YR21 Energy Investment Decision Support System

Case Studies

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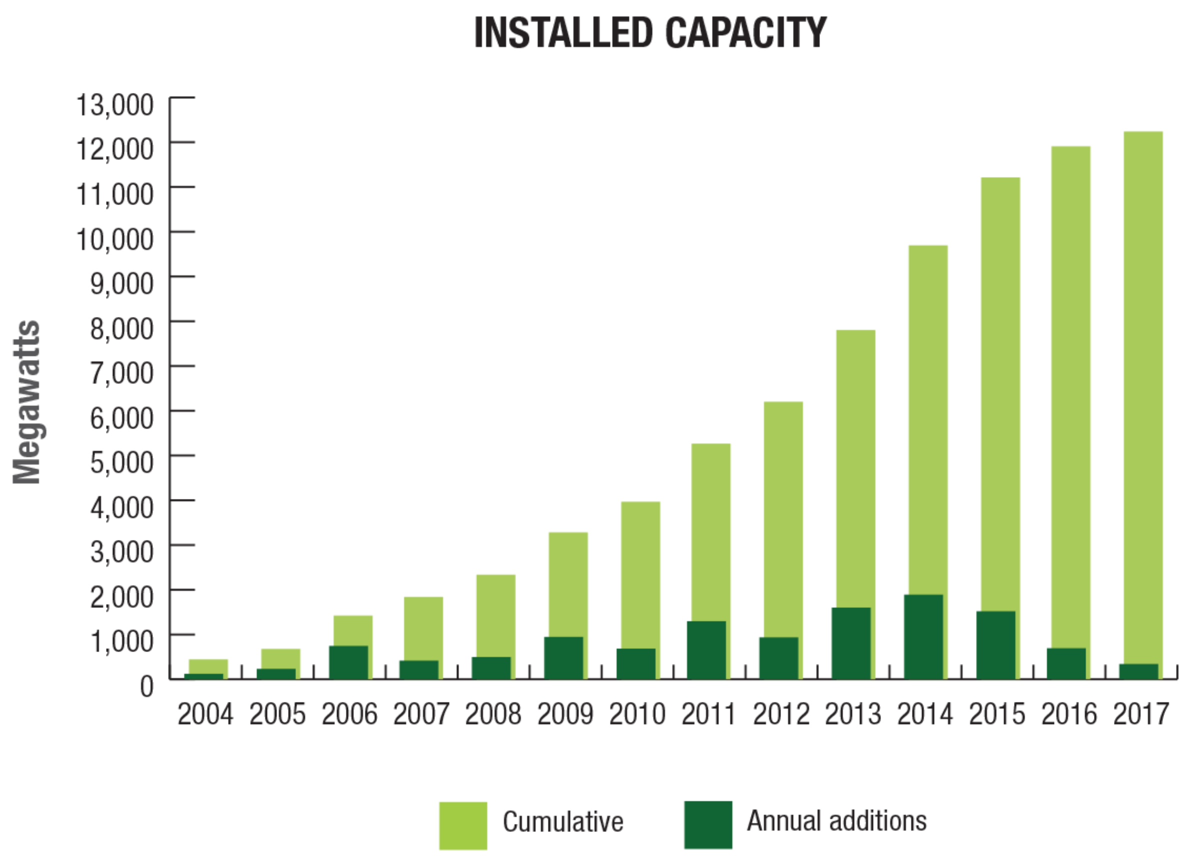
The Year 21 Problem

- The remarkable rise of Wind power in Ontario has been enabled by generous, 20 year long, Feed in Tariff contracts.
- These allow wind energy producers to sell the first 20 years of their production at a fixed individual tariff which substantially exceeds the market price.
- Much of the physical wind turbine plant was expected to last about 20 years also.
- What happens at year 21?

Large growth in Canadian Wind Power: Source NRCAN



At Year 21

Close

- Power price received falls by factor of up to 10
- Many components (blades, generators, power electronics) starting to fail
- Just close the farm and walk away.

What if a blade breaks Year 18?

- Is it worth it to fix or should the turbine be decommissioned even before year 20?

Continue

Drivers

- A lot of the cost of a wind farm is bound up in the land and the social license to use it, the foundation (100 year asset), the tower (50+ years?), the access roads and transmission link
- Technological improvements to some pieces

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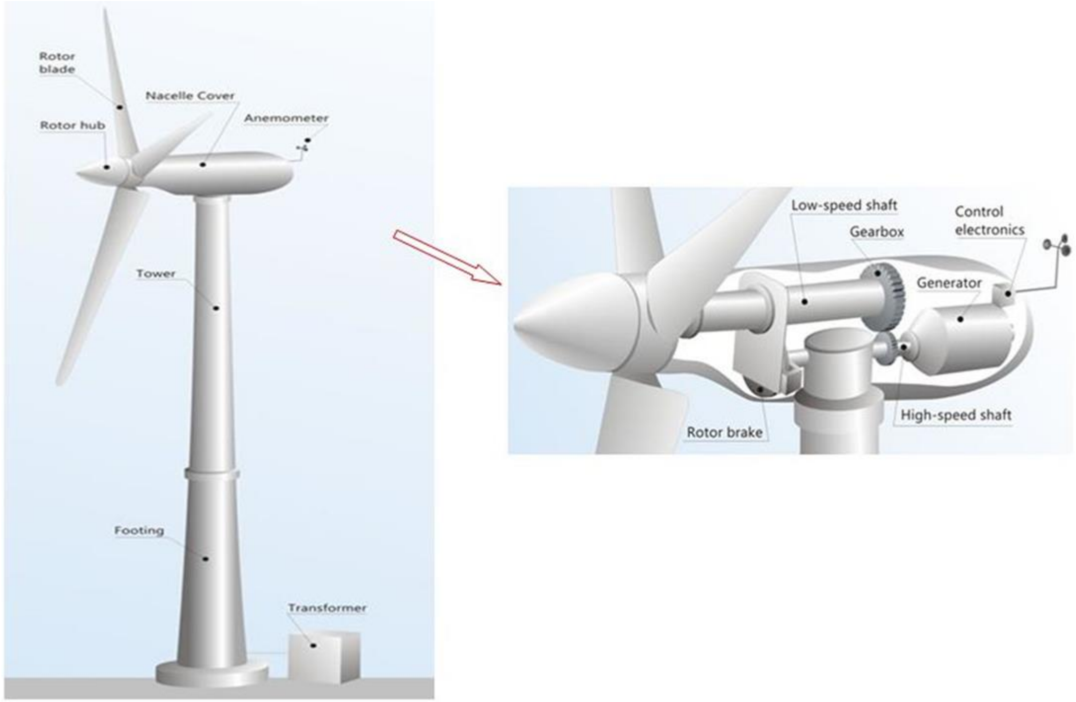

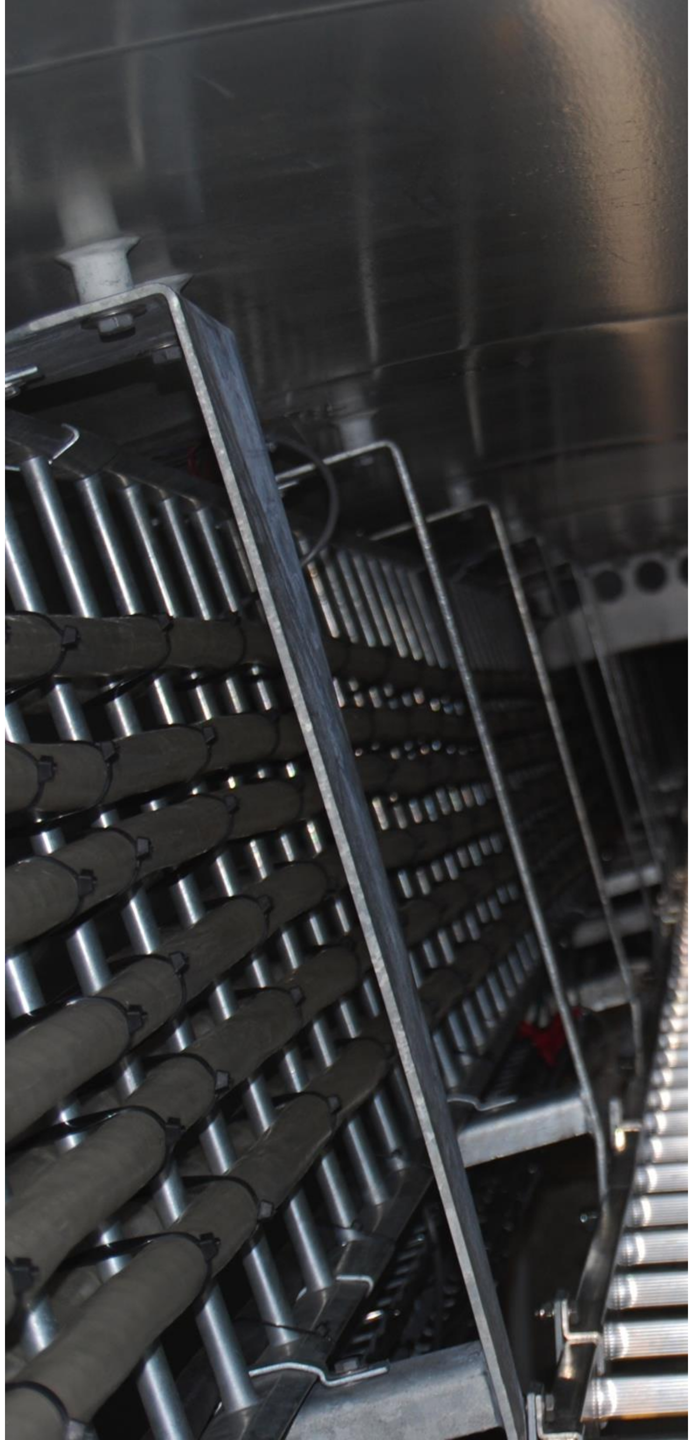

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YR21 Background

- **Academic-Industrial Collaboration**

- **Objectives**
  - ✓ **Maximize the value of historical and future investments in energy assets**
  - ✓ **Provide informed direction for business decisions**

- **Methodology**
  - ✓ **Leverage all *available* farm data to develop prediction models and multiple investment scenarios**

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Three Case studies

- Generator Failure Case Study – age structured population modelling
- Delta Unit study – the power of technical improvement
- Scenario Analysis for post year 21

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Case Study: Background

PROBLEM SETUP

- Pre-midlife wind farm has N generators
- n generators have failed already
- If a generator fails unexpectedly you must:
  - ✓ Order a crane
  - ✓ Wait for the crane to arrive
  - ✓ Repair generator
- While you are waiting for the crane you are not producing power

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Case Study: Background

INDICATIVE ASSUMPTIONS

- Cost of generator = $60,000
- Cost of crane = $12,000/week (1 week minimum rental)
- Cost of labour to replace generator = $5,000 (takes one day)
- Time spent waiting for crane 1-4 weeks (average = 2 week)
- Estimate of lost revenue = 14 d*24 hr*2.0 MW*0.30CF*$140/MWh = $28k

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Case Study: Simple Financials

FINANCIAL IMPACTS

Proactive Approach [Replace 5 generators at once] = $69,400*/gen
***save on crane rental and lost production**

Reactive Approach [Replace 5 generators as they fail] = $95,800/gen

- **The ratio of these costs is about 1.37**
- **If repair proactively we pay a cost = C**
- **If repair reactively we pay 1.37C**
- **If we wait there is a probability p that the generator fails and we pay 1.37C, but there is also probability (1-p) that we get away with it and pay nothing**
- **The breakeven probability for this when C = p*1.37C OR p = 73%**
- **To work this out we need a failure model**

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Case Study: Failure Modeling

LIFE DATA ANALYSIS

- **Utilize a Weibull failure model that incorporates aging**

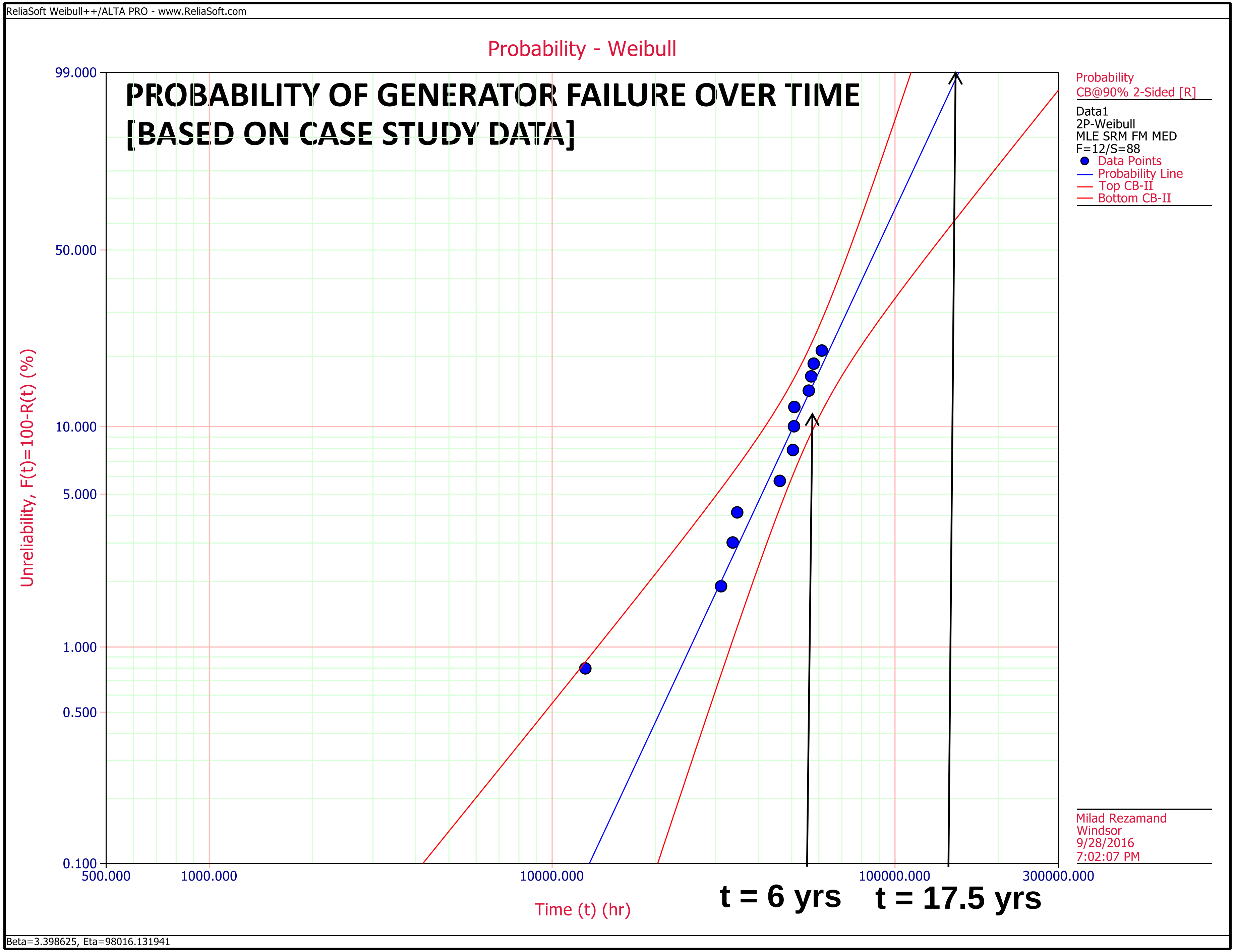
$$f(T;\eta,\beta) = (\beta/\eta)(T/\eta)^{\beta-1}\exp[-(T/\eta)^{\beta}], \quad T > 0$$

- **Where is the T is time to failure of component from birth, η is the scale parameter, and β is the shape parameter**

- **We use Maximum Likelihood Estimation to fit the model to our data set**

Failure rate

- Failure rate at time t is given by
- $h(t,\beta,\eta) = (\beta/\eta)(t/\eta)^{\beta-1}$
- For our generator failure data, $\beta = 3.39$ and $\eta = 98{,}000$ hours = 11.2 years [MD this is for age, or use life?]
- This corresponds to a mean life of $\eta\Gamma(1+1/\beta) = 10.06$ years
- (Significant uncertainty in these estimates which are based on 12 failures, 77 non failures, of generators on 88 wind turbines, none of which are older than about 6 years CHECK ALL THIS – numbers don't add up because one fails twice.


ReliaSoft Weibull++/ALTA PRO - www.ReliaSoft.com
Probability - Weibull
PROBABILITY OF GENERATOR FAILURE OVER TIME
[BASED ON CASE STUDY DATA]
Probability
CB@90% 2-Sided [R]
Data1
2P-Weibull
MLE SRM FM MED
F=12/S=88
Data Points
Probability Line
Top CB-II
Bottom CB-II
99.000
50.000
10.000
5.000
1.000
0.500
0.100
Unreliability, F(t)=100-R(t) (%)
500.000
1000.000
10000.000
100000.000
300000.000
Time (t) (hr)
t = 6 yrs
t = 17.5 yrs
Milad Rezamand
Windsor
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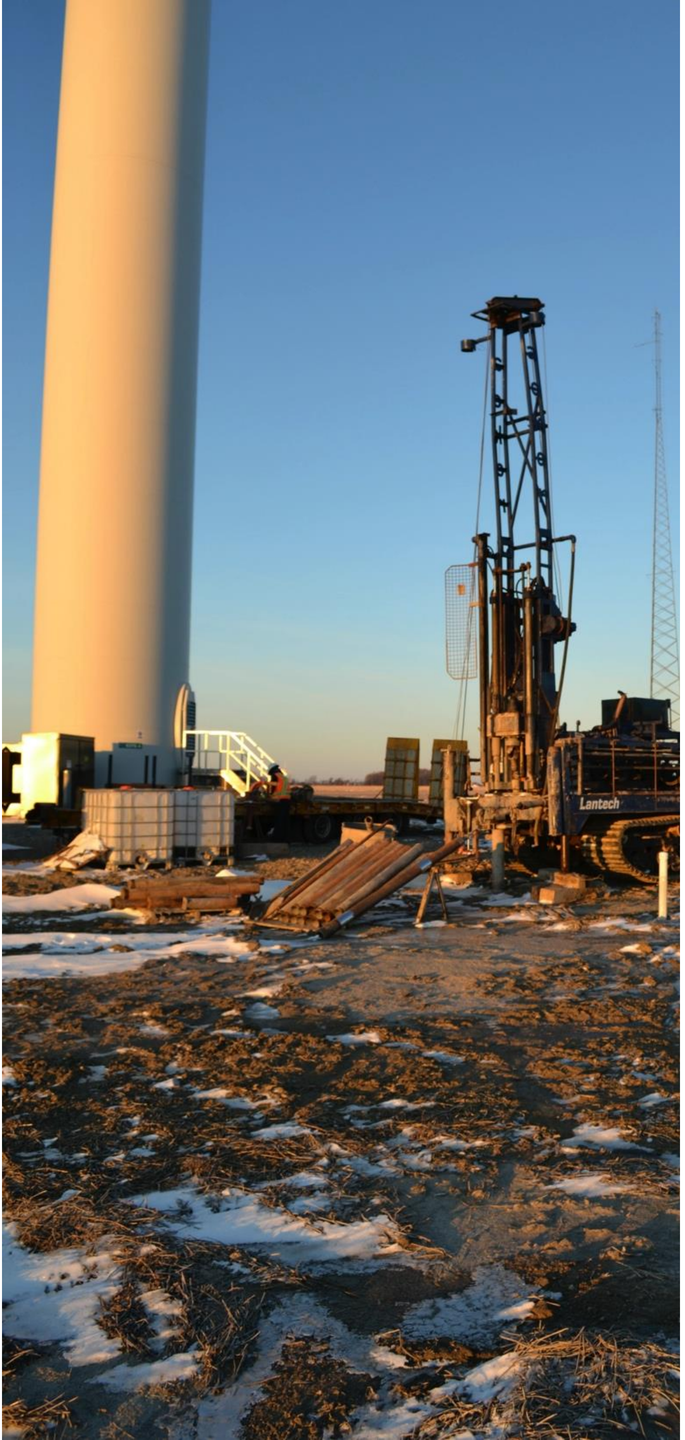

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Case Study: Failure Modeling

FAILURE RATES

- **Failure rate at a time t is given by**

  $$h(t,\beta,\eta) = (\beta/\eta)(t/\eta)^{\beta-1}$$

- **For our generator data $\beta = 3.39$ and $\eta = 98{,}000$ usage hours***

***great to have real data – but still large uncertainty with such small sample of 12 failures in 88 components**

t	h(t)	0.5*[h(t)+h(t+1)]
12	0.358324	0.396095
13	0.433867	0.475903
14	0.517939	0.564363
15	0.610788	0.661721
16	0.712654	0.768211
17	0.823768	

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Case Study: Failure Modeling

OBSERVATIONS

- **Our break-even proactive vs reactive failure intensity of 73% is met near 16 years**
- **Thus, based on this analysis (user hours only), you should wait until year 16 to start replacing generators**

t	h(t)	0.5*[h(t)+h(t+1)]
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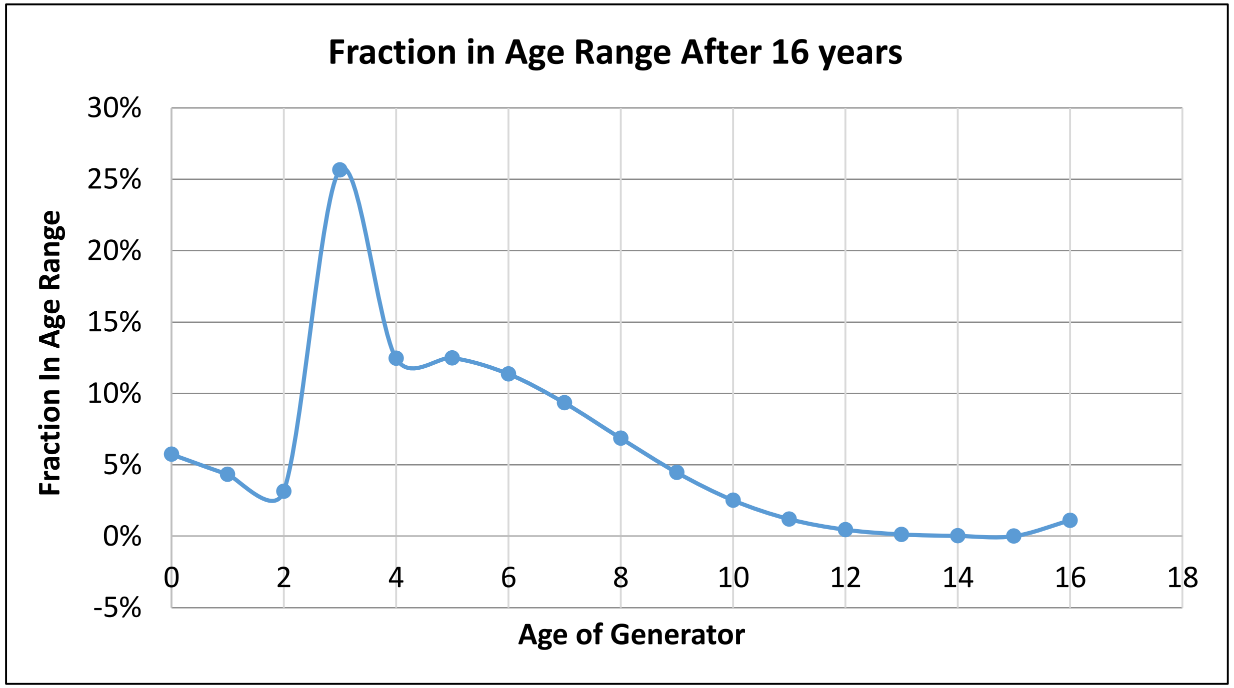
Case Study: Failure Modeling

OBSERVATIONS

- **This would result in a dynamic age structure of generators assuming they are replaced as soon as they fail**
  - **Number(time k, age j) = Number (time k-1,age j-1)*(1-mort(j-1))**
  - **Number (time k, age 0) = sum_{all j} Number(time k-1, age j-1)*mort(j-1)**



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Case Study: Interpretation

TAKE AWAYS

- Thus, based on this data, generators should not be maintained until year 15 or 16
- That said, most generators will not last 16 years
- Thus, attempting proactive maintenance at the proactive vs reactive breakeven year (YR16 in this case) is not strategic – you would be replacing younger generators
- At this point most of the failures will be of younger generators so preventative maintenance is still more or less irrelevant
- Just using the age (or even the use life) is like ignoring your oil light going on because the sticker on your windshield says you still have 3 weeks and 1000km until your next oil change!
- You have more data – USE IT!

Take homes

- Most turbines not lasting as long as 16 years
- But, *if they do*, their conditional probability to last another year is still quite high
- (The same goes for people: if you live to 100, there is a sizeable chance you’ll live to 101)
- So waiting until it makes sense to do preventative maintenance, based on age alone, is pointless.

First case study

- Replacement of generators
- Value proposition was to extract savings from using the same crane to replace multiple generators.
- However cost of replacing generator “early” was not balanced by savings in crane.
- What if we can replace one component with a better version of the same?

Converter unit

- According to a June 2012 Intl Renewable Energy Association Report *Renewable Energy Technologies: Cost Analysis Series* Volume 1: Power Sector Issue 5/5 – Wind Power
- Power Converter accounts for 5% of the cost of wind turbine (pg. 23)
- And this component has opportunities for cost reductions through increased manufacturing efficiency and R&D efforts, which could see cost reductions of 10-15% by 2020. (pg. 38)
- We believe that efficiency improvements are also possible.

Delta Unit Failure Case:

The Delta Unit

- Wind turbine generators produce AC power.
- But some wind turbines drive an AC/AC converter: which converts AC to DC with a rectifier and then back to AC with an inverter.
- This allows precise matching to the frequency and phase of the grid.
- Efficiency losses both at the rectifier and the inverter stages.
- As always, this is done by switching the direction of the DC power using a power electronic component like a thrysitor and then using other power electronics to shape the resulting square wave into a cleaner sinusoid.
- This process is highly, but not perfectly, efficient.
- Efficiencies as high as 90% range.

Improvements being made

- Battery technology has been driven by consumer applications (cellphones); Inverter technology receiving a similar boost
- In July 2014, Google and IEEE launched the $1 Million Little Box Challenge to design and build a small kW-scale inverter with a power density greater than 50 Watts per cubic inch while meeting a number of other specifications

Converter Efficiencies

- Efficiencies of 95% are possible. (Khan et al. 2016)
- "High Efficiency Single-Phase AC-AC Converters without Commutation Problem", A.A. Khan, H. Cha, and H.F. Ahmed (2016), IEEE Trans Power Electronics 31(8) 5655-5666.
- 2MW turbine, 95% efficiency at inverter stage.
  Still generates 100kW of waste heat.
- That's a lot of heat!
- Converters have heat exchanger features like fins.

Efficiency Table

Efficiency	Intermediate Boost Converter	Intermediate Buck-Boost Converter	Back to Back Converter	Matrix Converter
10kHz	91%	88%	87%	84%
20 kHZ	86%	83%	81%	80%
30 kHz	80%	78%	74%	73%

Some numbers and some questions

- The cost here is Delta Unit failures:
- Current Skiip 3 v3’s are failing (SEMIKRON Intelligent Integrated Power)
- This require replacement of the unit and its mate when it occurs: should we just continue the replacement or go to a new improved Skiip 4 (unproven quality)? (In other words, current practice is simple to replace on failure). The 6.25 year probability of failure is 30% and the cost of replacement is $80-$100K per turbine.
- How can we model the arrival of these failures? (What is the history of failures?) With data we could do Weibull modelling as per the generator replacement case study

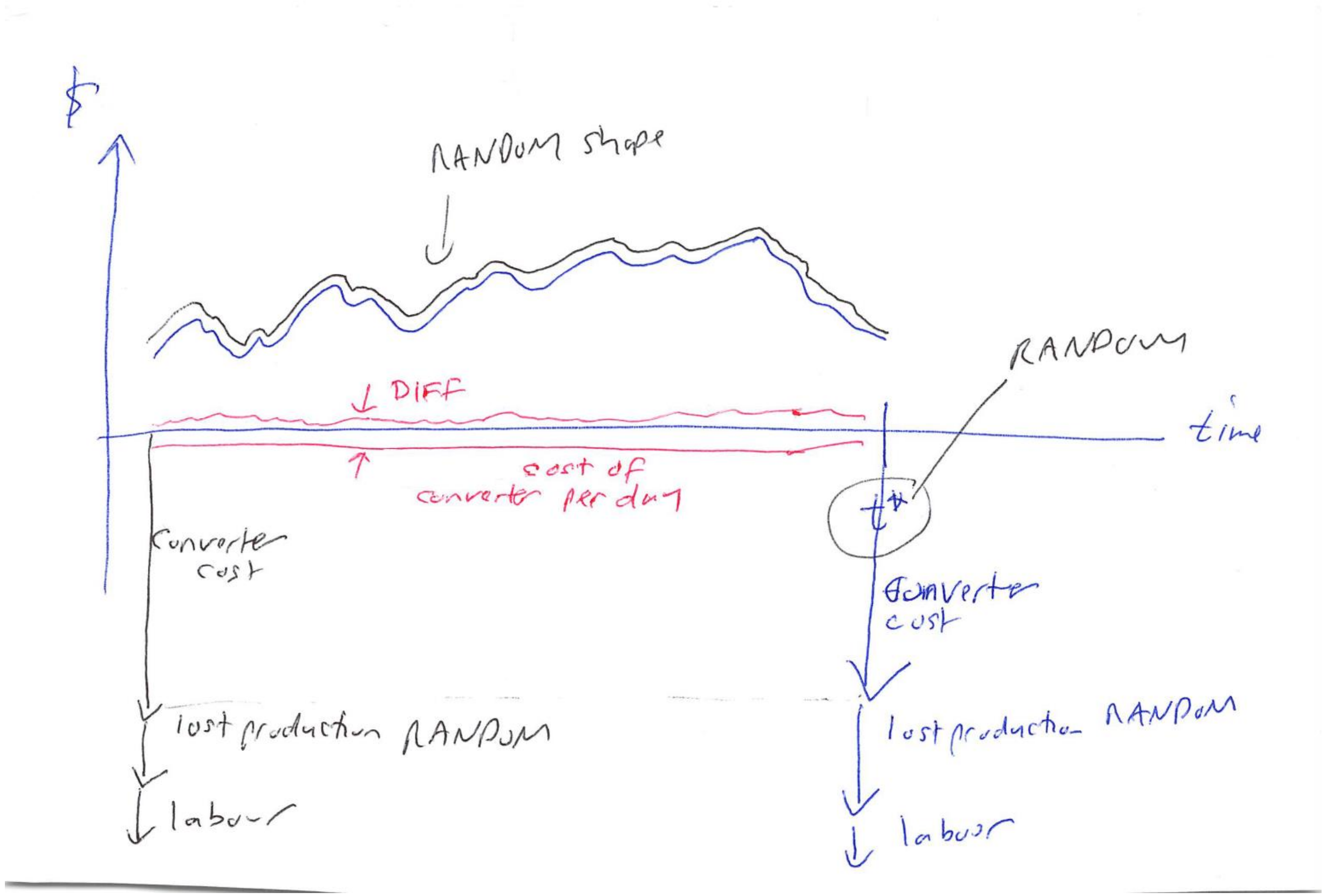
Replacement process

- Convertor located on the ground; fixing it doesn’t require a crane.
- Costs include: replacement cost of unit, labour, and down time.
- Easy and quick replacement if part on hand:
- Assume parts are readily available either onsite (likely prudent to have 1-2 in a storage room);
- We assume that the entire job can be completed in a single day
- Associated labour cost of $500

The financial model

- All using expected values; suppresses many sources of randomness which might be considered.
- Retain: generate income until (random) failure t* years from now
- Replace:
- In both cases we must pay for the new unit, shut down the turbine for the day with losses that entails, pay labour costs.
- Benefit of replacing is: a) access to improved efficiency of new converter for next t* years b) control of exact timing of repair to minimize shutdown losses
- Cost of replacing is: Lose a fraction t*/T of cost of new unit.

The picture


$
RANDOM shape
DIFF
time
RANDOM
cost of converter per day
t^*
converter cost
converter cost
lost production RANDOM
lost production RANDOM
labour
labour

Install Cost

- Labour cost relatively small ($500?), relatively fixed, and the same whether the unit is replaced now or later.
- Time value of money considerations might come in, but might also be balanced by pay raises.
- Safe to consider this a “wash” across the two courses of action.

Lost production

- Idling the turbine for ≤ 24 hours should be enough.
- In the event of an unforeseen failure the lost revenue could be considerable: 24 hours x 2.2MW x $140/MWh = $7392
- If replacement is planned for a “dead calm” day the cost could be nearly zero and/or   be “divided” among several maintenance tasks. (**next slide)**
- Assuming we pick a day at random a 30% load factor → a cost of $2200
- Given enough notice (> 1 month?) we can model nominal, and same across course of action, production costs.
- Model $500 lost production cost for waiting to account for risk of waiting until unforeseen failure.
- This suggests focus on short term prediction.

Cost of unit

- Given lifetime of new unit is expected to be T
- And time to failure is t^
- And cost of unit is C – between $80,000 and $100,000
- Then we ascribe a cost of Ct^/T to buying the new unit
- Determining T is tackled later

Formula

- Benefit of switching now is:
- $\$500 + \$809{,}400*(\Delta\eta)*\hat{t} - C*\hat{t}/T$. Taking $C = \$100{,}000$
- $= \$500 + \$100{,}000[8.094*(\Delta\eta) - 1/T]*\hat{t}$
- Recall t^ is expected time to failure.
- If this is really small the decision is to switch now while you can still make it at least somewhat planned.
- For longer t^ like 1 year, though, the linear term dominates and it's really all about comparing per year cost of new unit vs. efficiency pickup.

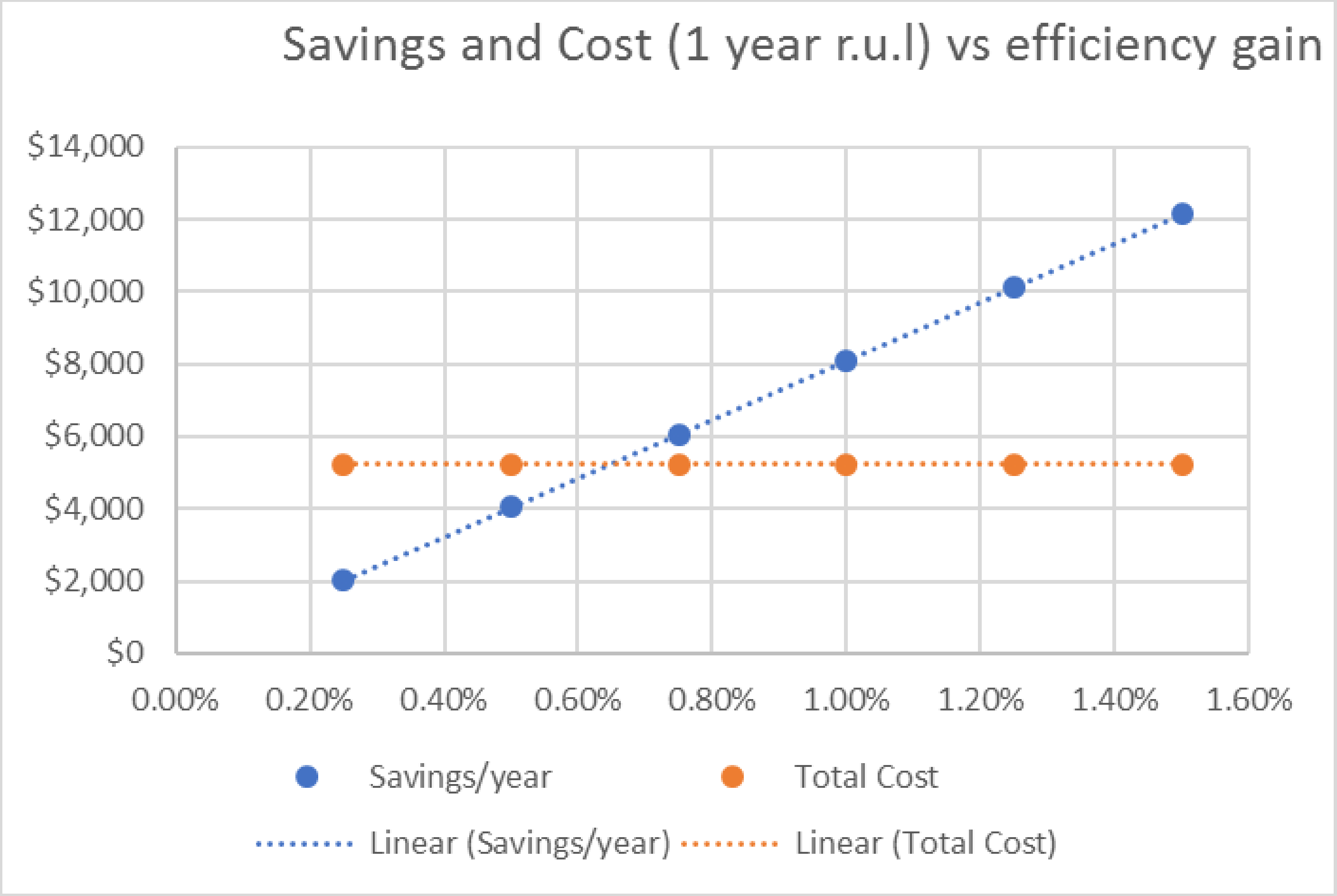
Simplest failure model

- Exponential time to failure (memoryless)
- Prob(failure between t and t + dt|running at time 0) = $(1/\lambda)\exp(-t/\lambda)dt$
- To solve for λ use that probability of failure is 30% in 6.25 years
  $\int_0^{6.25} (1/\lambda)\exp(-t/\lambda)dt = 0.3$
- Corresponds to a mean expected lifetime of $\lambda = 17.5$ years
- = \$500 + \$100,000[8.094*(Δη) - 1/T]*t^
- = \$500 + \$100,000[8.094*(Δη) – 0.057]*t^

Efficiency pickup:

- \$500 + \$100,000[8.094*($\Delta\eta$) – 0.057]*t^
- Switch vs. hold decision boils down to:
- If $8.094*(\Delta\eta) - 0.057 > 0$ replace
- $\Delta\eta > 0.057/8.094 = 0.7\%$
- 100K of cost is top of current range; reduction to 80 or even 70K would reduce this break even efficiency gain proportionately.
- Note F/X fluctuations are a source of randomness here as well.
- This is a fairly large efficiency gain given that the converter units are already quite efficient.
- This is also assuming an exponential (constant hazard rate) model.

Cost/Savings with RUL t^ = 1 year, cost 100K)



What if we can get a better failure prediction?

- If we could convince ourselves that failure was going to happen in the next month, nothing much would change about the ‘cost balance’ in the previous figure.
- The opportunity cost of replacing the unit 1 month before we had to would be 1/12 as much, but also the value of upgrading the unit early would only apply for 1/12 as long.
- Slightly better argument for replacement as the risk of not being able to plan for a cheap replacement day rises.
- The only way it makes sense to replace is with HIGH efficiency gains or if the cost of an emergency failure is crippling.
- Our budgeted $500 charge for “emergency replacement” could have been $8000 if we really had bad luck!

Summary

- Not overwhelming support for replacing delta units before they fail
- Valuable perhaps to see useful precursors of failure so that that changes are always planned tactically, if not strategically.
- Suggests key drivers of change are:
    - – Expected lifetime of new units
    - -- Efficiency pickup in moving to new unit
    - -- Cost of emergency replacement
- Reminder: All of these calculations done “on average”.
- Component lifetimes are random and simulating these over many realizations may be insightful.

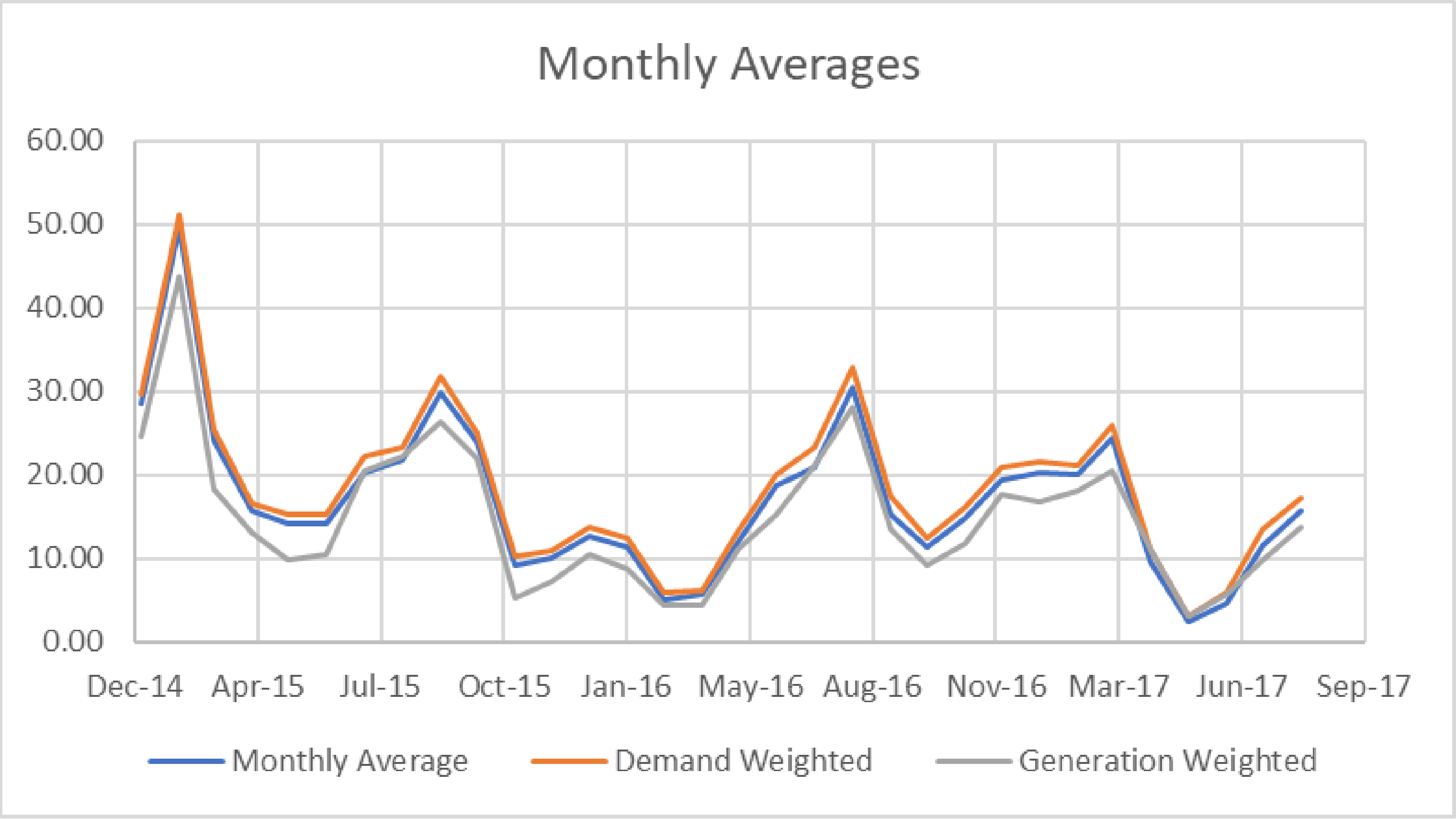
Optimal repair with POST-PPA IN VIEW

Matt Davison, May 11 2018

STYLIZED FEATURES OF Current HOEP

- Very low: MUCH lower than PPA: Monthly average prices $10-$30 Wind weighted Average < Arithmetic Average < load weighted average
- Frequent negative prices
- Much of market “cost” is in Global Adjustment
- See slide deck from Sept 2017 for much more detai

Various price averages



INSIGHT

Wind producers offer power at negative prices because they are PPA protected

Non PPA protected wind producers might still offer power at low prices, but would probably not go negative.

Unlike Nukes, for whom it makes sense to take a negative price for a few hours in order to take a positive price for most of the rest of the hours for a week

A wind producer can simply idle for the negative hours and ramp back up for the positive prices

This suggests that in the long run negative prices will disappear from the Ontario market (they weren't' around before PPAS)

But it also suggests that the ORDER in which PPAs expire is important

HOW to quantify this?

- The idea is that the price should be driven by a combination of system load and the contribution of various generation types to serving this load. The capacity of the various system components matters as well as the output, as it influences bidding behaviour.
- To that end we did a big regression study.
- We downloaded data from the IESO (Jan 1 2010 – Dec 31 2017) http://www.ieso.ca/power-data

- The Hourly Generator Energy Output and Capability Report presents the energy output and capability for generating facilities in the IESO-administered energy market with a maximum output capability of 20 MW or more.

Regression study

- Then we did a multiple regression study of all the various drivers (nuclear capacity, nuclear output, wind capacity, wind output, etc for other power types, load, and total capacity. Total 16 independent variables driving dependent HOEP variable.
- On each of hourly, daily, weekly, and monthly data.
- We let the data tell us what the significant drivers were.
- Results as follows:

RESULTS

- Hourly fitting not informative (makes sense because diurnal patterns really confuse things)
- The longer the averaging window the better the fit
- Monthly averages pretty good, and what we want for long run planning purposes

Monthly model

- $\hat{Y}$ = -0.62+ (0.001) * x_1+ (-0.009) * x_2 +(-0.0007) * x_3+ (-0.0009) * x_4+ (-0.00227) * x_5
- HOEP = (λY + 1)^(1/λ) (Box Cox Transformation): λ = 0.35
- **X_1 :** Monthly average Demand (MW)
- **X_2 :**Monthly average Solar Output (MW)
- **X_3 :**Monthly average Nuclear Output (MW)
- **X_4 :** Monthly average Wind Capacity (MW)
- **X_5 :**Monthly average Biofuel Capacity (MW)
- The coefficient of independent variables completely make sense.

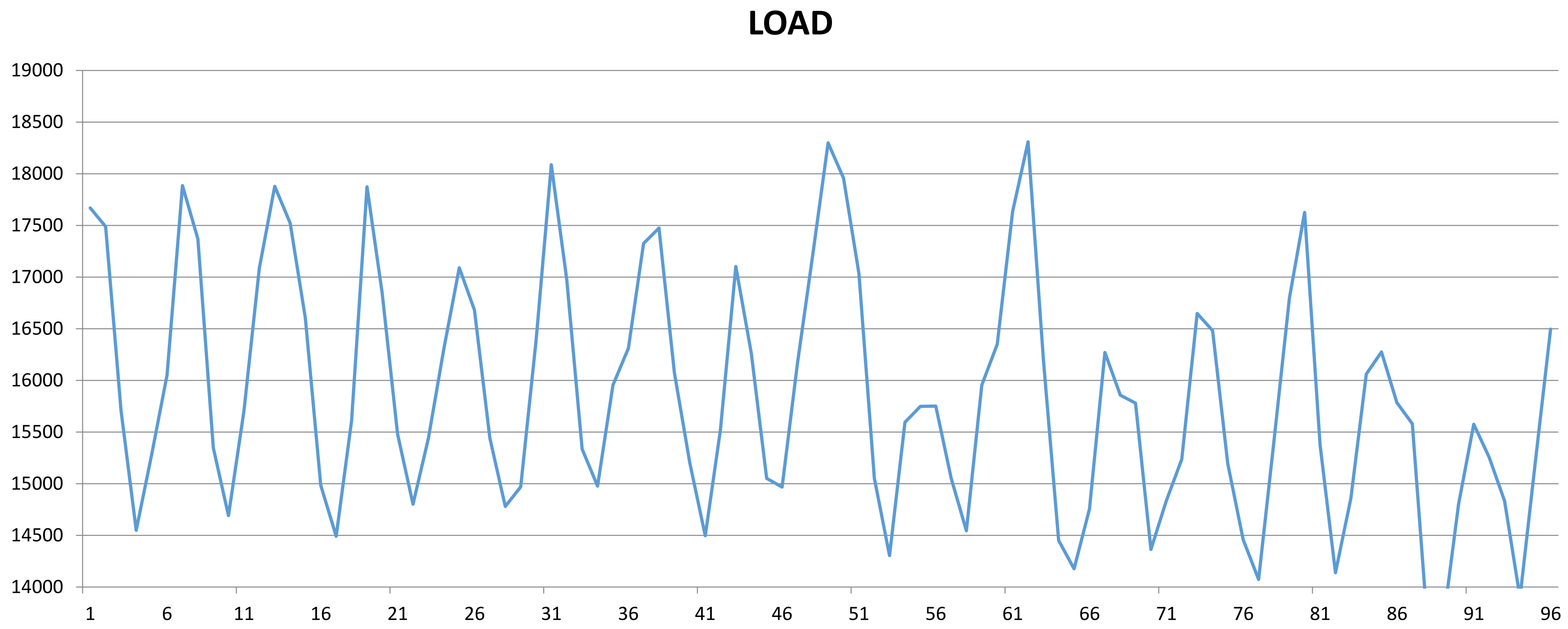
Diagnostics/DISCUSSION

- Residuals are fairly normal
- R2 is 85% which is pretty good
- However solar and biofuel bits don’t make much difference economically.
- So we can look at a slightly simpler model:

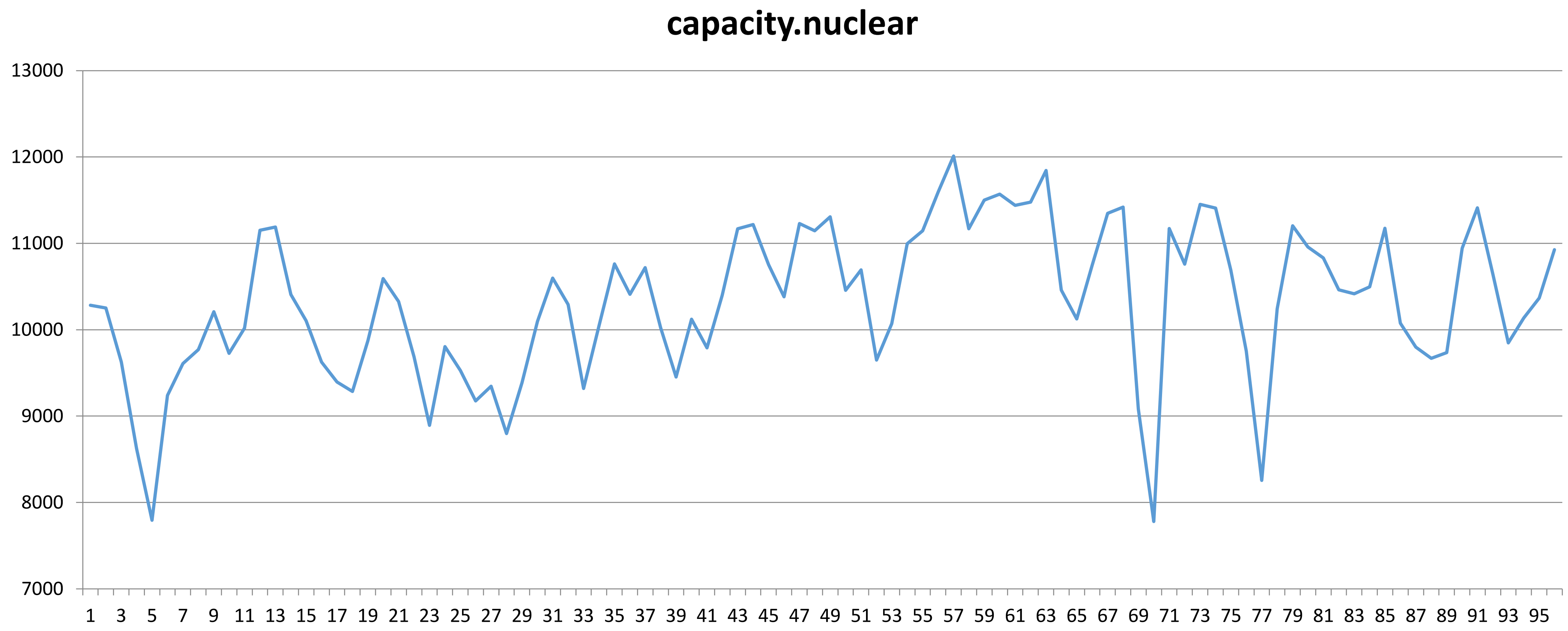
Simplified post PPA model

- Y= -0.62+ (0.001) * x_1 +(-0.0007) * x_3+ (-0.0009) * x_4
- HOEP = $(\lambda Y + 1)^{(1/\lambda)}$; $\lambda = 0.35$
- **x_1 :** Monthly average Demand (MW)
- **x_3 :**Monthly average Nuclear Output (MW)
- **x_4 :** Monthly average Wind Capacity (MW)
- The coefficient of independent variables completely make sense.

MONTHLY DRIVERS



MONTHLY DRIVERS



Sanity check (Note Price(Avg) < **AvG(Price)**)

x1: Load (MW)	x3: Nuclear	x4: Wind (MW)	P
18000	10000	2000	$52.61
16000	10000	2000	$30.38
14000	10000	2000	$15.38

Some Scenarios: Pickering Closed

x1: Load (MW)	x3: Nuclear	x4: Wind (MW)	P
18000	7000	2000	$85.17
16000	7000	2000	$53.94
14000	7000	2000	$31.31

Some Scenarios: 1MM Teslas on the road, charged every day, 60KWH battery

x1: Load (MW)	x3: Nuclear	x4: Wind (MW)	P
20400	10000	2000	$90.67
18400	10000	2000	$58.04
16400	10000	2000	$34.21

PICKERING CLOSED, ELECTRIC CARS

x1: Load (MW)	x3: Nuclear	x4: Wind (MW)	P
20400	7000	2000	$135.77
8400	7000	2000	$92.56
16400	7000	2000	$59.46

Possible scenario

- First guy – his PPA expires but all other wind producers still have PPAs
- He can't afford to offer negative
- But all the other wind guys still can
- So he participate in a tough market
- UNLUCKY!
- However based on above scenarios it's unlikely that the price would be low enough to flush any but the weakest hands out of the market.

Company with last PPA to expire: lucky

- His PPA is the last to expire
  He emerges into a market with no negative prices
- (And, a market in which the cost of power is more equitably balanced between HOEP and Global Adjustment than at present)

Conclusions/questions

- Even relatively simple changes in market composition can have big impact on HOEP
- Post PPA world will inject exactly this additional uncertainty into the market
- Our regression model is not really accounting for rule changes, which could really make dramatic changes.
- However, I would see more likely rule changes as equalizing market cost between Global Adjustment and HOEP, which would be to the benefit of the wind industry and at no cost to other heavy industry/retail.

Overall conclusions

- Interesting to use Financial Modelling from actuarial Science and Risk Management to look at real Wind farm operation decisions.
- Need to work hard to connect the math with the information at hand and to focus on actionable decisions.
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