Short term hourly load forecasting during the peak period using quantile regression with an application to the unit commitment problem

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Outline

Introduction

- The energy industry has been going through a significant modernization process in the recent decade.
- Infrastructure is being rapidly upgraded.
- Supply, demand and prices are becoming more volatile and less predictable than ever before.
- This requires probabilistic forecasts to quantify the uncertain future.

The Problem

- We want to forecast the quantiles of hourly loads and use the forecasts as input to the unit commitment problem.
- We have eleven years of hourly electricity demand and temperature data.
- South African aggregated hourly data are used.

The Problem

The problem

- Recently the Southern African region experienced extreme heat waves
  - How frequently will they occur?
  - How long will they last for?
  - What area will they cover?
  - How will they vary with climate?
  - What is the chance of getting a more extreme event?
  - How much more electricity are we going to use during a heat wave period?

Heat waves

Hot spell makes Eskom sweat

October 9 2015 at 12:01pm
By Ilanit Chernick Comment on this story

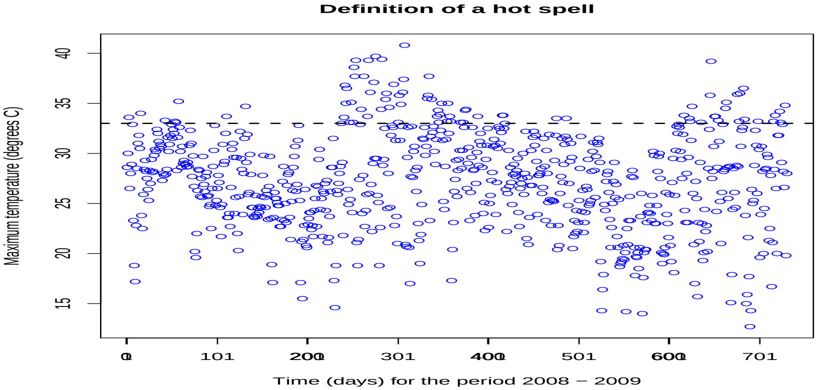
Picture: Dean Hutton

Following over two months of no load shedding, Eskom consumers were this morning warned that things could change due to power capacity concerns and the strain caused by the current heatwave.

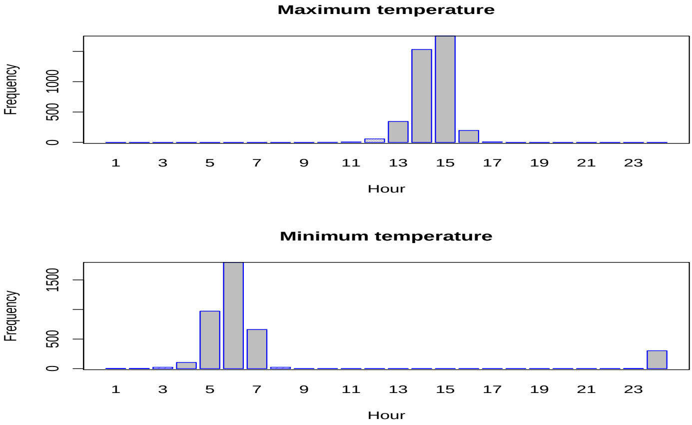
Starting from 6am, the risk of load shedding was so high that power could go off any time till 10pm due to a shortage of generation capacity.

"Load shedding is implemented as a necessary measure to protect the power system. We do this to ensure that maintenance is carried out properly in order to guarantee that our supply of electricity can be maintained in the long term," it said.

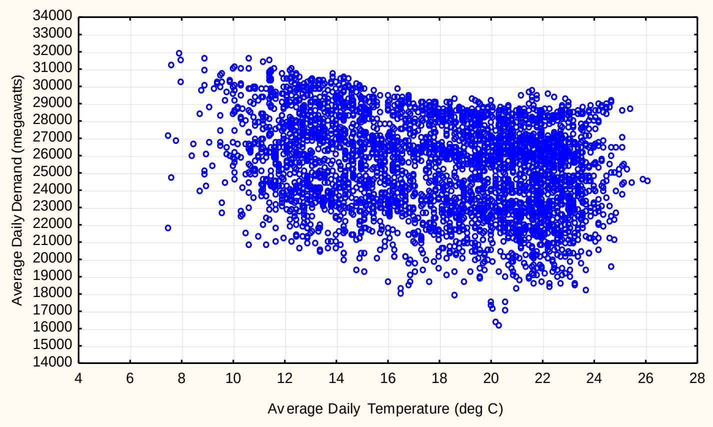
Complex extreme climate events



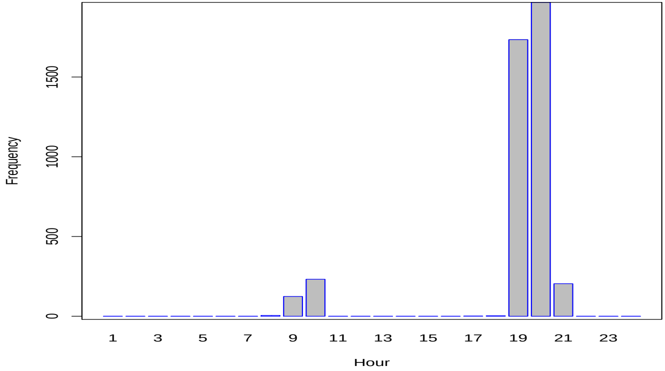
Frequency of occurrence of Max and Min temperatures



Average daily temperature versus average daily demand



Frequency of daily peak demands occurring in different hours of the day



Probabilistic load forecasting: Some applications

Load flow analysis

Uncertainties include generation outages, changes in network configuration, and load forecasting errors.

Reliability planning

Loss of load probability (LOLP)–the probability that the generation supply will not be sufficient to support the electricity demand.

Unit commitment

Determines when to run which generator at what level to satisfy the electricity demand with an objective of minimising the costs subject to several constraints on the units and the system.

Quantile regression with generalized additive models

Generalized additive models (GAMs)

Introduced by Hastie and Tibshirani (1986).

$$\begin{aligned} \boldsymbol{Y}_t &= \mu(\boldsymbol{X}_t) + \varepsilon_t, t = 1, ..., n \\ g(\mu(\boldsymbol{X}_t)) &= f_1(X_{t,1}) + f_2(X_{t,2}) + f_3(X_{t,31}, X_{t,4}) + ... \end{aligned}$$

Find f such that

- fit to data is as best as possible and
- f is as smooth as possible

Quantile regression with generalized additive models

Penalized cubic splines

$$\sum_{t=1}^{n}\left(Y_t - \sum_{i=1}^{p} f_i(X_t^i)\right)^2 + \sum_{i=1}^{p}\lambda_i \int (f_i''(x))^2\, dx$$

Quantile regression with generalized additive models

Quantile regression

Introduced by Koenker and Bassett (1978). Linear QR

$$
\begin{aligned}
Q_\tau(\boldsymbol{Y}|\boldsymbol{x}) &= \boldsymbol{X}'\beta(\tau), 0 \leq \tau \leq 1 \\
\beta(\hat{\tau}) &= \text{argmin}_\beta \sum_{i=1}^{n} \rho_\tau(y_i - x_i'\beta) \\
\rho_\tau(u) &= u\left\{\tau - I(u < 0)\right\} \\
Q(\beta(\tau)) &= \sum_{i:y_i \geq x_i'\beta)}^{n} \tau(y_i - x_i'\beta) + \sum_{i:y_i < x_i'\beta)}^{n} (1-\tau)(y_i - x_i'\beta)
\end{aligned}
$$

Quantile regression with generalized additive models

Two-step approach

1. The GAM is used to linearize the problem
2. For each $\tau \in \{0.01, 0.02, ..., 0.99\}$ we apply linear quantile regression.
3. Our objective is to forecast the τ-quantiles of electricity demand for the next 168 hours. The performance of the prediction at time t is measured by the average pinball loss function over the quantiles:

$$\frac{1}{99}\sum_{\tau=1}^{99}\rho_\tau(Y_t - \hat{q}_{\tau,t})$$

Quantile regression with generalized additive models

Proposed demand model

$$
\begin{aligned}
y_{t,p} &= \text{Box.Cox}(x_{t,p}, \text{lambda}) \\
&= C_p(t) + f_p(\text{temp}) + d_p(y_{t-}, p) + \eta_t
\end{aligned}
$$

Proposed weather station selection methods

1. Denote the weather stations as $s_i, i = 1, ..., S$. Determine the impact of each weather station and rank the stations based on GCV. Select a sample of m of the weather stations and find a weighted average.
2. Divide South Africa into k thermal regions, find the average in each thermal region and determine the impact of each thermal region and rank based on GCV.
3. Use proposed method by Hong et al. (2015)
4. Use proposed method by Hyndman and Fan (2010)

Unit Commitment

The Lagrange relaxation method

The objective function is given as:

$$\min \sum_{h=1}^{H} \sum_{i=1}^{n} \left[F_i \left(P_{Gi}^h \right) x_i^h + F_{si}(h) x_i^h \right] = F \left(P_{Gi}^h, x_i^h \right)$$

The constraints are:

Load balance equation

$$\sum_{i=1}^{n} P_{Gi}^h x_i^h = P_D^h, h = 1, ..., H$$

Generator power output limits

$$x_i^h P_{Gi\min} \leq P_{Gi}^h \leq x_i^h P_{Gi\max}, h = 1, ..., H$$

Unit Commitment

The Lagrange relaxation method

Power reserve constraints

$$\sum_{i=1}^{n} P_{Gi}\max x_i^h \geq P_D^h + P_R^h, h = 1, ..., H$$

Minimum up/downtime constraints

$$\left(U_{h-1,i}^{up} - H_i^{up}\right)\left(x_i^{h-1} - x_i^h\right) \geq 0, h = 1, ..., H,\ i = 1, ..., n$$

$$\left(U_{h-1,i}^{down} - H_i^{down}\right)\left(x_i^h - x_i^{h-1}\right) \geq 0, h = 1, ..., H,\ i = 1, ..., n$$

Unit Commitment

The Lagrange function

$$L(P,x,\lambda,\beta) = F\left(P_{Gi}^h, x_i^h + \sum_{h=1}^{T}\lambda_h\left(P_D^h - \sum_{i=1}^{n}P_{Gi}^h x_i^h\right)\right.$$
$$\left.+\sum_{h=1}^{H}\beta_h\left(P_D^h + P_R^h - \sum_{i=1}^{n}P_{Gi}\mathrm{max}\, x_i^h\right)\right)$$

The Lagrange relaxation model

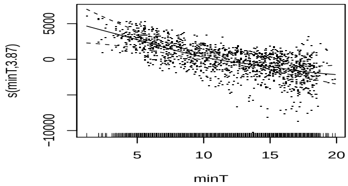
$$q(\lambda,\beta) = \min_{P,x} \sum_{i=1}^{n} \sum_{h=1}^{H} \left\{ \left[F_i\left(P_{Gi}^h\right) + F_{si}(h) \right] x_i^h - \lambda_h P_{Gi}^h x_i^h - \beta_h P_{Gi\max} x \right.$$

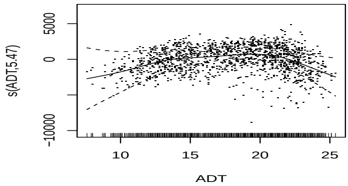
$$x_i^h P_{Gi\min} \leq P_{Gi}^h \leq x_i^h P_{Gi\max}, h = 1, ..., H$$

$$\left(U_{h-1,i}^{up} - H_i^{up}\right)\left(x_i^{h-1} - x_i^h\right) \geq 0, h = 1, ..., H,\ i = 1, ..., n$$

$$\left(U_{h-1,i}^{down} - H_i^{down}\right)\left(x_i^h - x_i^{h-1}\right) \geq 0, h = 1, ..., H,\ i = 1, ..., n$$

20:00 hours


s(minT,3.87)
5000
0
-10000
5
10
15
20
minT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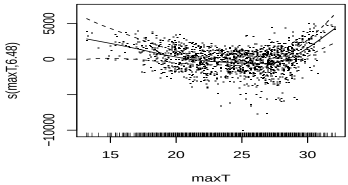
5000
0
-10000
10
15
20
25
ADT


s(maxT,6.48)
5000
0
-10000
15
20
25
30
maxT

Results for out-of-sample test

Table : Results for out-of-sample test for 1 July to 27 August 2010 (Unit of index: MAPE(%); MAE(MW)).

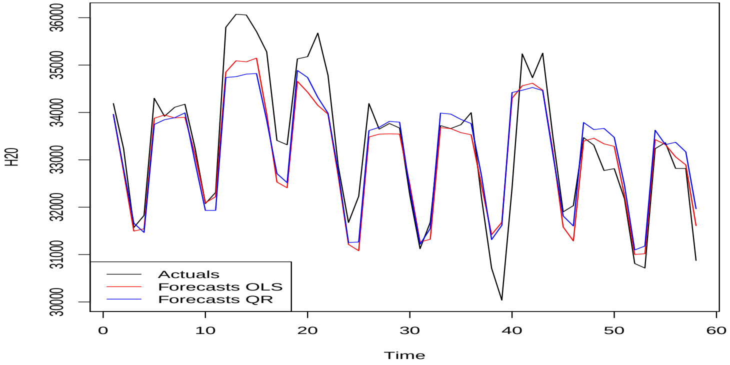
	H19		H20		H21	
	OLS	QR	OLS	QR	OLS	QR
RMSE	800.94	812.96	637.84	672.79	741.73	743.72
MAE	638.66	659.35	471.32	513.58	565.33	561.15
MAPE	1.91	1.97	1.41	1.54	1.75	1.74

Results for out-of-sample test

Table : Results for out-of-sample test at different quantile levels.

Date	**fq0.01**	**fq0.25**	**Actual**	**fq0.5**	**fq0.75**	**fq0.9**	**fq0.99**
1/7/10	31817	33367	**34190**	**33959**	34378	34736	35244
2/7/10	31112	32232	**33235**	**32801**	33329	33629	33969
3/7/10	29817	31084	**31570**	**31662**	32246	32596	32829
4/7/10	29482	30981	**31827**	**31467**	31933	32376	32892
5/7/10	31268	33252	**34299**	**33746**	34190	34525	35044

20:00 hours


H20
30000
31000
32000
33000
34000
35000
36000
0
10
20
30
40
50
60
Time
Actuals
Forecasts OLS
Forecasts QR

Research maturity and future research directions

For details see (Hong et al., 2016)

- Fusion of energy forecasting problems, e.g., when residential customers install solar rooftops without sub-metering.
- Increased use of high resolution data, temporally and spatially.
- With the increasing penetration of solar power (in the forms of both rooftops and solar farms), research of solar power forecasting is expected to grow.

Research maturity and future research directions

- Organize energy forecasting competitions
- Organize regular conferences in energy forecasting.
- Interdisciplinary collaborations with other communities (SAURAN, meteorological forecasting community (SAWS), etc).
- A society for energy forecasters: The researchers working on energy forecasting are spread across various different technical societies.
- ICCSSA/SASA/ORSSA Grant to promote research on forecasting.

Challenges posed by the evolution of the electric grid

Some of the challenges are forecasting (Hong et al., 2016)

- demand at the premises level,
- trend of rooftop PV penetration,
- changes in load due to demand response programs,
- system interruptions due to severe weather conditions (heatwaves, snow, etc).

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References

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