

# IEEE-CIS Predict-Optimize Technical Challenge

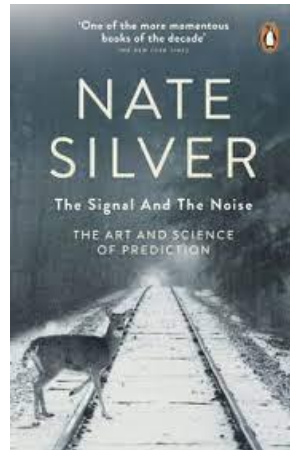
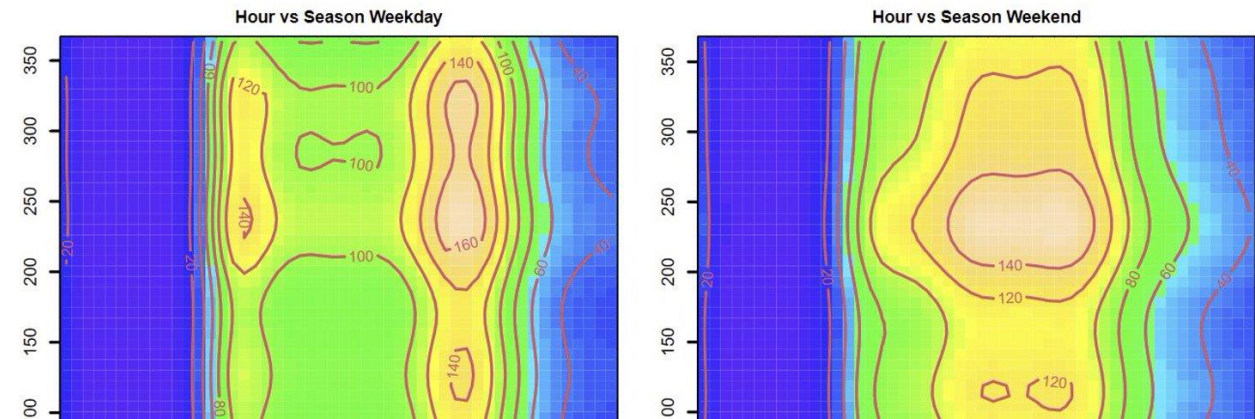
**Richard Bean**

Centre for Energy Data Innovation  
School of Information Technology and  
Electrical Engineering  
**University of Queensland**  
Australia

Newcastle Institute for Energy and Resources  
**University of Newcastle**  
Australia  
(most of the time physically based in  
Newcastle, NSW)



- Ph.D. mathematics (UQ 2001, combinatorics)
- ROAM Consulting (now EY) 2007-2012
- AEMO (Australian Energy Market Operator) 2013
- Redback Technologies (2016-2019)
- University of Queensland (2019-2022)
  - Centre for Energy Data Innovation <https://cedi.uqcloud.net/>
- Australian and NZ Electricity Market regional and sub-regional demand at ROAM/AEMO – “macro” forecasting
- Individual buildings/solar/distribution transformers at Redback/UQ from inverter or smart meter data - “micro” forecasting
- Cybersecurity – localization of houses with ERA5 solar / load data
- ROAM – simple quadratic programming for modelling NEM bidding (COIN-OR)
- Battery/inverter scheduling at Redback – linear programming
- Combinatorics / graph theory – 0-1 integer programming (CPLEX, BonsaiG, COIN-OR, Gurobi)
- Bike sharing forecasting with GAMs and ERA5 data emph. explainability >> error rate ~ energy
- Classical cryptanalysis – pattern recognition (closely connected)



- The most important step! Reproducible code
- Find the approach that gives the lowest MASE for each time series on phase 1
- R script change PHASE value to 2 and rerun

```
rm(list=ls())
PHASE <- 1
FLIST <- c("phase_1_data.tsf", "phase_2_data.tsf")
PDAY <- c(31, 30)
PMONTH <- c(10, 11)
DAYS <- PDAY[PHASE]
PERIODS <- DAYS * 24 * 4
HOURS <- DAYS * 24
HOUR1 <- HOURS - 1
FIRSTPERIOD <- paste("2020-", PMONTH[PHASE], "-01 00:00:00", sep="")
```

## Data Replication & Reproducibility

PERSPECTIVE

### Reproducible Research in Computational Science

Roger D. Peng

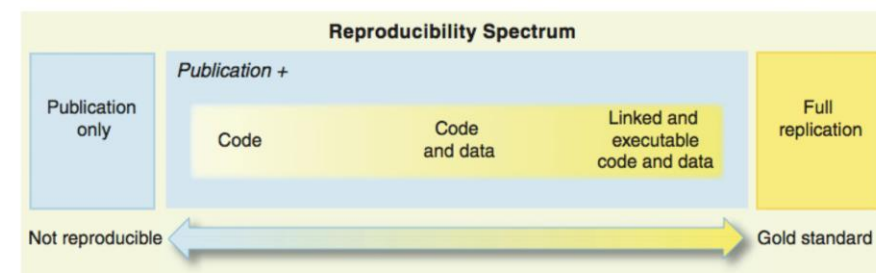
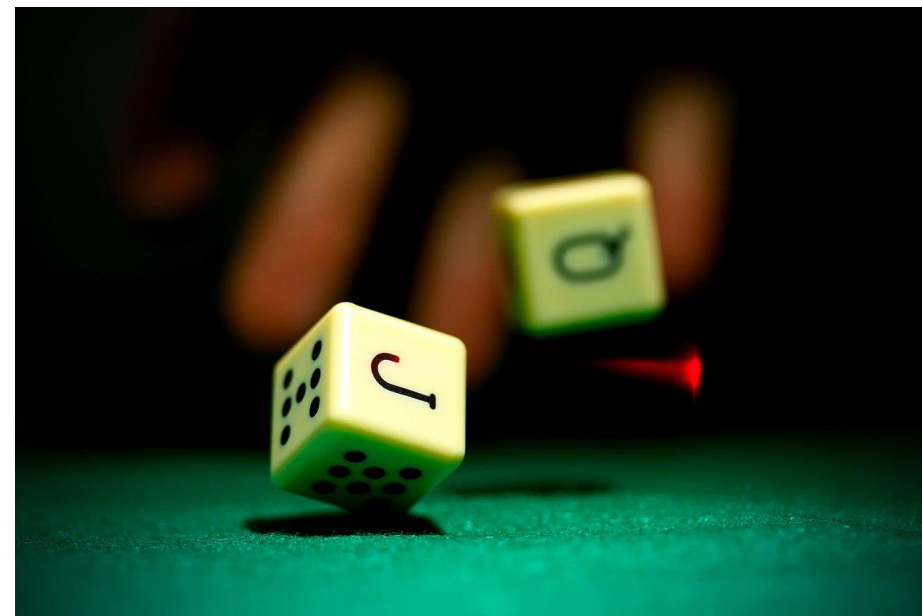


Fig. 1. The spectrum of reproducibility.

1226

2 DECEMBER 2011 VOL 334 SCIENCE www.sciencemag.org

If you think the competition is just pure skill you won't enter Phase 2 but if you think luck is involved you'll definitely just run your Phase 1 model on Phase 2. i.e. it's better for the competitors and competition organizers if they believe luck is involved.







**Pedro Domingos** @pmddomingos · Sep 30

...

Considering that **random forests** have many layers and beat **deep learning** in most applications, maybe we just need to rebrand them as deep forests and they'll be the next big thing.

35

95

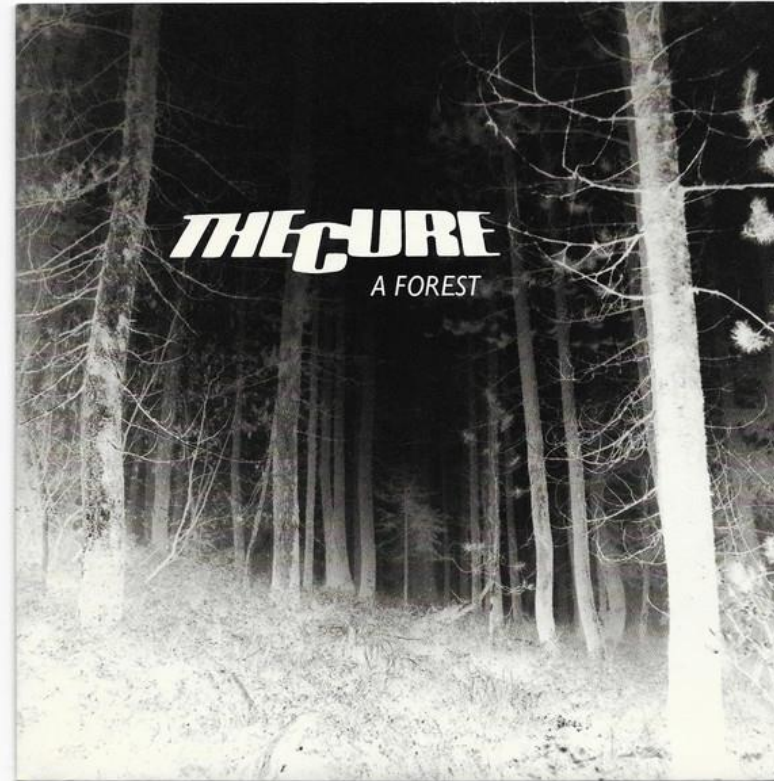
731



Led Zeppelin - Stairway To Heaven - Seattle 07-17-1977 Part 18  
5,304,014 views · 19 Dec 2014

22K 1.7K SHARE SAVE ...

Led Zeppelin

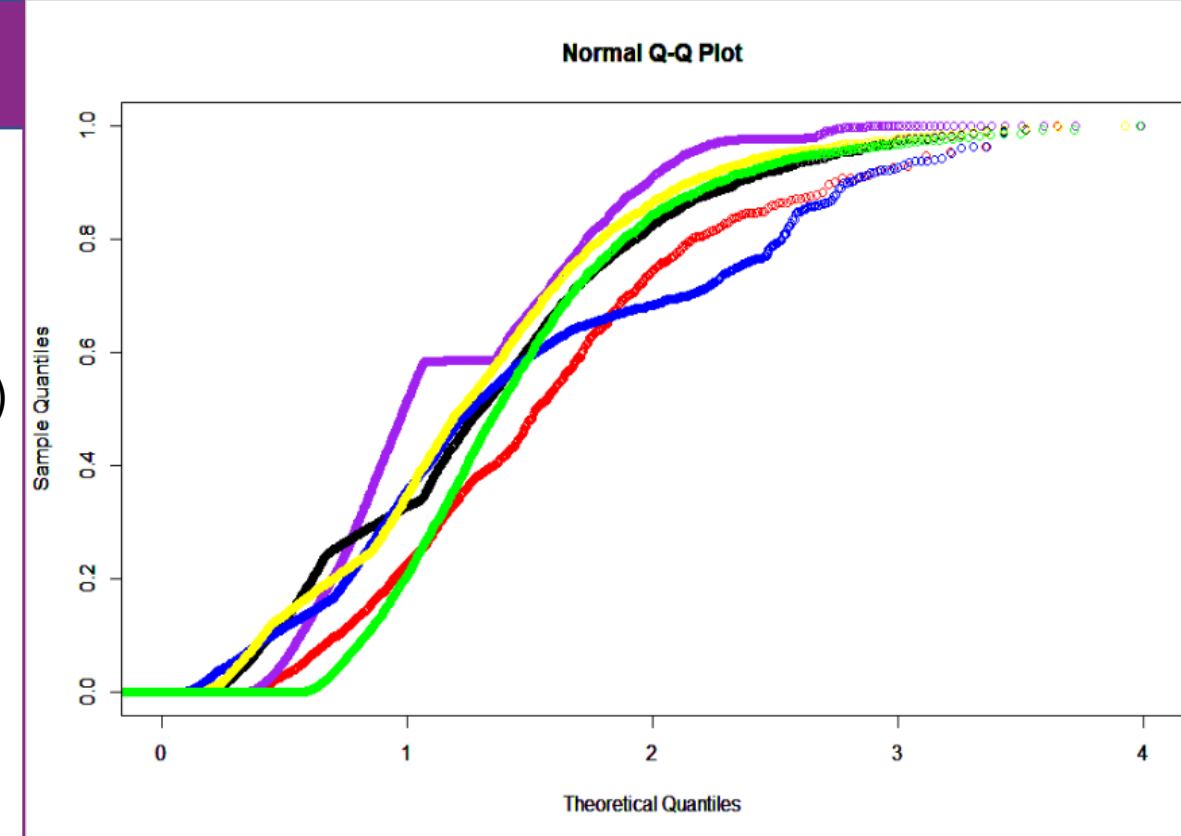


The Cure



Thom Pace

- Quantile regression forest – forecast **median** to minimise MAE
- (i.e. sum of deviations from actual value)
- Most important parameter to tune – “*mtry*”
- Training against individual phase 1 time series (without overfitting)
- Each hour gets 4 random forests (each quarter hour)
- Choosing building start months of 2020 (Building 0,1,3,6)
- Removing building outliers
- Choosing solar start months (Solar1 has some cumulative data)
- Predictor variables: ECMWF vars lead/lag 3h, day of week, day of year etc
- Public holiday – 23 October Grand Final holiday excluded from training
- Building4 and Building5 set to median values of Oct 2020 (1 and 19 kW)
- Forecast groups of buildings and solar together with normalization (critical, but mentioned by organizers “*cross-learning across time series*”)
- Using BOM daily and ECMWF 1 hour data together (critical ... is this surprising?)
- Solar0 and Solar5 thresholding hugely improves MASE (critical)

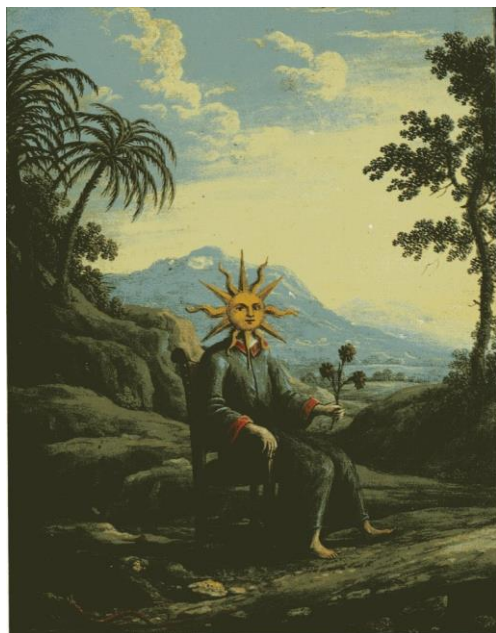


# MASE EXPECTATION

Almost all my forecast MASE improvement came after Phase 1 data was released.

Obviously lots of room to improve Solar0/5 still

*“Progress usually comes from many small improvements; a change of 1% can be a reason to break out the champagne.”*

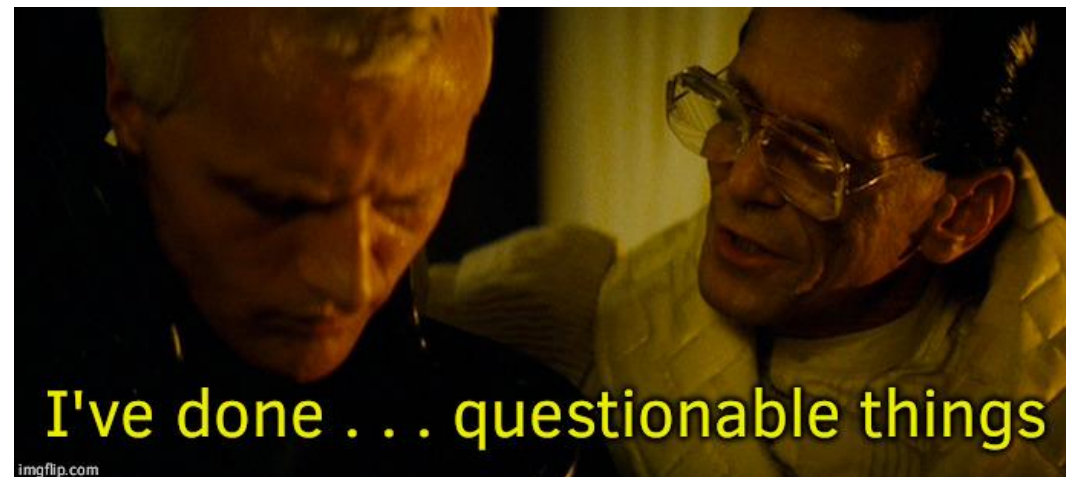


| Case      | MASE Phase 1 | MASE after tuning |
|-----------|--------------|-------------------|
| Building0 | 0.4301       | 0.3859            |
| Building1 | 0.6115       | 0.4251            |
| Building3 | 0.3310       | 0.2913            |
| Building4 | 0.5637       | 0.5637            |
| Building5 | 1.0370       | 0.8383            |
| Building6 | 0.7676       | 0.7336            |
| Solar0    | 0.8479       | 0.6558            |
| Solar1    | 0.4619       | 0.3619            |
| Solar2    | 0.5251       | 0.4139            |
| Solar3    | 0.5910       | 0.4990            |
| Solar4    | 0.5624       | 0.4219            |
| Solar5    | 0.8559       | 0.6092            |
| Mean      | 0.6320       | 0.5166            |

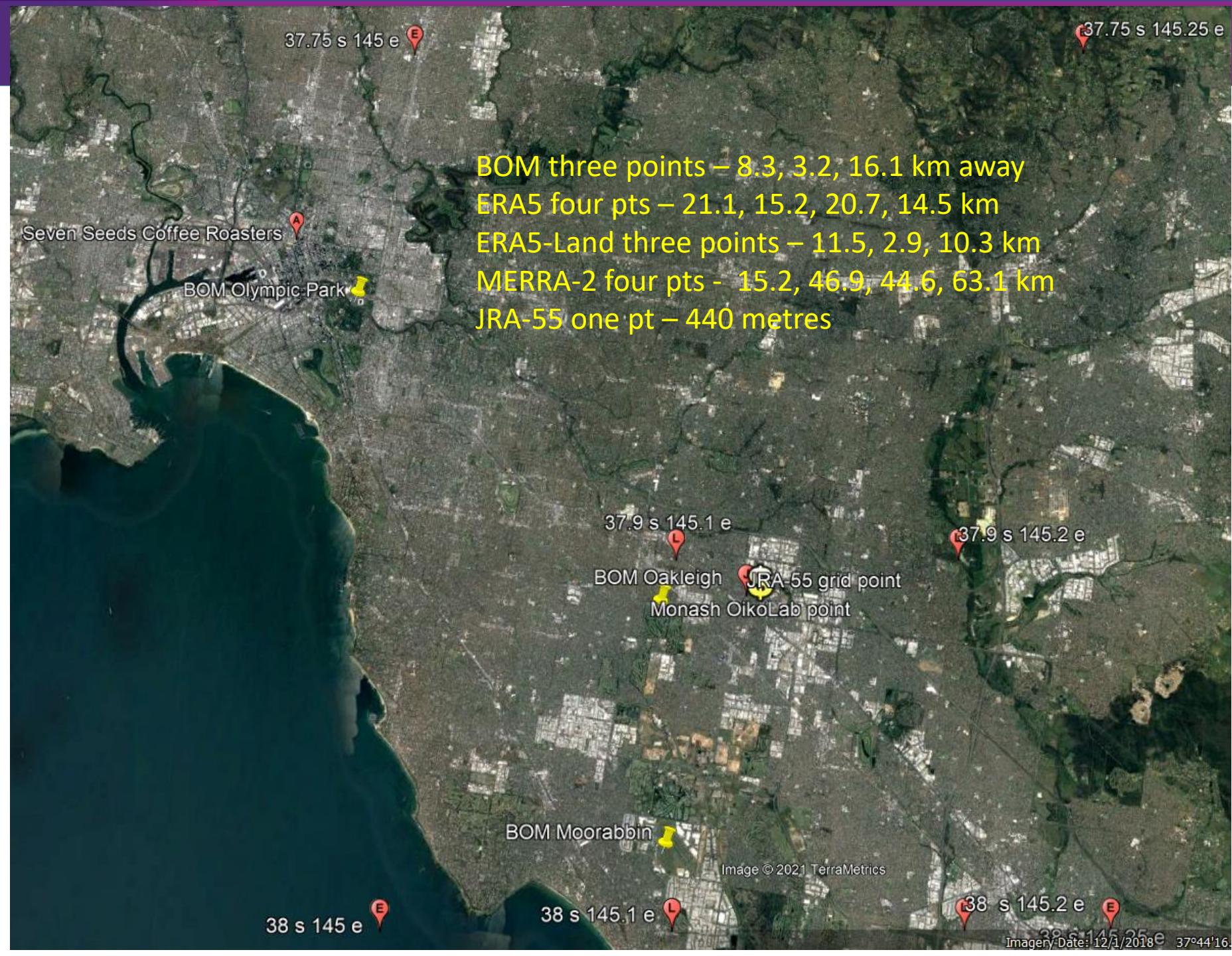
Questioning how provided ERA-5 data was derived.

Inverse distance weighting (exponent 2) of four ERA-5 points (0.25 degrees).

Lots of subtleties e.g. exponent choice in IDW, losing wind speed dir/quant nuances.







BOM three points – 8.3, 3.2, 16.1 km away  
ERA5 four pts – 21.1, 15.2, 20.7, 14.5 km  
ERA5-Land three points – 11.5, 2.9, 10.3 km  
MERRA-2 four pts - 15.2, 46.9, 44.6, 63.1 km  
JRA-55 one pt – 440 metres

- Could Phase 1 forecast have been improved with extra data (NWP, AEMO etc) or a different approach? (using AEMO data might be a bit circular)

Yes, but not by large amounts

- [AEMO](#) price and [demand](#) data (had to download 3 files for competition Phase 1 & 2) is *half hourly* – is microgrid subject to wholesale price? Price/Demand improves B0/B6 forecast!
- [AEMO](#) Rooftop PV Actual data from NemWeb is *half hourly*
- [ERA5](#) precipitation data – e.g. ILSPF “Instantaneous large-scale surface precipitation fraction”
- [ERA5-Land](#) data is 0.1 degrees – but only 3 points to interpolate from
- Other solar vars for PVLib: FDIR ~ GHI, SSRDC, CDIR to derive DNI, DHI etc. Diffuse radiation.
- Wind direction
- [JRA-55](#) has 3-hourly data grid point 400 m from Monash
- NASA [MERRA-2](#) 1h data - SWGNT ~ SSRD
- [GFS](#) reanalysis data (3-hourly) is painful to process
- [PvOutput.org](#) has many nearby points (5 min data, \$15 donation for 1 year access) or [Solar Analytics](#)
- [WeatherMan/Solcast](#) approach – derive solar installation parameters from data, resimulate



- Solving the model as a **MIP** is much easier than solving the MIQP.
- Almost all of the submitted solution depends on first deriving the best MIP solution possible (i.e. **minimizing the recurring load or minimizing the recurring + once-off load**) and only then solving as an MIQP
- Gurobi 9.1.2 (laptop phase 1, UQ HPC phase 2)
- Various papers about “Predict+Optimize” problem but Phase 1 and leaderboard seem to indicate **no close relationship between forecast result and cost**. Complex problem, competition issues, limited time

## problem formulation: arrays



| Decision Variables |                                  |                       | Parameters |                  |                       |
|--------------------|----------------------------------|-----------------------|------------|------------------|-----------------------|
| Name               | Dimension                        | Description           | Name       | Dimension        | Description           |
| $x$                | $\{0, 1\}^{P \times C \times T}$ | Schedule              | $P$        | $\mathbb{Z}_+$   | # production lines    |
| $y$                | $\{0, 1\}^{P \times C}$          | Production line       | $C$        | $\mathbb{Z}_+$   | # cheeses             |
| $s$                | $\{0, 1\}^{C \times T}$          | Production start time | $T$        | $\mathbb{Z}_+$   | # time periods        |
|                    |                                  |                       | $k$        | $\mathbb{R}_+^C$ | Unit production times |
|                    |                                  |                       | $d$        | $\mathbb{R}_+^C$ | Demand                |

minimize  $L$   
subject to  $L \geq (t \cdot x_{p,c,t}) \quad \forall p, c, t$   
 $(\sum_{p,t} x_{p,c,t}) \geq k_c \cdot d_c \quad \forall c$   
 $(\sum_c x_{p,c,t}) \leq 1 \quad \forall p, t$   
 $y_{p,c} = \max_t \{x_{p,c,t}\} \quad \forall p, c$   
 $(\sum_p y_{p,c}) \leq 1 \quad \forall p, t$   
 $s_{c,t} = \max(0, x_{p,c,t} - x_{p,c,(t-1)}) \quad \forall t > 0$   
 $(\sum_t s_{c,t}) \leq 1 \quad \forall c$

## problem formulation: tuples



| Decision Variables |                             |                              | Parameters |                  |                       |
|--------------------|-----------------------------|------------------------------|------------|------------------|-----------------------|
| Name               | Dimension                   | Description                  | Name       | Dimension        | Description           |
| $(s, e, \ell)$     | $\mathbb{Z}_+^{3 \times C}$ | (Start time, End time, Line) | $P$        | $\mathbb{Z}_+$   | # production lines    |
| $r, \hat{r}$       | $\{0, 1\}^{C \times C}$     | Comparison of start times    | $C$        | $\mathbb{Z}_+$   | # cheeses             |
| $m, \hat{m}$       | $\{0, 1\}^{C \times C}$     | Same production line         | $T$        | $\mathbb{Z}_+$   | # time periods        |
|                    |                             |                              | $k$        | $\mathbb{R}_+^C$ | Unit production times |
|                    |                             |                              | $d$        | $\mathbb{R}_+^C$ | Demand                |
|                    |                             |                              | $M$        | $\mathbb{R}$     | Big M (e.g., 1e6)     |

minimize  $L$   
subject to  $L \geq e_c \quad \forall c$   
 $(e_c - s_c) > k_c \cdot d_c \quad \forall c$   
 $\hat{r}_{c_1, c_2} \geq (1/M) \cdot (s_{c_1} - s_{c_2}) \quad \forall c_1, c_2$   
 $r_{c_1, c_2} = 1 - \hat{r}_{c_1, c_2} \quad \forall c_1, c_2$   
 $\hat{m}_{c_1, c_2} \leq (1/M) \cdot |\ell_{c_1} - \ell_{c_2}| \quad \forall c_1, c_2$   
 $\hat{m}_{c_1, c_2} \leq M \cdot |\ell_{c_1} - \ell_{c_2}| \quad \forall c_1, c_2$   
 $m_{c_1, c_2} = 1 - \hat{m}_{c_1, c_2} \quad \forall c_1, c_2$   
 $\min(m_{c_1, c_2}, r_{c_1, c_2}) \cdot (s_{c_2} - e_{c_1}) > 0 \quad \forall c_1, c_2$

$r_{c_1, c_2} = 1$  iff  $c_1$  production starts before  $c_2$

#optimization #datascience #dataanalytics  
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# NOW THAT WE HAVE A GOOD STARTING POINT ...

- **Conservative** is just choosing the lowest recurring load and lowest recurring + once off load and evaluating cost using a naive or flat forecast. This was probably the winning approach for cost in Phase 1, as some competitors had winning results with no forecast, or a poor forecast, but seemed pointless to me as the organizers said quality of forecast should contribute to results in phase 2.
- **Forced discharge** forbids any charging in peak hours, and forces at least one of the two batteries to be discharging in every peak period.
- **No forced discharge** forbids any charging in peak hours, but the MIQP solver decides whether to discharge or do nothing in those hours.
- **Liberal** allows charging in peak, but the maximum of recurring + once off + charge effect for each period is limited to the maximum of recurring + once off load over all periods. This is to avoid nasty surprises when the solver thinks that a period has low underlying load and schedules a charge (due to a low price in that period) but then accidentally increases the maximum load over all periods, which can be very costly.
- **Very liberal** allows charging over peak and does not attempt to control the maximum of recurring + once off + charge effect. This would be the best approach if the forecast was perfect.

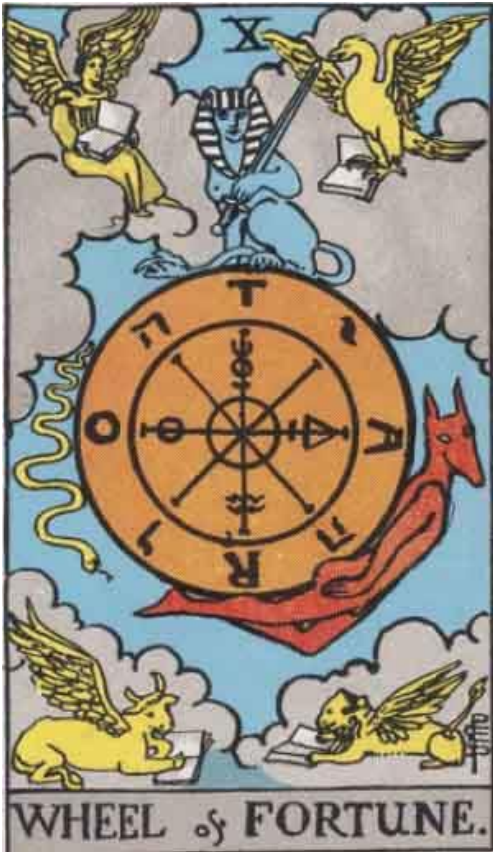


Estimated total cost (3 November) -- \$261,906

| Case   | Estimated Cost | Actual Cost |
|--------|----------------|-------------|
| small0 | 26681          |             |
| small1 | 26233          |             |
| small2 | 26251          |             |
| small3 | 26452          |             |
| small4 | 26107          |             |
| large0 | 26265          |             |
| large1 | 26666          |             |
| large2 | 25389          |             |
| large3 | 26010          |             |
| large4 | 25849          |             |
| Total  | 261906         |             |

Only Large2/Large4 had the once-off load in, all activities, in peak.

The estimated cost is very different from the real cost.



- Random forest – 4 models for each hour
  - Use daily BOM solar data + ECMWF hourly data + temporal variables
  - Train buildings and solar together in groups
  - Thresholding two solar series
- 
- Arrays approach with 0-1 Mixed Integer Program (MIP)
  - First minimize recurring and recurring + once-off load, then solve MIQP
  - “No forced discharge” approach chosen from 5 approaches



Contact information

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