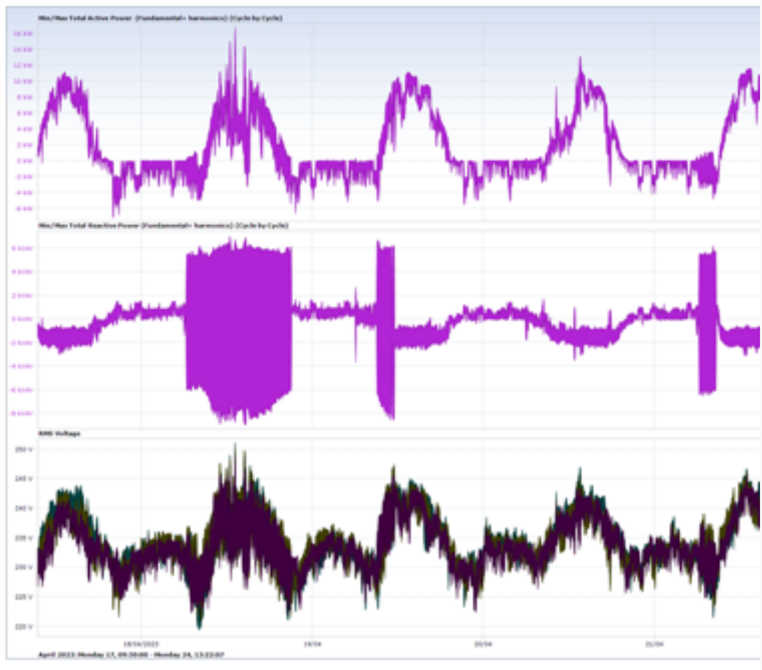
Isc 10,3A
10,53kWp
Inverter
3x6CU



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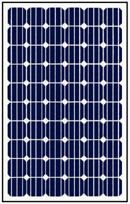
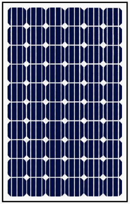
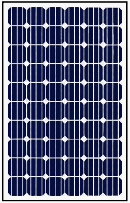
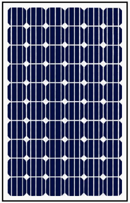
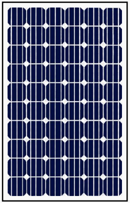
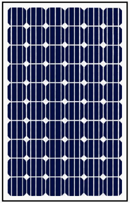




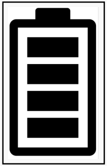




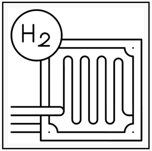




Nettverksanalysator

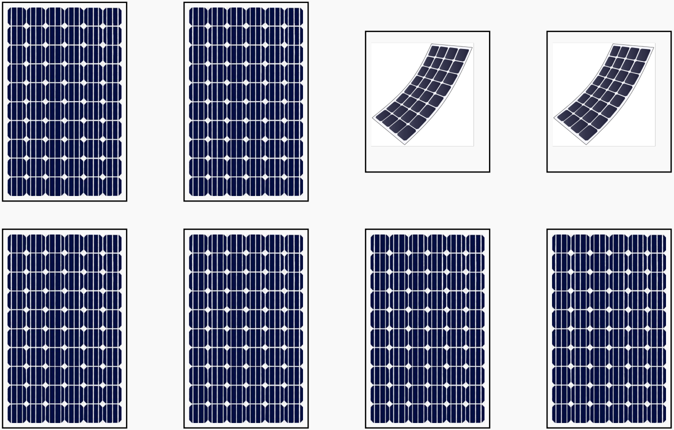


Batteri



Brenselcelle

Solcellepanel



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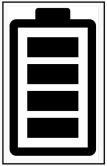

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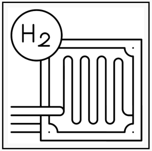

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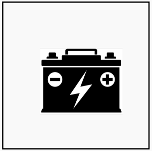
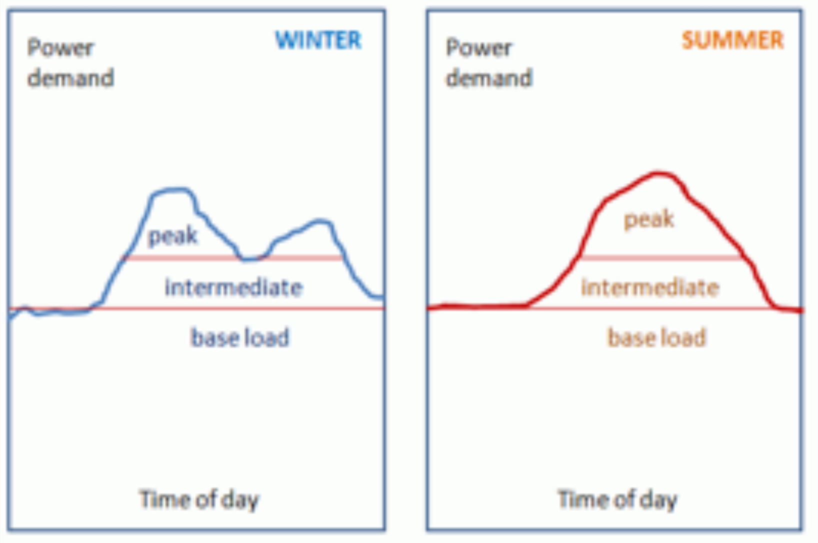


Test-batteri

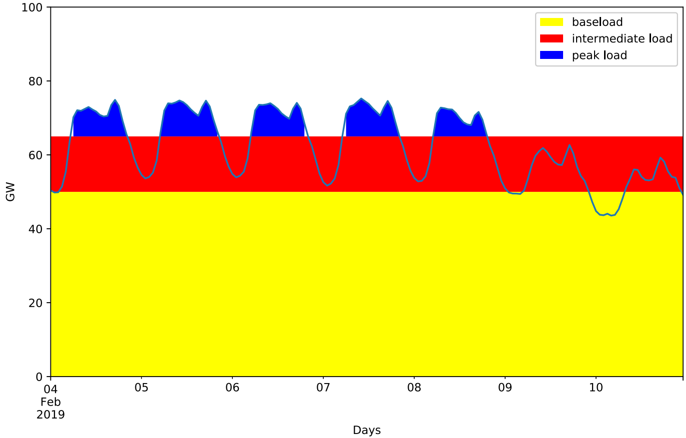
Load Forecasting Analysis

Load Analysis



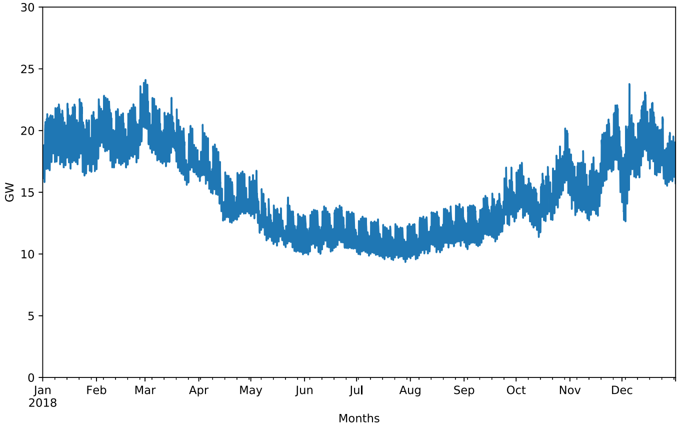
source: PENN STATE
(https://www.e-education.psu.edu/eme807/node/667)

Load Analysis



(ENTSOE-E)

Load Analysis



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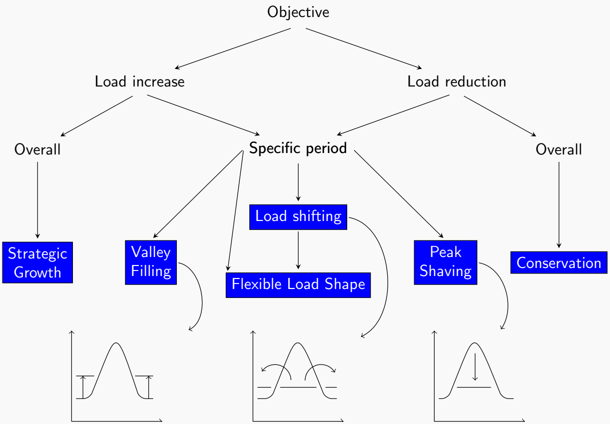
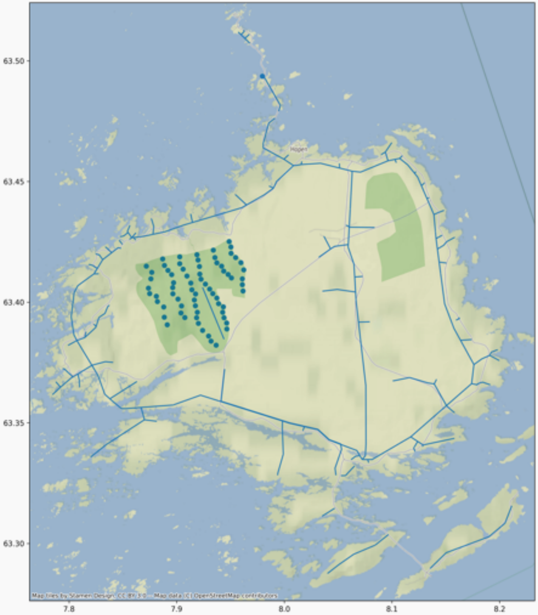
Flexible Load Shapes



Johannesen, N. J., Kolhe, M. L. (2021). Application of regression tools for load prediction in distributed network for flexible analysis. In Flexibility in Electric Power Distribution Networks (pp. 67-94). CRC Press.

Power Distribution Network

Smøla


63.50
63.45
63.40
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Map tiles by Stamen Design, CC BY 3.0 — Map data (C) OpenStreetMap contributors

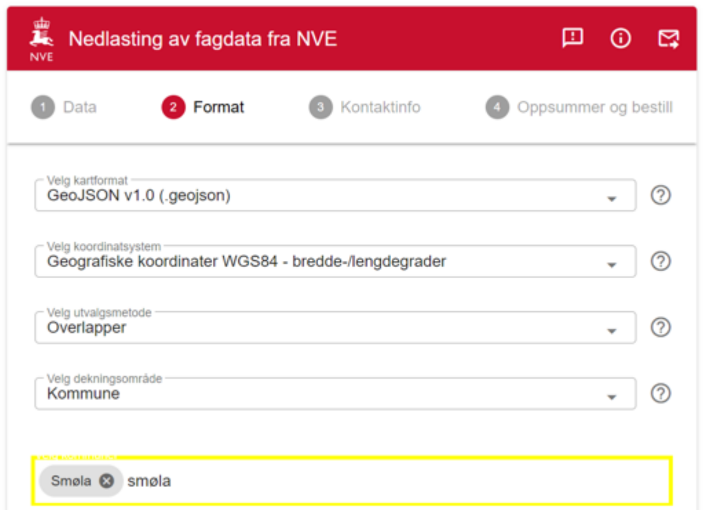


Figure 2: Downlaodable Geographical information system (GIS) from The Norwegian Water Resources and Energy Directorate (NVE)

Smøla - Nordheim

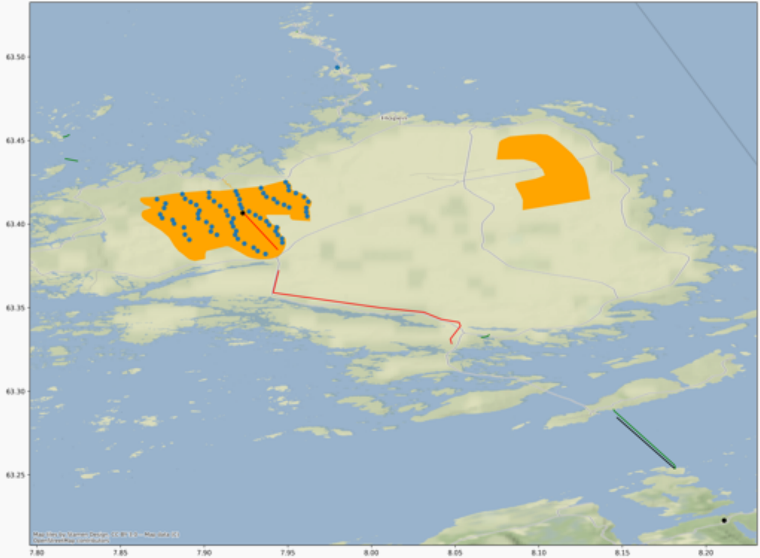


Figure 3: Transmission system to mainland

System overview

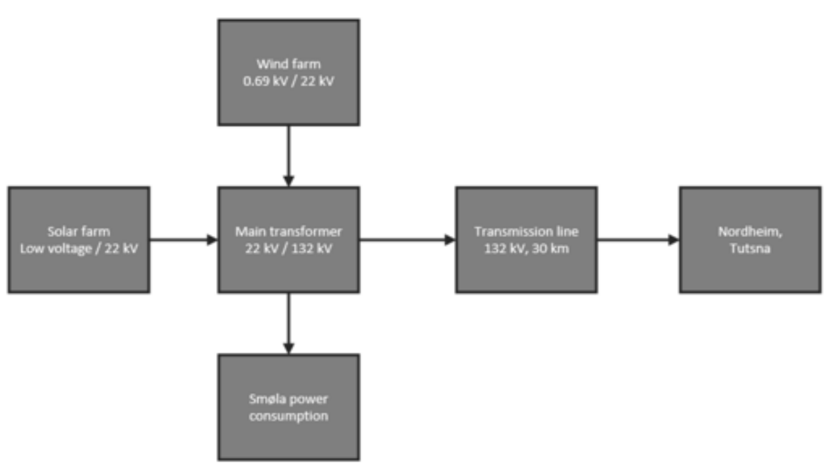


Figure 4: System overview from generation at Smøla to Transformer at Nordheim Tutsna

Feature Engineering

Feature Engineering: Important influences on Load Pattern

Feature Engineering: Important influences on Load Pattern

i)
Time

Feature Engineering: Important influences on Load Pattern

i) Time

ii) Weather

Feature Engineering: Important influences on Load Pattern

i) Time

ii) Weather

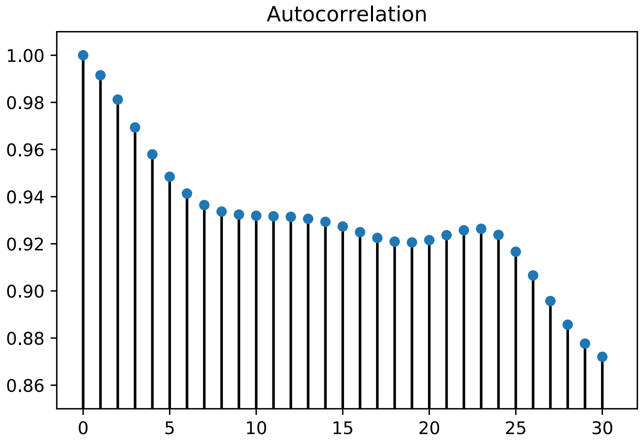
iii) Random Effects

Time: Autocorrelation

$$\rho_k(t) = \frac{\sum_{t=1}^{n-k}(y_t - \hat{y}) \sum_{t=1}^{n-k}(y_{t+k} - \hat{y})}{\sqrt{\sum_{t=1}^{n-k}(y_t - \hat{y})^2}\sqrt{\sum_{t=1}^{n-k}(y_{t+k} - \hat{y})^2} \tag{1}$$

G. Box and G. M. Jenkins, Time Series Analysis: Forecasting and Control. Holden-Day, 1976

ACF-plot



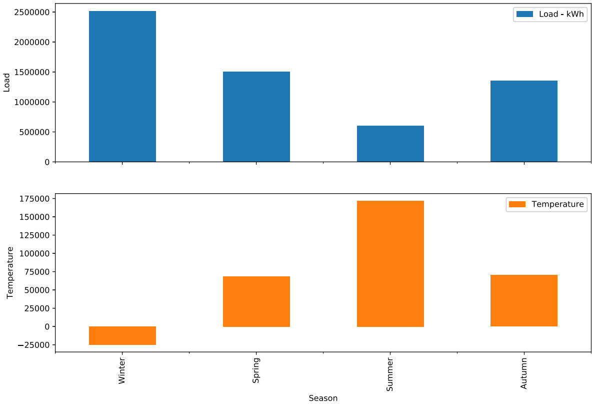
N. J. Johannesen, M. Kolhe, and M. Goodwin, “Deregulated electric energy price forecasting in nordpool market using regression techniques,” in 2019 IEEE Sustainable Power and Energy Conference (iSPEC), 2019, pp. 1932–1938

Weather: Cross-correlation

$$\rho_{xy}(t) = \frac{\sum_{i=1}^{n}(x_i - \hat{x})\sum_{i=1}^{n}(y_{i-t} - \hat{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \hat{x})^2}\sqrt{\sum_{i=1}^{n}(y_{i-t} - \hat{y})^2}} \tag{2}$$

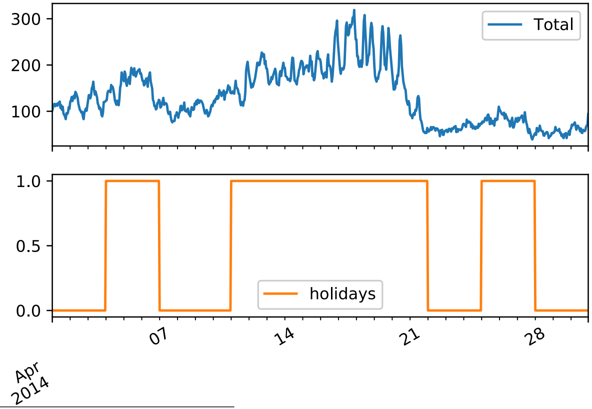
G. Box and G. M. Jenkins, Time Series Analysis: Forecasting and Control. Holden-Day, 1976

Seasons-plot



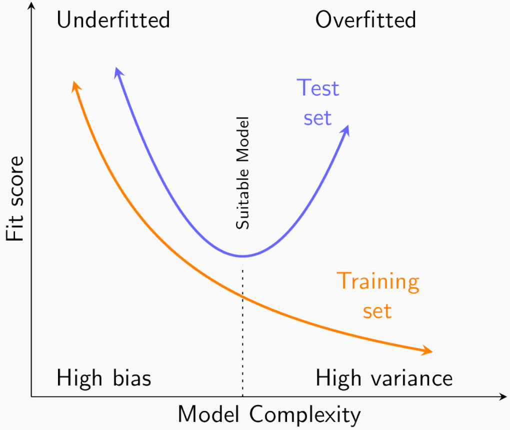
N. J. Johannesen, M. Lal Kolhe, and M. Goodwin, “Load demand analysis of nordic rural area with holiday resorts for network capacity planning,” in 2019 4th International Conference on Smart and Sustainable Technologies (SpliTech), 2019, pp. 1–7

Seasons-plot



N. J. Johannesen, M. Lal Kolhe, and M. Goodwin, “Load demand analysis of nordic rural area with holiday resorts for network capacity planning,” in 2019 4th International Conference on Smart and Sustainable Technologies (SpliTech), 2019, pp. 1–7

Bias vs. variance trade off



P. Bacher and H. Madsen, "Identifying suitable models for the heat dynamics of buildings," Energy and Buildings, vol. 43, no. 7, pp. 1511 – 1522, 2011

Demand Side Management and Electricity Markets

Why do we need this work? I

Innlegg Nils Jakob Johannesen

Hva kan vi lære av Texas-krisen?

Delstaten Texas opplevde katastrofe etter rekordlave temperaturer og rekord i strømforbruket. Smarte nettverk er løsningen i fremtiden.

Nils Jakob Johannesen

Nils Jakob Johannesen, Doktorgradsstipendiat, Fornybar Energi, Universitetet i Agder

● **I Texas** fører minusgradene til krise i strømforsyningen. Høyt strømforbruk kombinert med at deler av strømproduksjonen har kollapset, er noe av forklaringen. Fleksibel kraftdistribusjon og smarte nettverk er viktig for styring av fremtidens strømnett.

Problemene i Texas var en ventet hendelse, værutsiktene lå an til rekordlave temperaturer, og rekord i strømforbruket var ventet mandag morgen. En varslet krise kommer sjeldent alene, og i covid-19 tider er strømforsyning til utsatte grupper prekært. Mandag nådde strømtoppen 69 GW. Til sammenligning nådde vi i Norge rekordtopp den 12. februar i år, på 25 GW.

Da denne toppen ble nådd mandag satte Electric Reliability Council of Texas (ERCOT) I gang sin 'Energy Emergency Alert 3', som tvang kraftforsyningsselskapene til å rotere på kraften. Southwest Power Pool instruerte sine strømprodusenter til å gjøre kontrollerte stans i strømmen for å sikre strømforsyningen.

Brown-outs ble gjort, for å forhindre

† Millioner av innbyggere i Texas mistet strømmen da vinterstormen Uri rammet delstaten.
Foto: Justin Sullivan/Getty Images/AFP/NTB

om 30 GW av forsyningskapasiteten satt ut av spill som følge av snø, is og kulde. Blant annet står vindturbiner og kjernekraftverk stille. Back-up generatorer i gass- og kull-

melig nok er også nettsiden til ERCOT nede, men noe informasjon slippes på Twitter. På Twitter var også Texas-guvernør Greg Abbott, der han varsler full etter-

Why do we need this work? II

Los Angeles Times

CALIFORNIA

A text asked millions of Californians to save energy. They paid heed, averting blackouts

After narrowly avoiding blackouts, California faces another bruising test of its power grid Thursday as a heat wave smothering the region builds, driving temperatures to dangerous levels. (Eric Thayer / Bloomberg via Getty Images)

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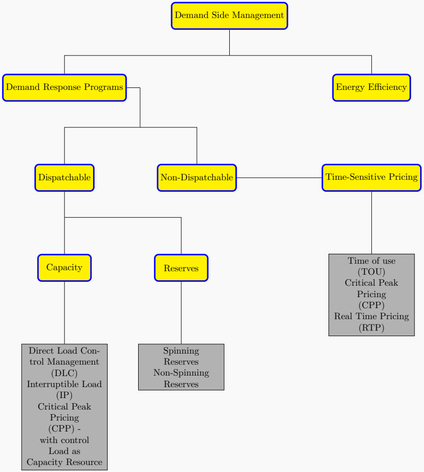
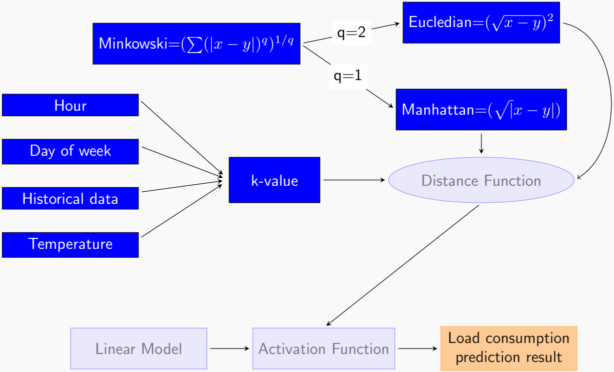
https://www.latimes.com/california/story/2022-09-07/a-text-asked-millions-of-californians-to-save-energy-they-listened-averting-blackouts



Johannesen, N. J., Kolhe, M. L., Goodwin, M. (2022). Recurrent neural networks for electrical load forecasting to use in demand response. Industrial Demand Response: Methods, Best Practices, Case Studies, and Applications, 41.

Regression Model



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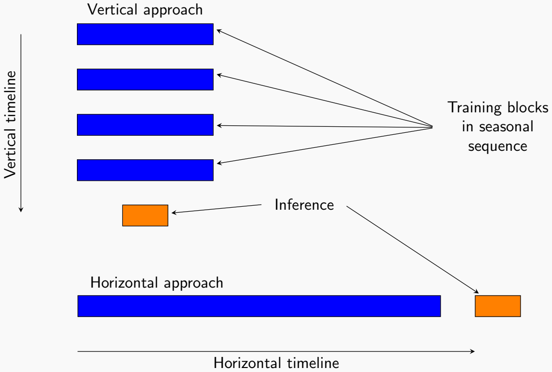
Vertical Approach



Johannesen, N. J., Kolhe, M. L. (2021). Application of regression tools for load prediction in distributed network for flexible analysis. In Flexibility in Electric Power Distribution Networks (pp. 67-94). CRC Press.

Seasons

Season	Months		
Season 1	December	January	February
Season 2	March	April	May
Season 3	June	July	August
Season 4	September	October	November

Table 1: Seasons

Johannesen, N. J., Kolhe, M. L. (2021). Application of regression tools for load prediction in distributed network for flexible analysis. In Flexibility in Electric Power Distribution Networks (pp. 67-94). CRC Press.

Performance Metrics

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}| \tag{3}$$

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|y_i - \hat{y}|}{(|y_i| + |\hat{y}|)/2}\right) * 100 \tag{4}$$

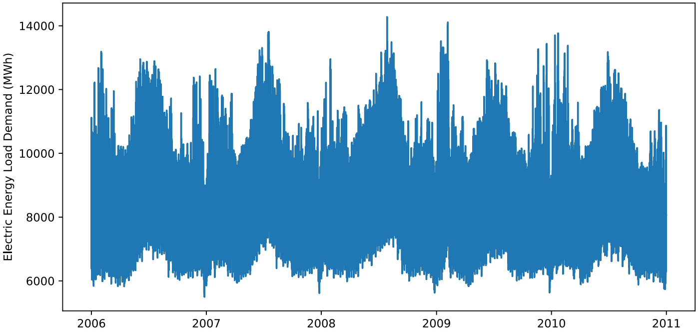
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2 \tag{5}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - \hat{y}}{y_i}| * 100 \tag{6}$$

Johannesen, N. J., Kolhe, M., Goodwin, M. (2019, November). Deregulated electric energy price forecasting in nordpool market using regression techniques. In 2019 IEEE Sustainable Power and Energy Conference (iSPEC) (pp. 1932-1938). IEEE.

Urban Area Load

Sydney Dataset - New South Wales



Johannesen, N. J., Kolhe, M., Goodwin, M. (2019). Relative evaluation of regression tools for urban area electrical energy demand forecasting. Journal of cleaner production, 218, 555-564.

Results

Table 2: MAPE for Urban Area Load

	Regressor		
Time	Random Forest	kNN	Linear
Season One Vertical Approach			
30 minutes	0.94(16*)	1.85(8**,1***)	1.76
24 hours	5.88(13*)	5.49(5**,2***)	5.83
Season Three Vertical Approach			
30 minutes	*0.86(17*)*	1.19(6**,1***)	2.15
24 hours	2.71(17*)	*2.61(17**,1***)*	4.26

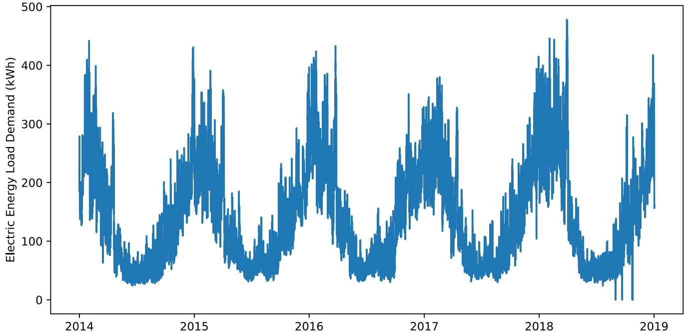
* n-estimator

** k-value

***q-value

Rural Area Load

Bjønntjønn Dataset - 125 Holiday Cabins



Johannesen, N. J., Kolhe, M. L., Goodwin, M. (2020). Smart load prediction analysis for distributed power network of Holiday Cabins in Norwegian rural area. Journal of cleaner production, 266, 121423.

Results

Table 3: Forecasting Results (24 hours prediction) for season 1 (winter) trained with time feature lags of 24-, 48- and 168-hours

Features	Vertical winter			Continous winter		
	SMAPE	**MAPE**	**MAE**	**SMAPE**	**MAPE**	**MAE**
kNN AC	9.88	10.06	26.07	9.72	9.74	25.60
RF AC	10.43	10.67	27.85	9.56	9.49	25.24
kNN AC AR	10.05	10.20	26.39	9.25	9.24	24.42
RF AC AR	10.87	11.03	28.67	10.34	10.34	26.91
kNN AC T H	9.48	9.66	25.09	9.05	9.09	23.89
RF AC T H	11.39	11.53	29.86	11.50	11.53	29.81
kNN AC AR T H	9.75	9.92	25.65	**8.88**	**8.86**	23.45
RF AC AR T H	12.03	12.18	31.56	10.88	10.96	28.06

Conclusions

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- Meaningful relation among pre-processing of data and regression results

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- Machine learning models can help planning for shifting loads

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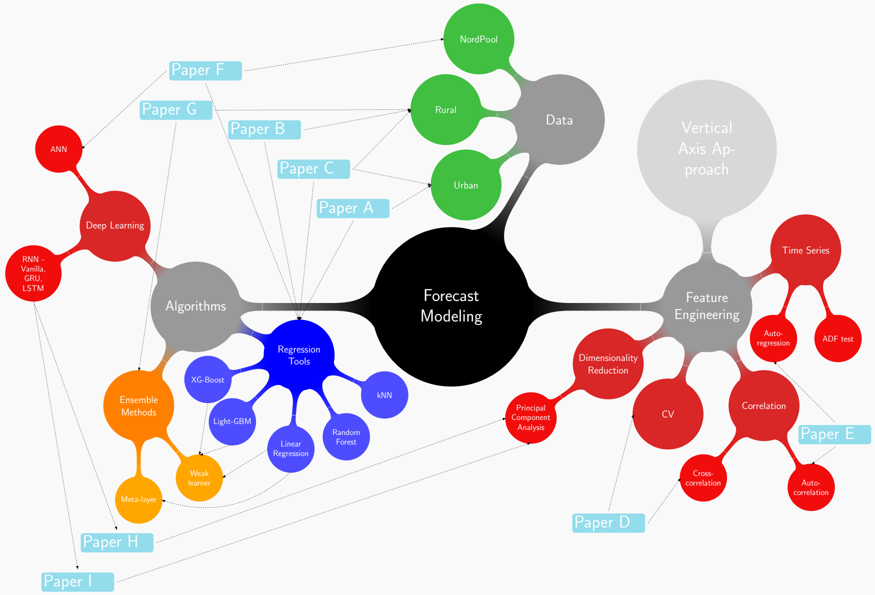
- Practical shifting of loads to help reduce energy consumption

Conclusions

- Meaningful relation among pre-processing of data and regression results
- Machine learning models can help planning for shifting loads
- Practical shifting of loads to help reduce energy consumption
- A future of distributed networks with autonomous networks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Data
NordPool
Rural
Urban
Vertical Axis Approach
Feature Engineering
Time Series
Auto-regression
ADF test
Dimensionality Reduction
Principal Component Analysis
CV
Correlation
Cross-correlation
Auto-correlation
Algorithms
Deep Learning
ANN
RNN - Vanilla, GRU, LSTM
Ensemble Methods
Weak learner
Meta-layer
Regression Tools
XG-Boost
Light-GBM
Linear Regression
Random Forest
kNN
Paper A
Paper B
Paper C
Paper D
Paper E
Paper F
Paper G
Paper H
Paper I