Power Curve: Concepts and Applications

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Outline

- Introduction
- Power curve definition
- What can be done with power curves
- Data mining and power curves

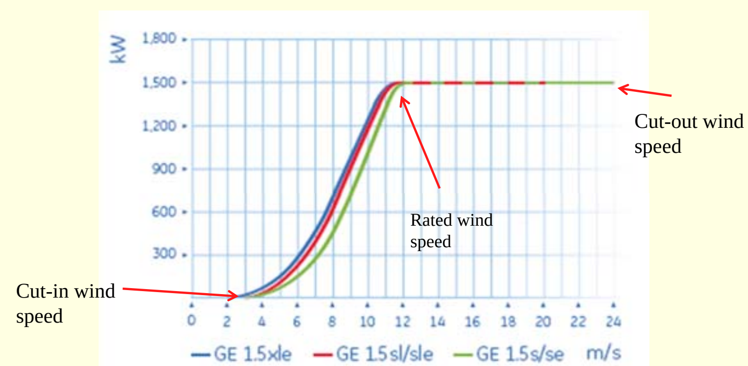
Power Curve

- Representation of the electric power produced by a wind turbine at different wind speeds (usually a graph)
- Power curve indicates the wind energy captured by a turbine

http://www.windpower.org/en/tour/wres/pwr.htm

Turbine Manufacture's Power Curve

- GE 1.5 MW wind turbine



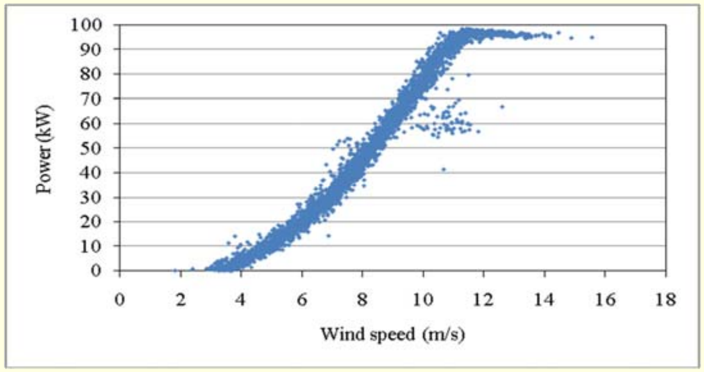
Power Curve Plotted from Field Data

- GE 1.5 MW wind turbine (10 minutes average)

Time Stamp	Wind speed	Electric Power
10:00 AM	7.08	352.18
10:10 AM	8.79	552.14
10:20 AM	9.36	784.91
10:30 AM	9.65	805.39
10:40 AM	9.86	940.64
10:50 AM	9.84	965.74
11:00 AM	11.03	1203.76
11:10 AM	10.28	1023.21
11:20 AM	9.96	974.13
11:30 AM	9.71	853.73
11:40 AM	10.84	1204.88

Power Curve Plotted from Field Data

- GE 1.5 MW wind turbine (10 minute average)



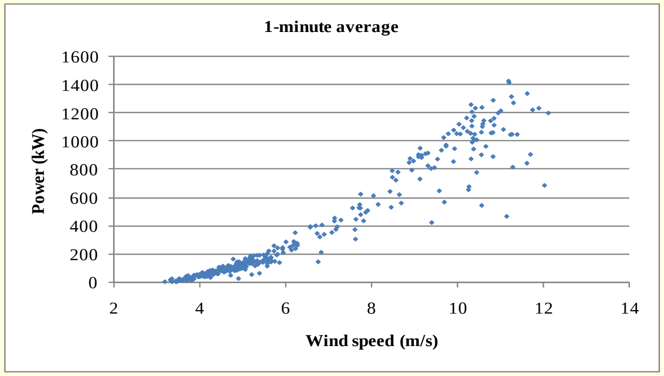
Power Curve Plotted from Field Data

- GE 1.5 MW wind turbine (1 minute average)

Time Stamp	Wind speed	Electric Power
1:00 PM	6.58	390.58
1:01 PM	6.23	351.57
1:02 PM	6.01	285.90
1:03 PM	6.20	288.90
1:04 PM	5.73	258.35
1:05 PM	5.74	220.68
1:06 PM	5.61	221.45
1:07 PM	5.27	187.55
1:08 PM	5.25	154.75
1:09 PM	5.48	154.25
1:10 PM	5.65	168.08
1:11 PM	5.65	174.10
1:12 PM	5.82	198.13

Power Curve Plotted from the SCADA Data

- GE 1.5 MW wind turbine (1 minute average)



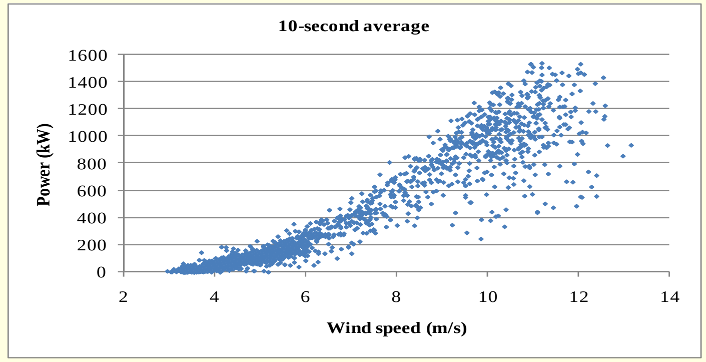
Power Curve Plotted from the SCADA Data

- GE 1.5 MW wind turbine (10 second average)

Time Stamp	Wind speed	Electric Power
4:35:20	6.74	371.60
4:35:30	6.77	417.90
4:35:40	6.47	389.40
4:35:50	6.32	369.60
4:36:00	6.24	372.60
4:36:10	6.93	422.40
4:36:20	6.70	403.30
4:36:30	6.38	381.80
4:36:40	6.11	361.20
4:36:50	6.04	339.20
4:37:00	6.00	313.00
4:37:10	6.13	310.89
4:37:20	5.86	300.20
4:37:30	5.65	286.80

Power Curve Plotted from the SCADA Data

- GE 1.5 MW wind turbine (10 second average)



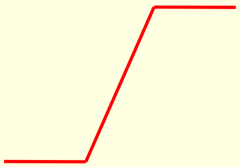
Summary

- Wind turbine is not controlled as expected
- Harmful loads could be imposed on the turbine's components
- Power is not smooth, and
- Power quality is not good

Applications of Power Curve

- Wind turbine (farm) power output estimation
  - Site selection
  - Layout design
  - Power forecasting
- Wind turbine (farm) monitoring
  - Outlier (fault) detection
  - Performance monitoring

Power Output Estimation



$$y = f(v) = \begin{cases} 0, v < v_{cut-in} \\ \lambda v + \eta, v_{cut-in} \le v \le v_{rated} \\ P_{rated}, v_{cut-out} > v > v_{rated} \end{cases}$$

Linear power curve function

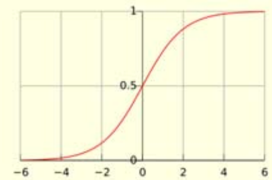
y power output

v wind speed

λ slope, η intercept

P_{rated} rated power

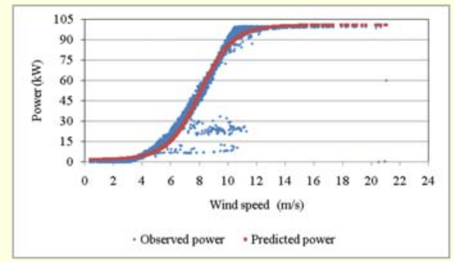
Power Output Estimation



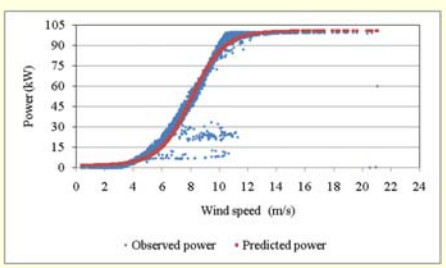
$$y = f(v, \boldsymbol{\theta}) = a\frac{1+me^{-v/\tau}}{1+ne^{-v/\tau}}$$

$$\boldsymbol{\theta} = (a, m, n, \tau)$$

Logistic function power curve



Logistic Function Approximation



Least square estimation of the power curve

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^{N} (f(v_i, \boldsymbol{\theta}) - y_i)^2$$

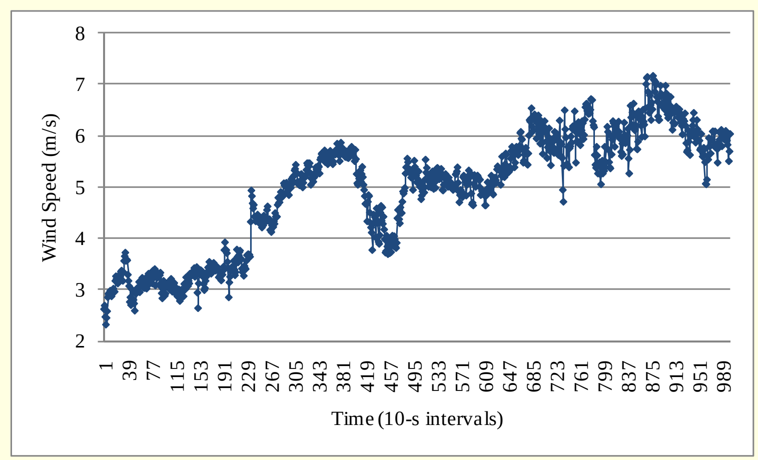
Number of field data points

Power curve function predicting power output

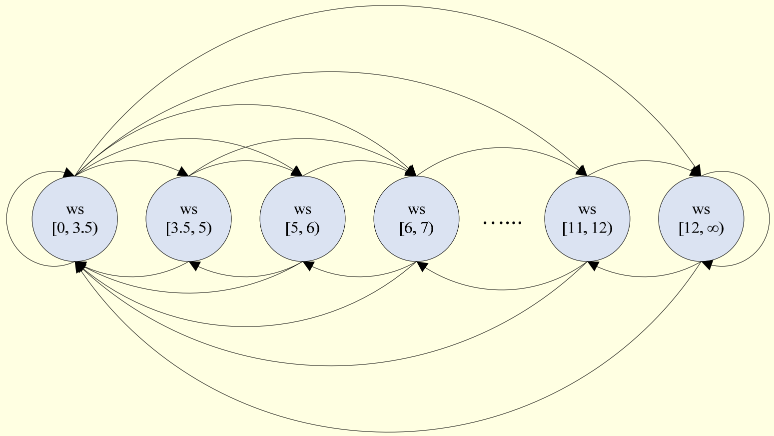
Change Theta to minimize the squared error

Actual measured power output

Run-chart of Wind Speed



Analysis of Wind Speed – Markov Chain



Analysis of Wind Speed – Markov Chain

- Transition Matrix for t+60-s

Transition Matrix	<3.5	(3.5,5)	(5,6)	(6,7)	(7,8)	(8,9)	(9,10)	(10,11)	(11,12)	>12
<3.5	0.8922	0.1015	0.0052	0.0007	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
(3.5,5)	0.1618	0.6397	0.1550	0.0345	0.0075	0.0014	0.0001	0.0000	0.0000	0.0000
(5,6)	0.0049	0.1213	0.6718	0.1574	0.0343	0.0084	0.0013	0.0005	0.0000	0.0000
(6,7)	0.0002	0.0147	0.1058	0.7075	0.1294	0.0327	0.0071	0.0021	0.0003	0.0002
(7,8)	0.0000	0.0026	0.0313	0.1949	0.4660	0.2276	0.0581	0.0146	0.0037	0.0013
(8,9)	0.0000	0.0001	0.0047	0.0446	0.2288	0.4392	0.2027	0.0568	0.0176	0.0053
(9,10)	0.0001	0.0000	0.0007	0.0101	0.0822	0.2766	0.3581	0.1775	0.0709	0.0238
(10,11)	0.0001	0.0000	0.0000	0.0027	0.0214	0.1066	0.2606	0.3227	0.1986	0.0874
(11,12)	0.0000	0.0000	0.0001	0.0005	0.0038	0.0347	0.1239	0.2637	0.3217	0.2516
>12	0.0000	0.0000	0.0000	0.0000	0.0007	0.0040	0.0201	0.0622	0.1448	0.7682

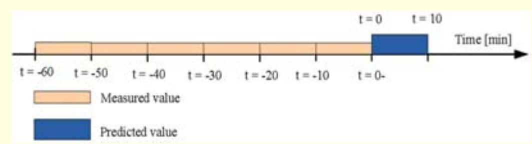
Analysis of Wind Speed – Markov Chain

- The probability of change of wind speed

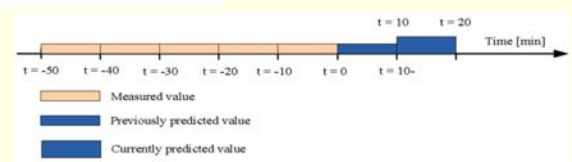
States\Time	t+10-s	t+20-s	t+30-s	t+40-s	t+50-s	t+60-s
<3.5	0.9998	0.9986	0.9974	0.9960	0.9947	0.9938
(3.5,5)	0.9947	0.9831	0.9739	0.9676	0.9613	0.9565
(5,6)	0.9911	0.9744	0.9662	0.9596	0.9532	0.9506
(6,7)	0.9884	0.9683	0.9586	0.9529	0.9466	0.9428
(7,8)	0.9722	0.9299	0.9129	0.9033	0.8951	0.8885
(8,9)	0.9646	0.9176	0.8971	0.8863	0.8762	0.8707
(9,10)	0.9458	0.8786	0.8488	0.8331	0.8240	0.8122
(10,11)	0.9313	0.8536	0.8214	0.8044	0.7874	0.7819
(11,12)	0.9571	0.9007	0.8725	0.8532	0.8444	0.8370
>12	0.9797	0.9501	0.9354	0.9260	0.9186	0.9130

Wind Speed Forecasting

$$\hat{v}(t+T) = f(v(t),\ v(t-T),\ldots,\ v(t-mT))$$



10 minute ahead



20 minute ahead

Wind Speed Forecasting

Double Exponential Smoothing

$$\hat{\upsilon}_t = \alpha\upsilon_t + (1-\alpha)(\hat{\upsilon}_{t-T} + b_{t-T})$$

$$b_t = \gamma(\hat{\upsilon}_t - \hat{\upsilon}_{t-T}) + (1-\gamma)b_{t-T}$$

$$b_0 = (\sum_{t=-5}^{-2}\upsilon_t - \sum_{t=-4}^{-1}\upsilon_t)/4$$

$$\hat{\upsilon}_0 = \upsilon_{-1}$$

$$\hat{\upsilon}_{t+T} = \hat{\upsilon}_t + b_t$$

$\hat{\upsilon}$	predicted wind speed
υ	observed wind speed
t	current time
T	sampling time
n	number of steps
α	smoothing constant
γ	smoothing constant
b	factor adjusting trend

Wind Speed Forecasting

Estimation of smoothing constants of double exponential smoothing

Minimize $f(\alpha,\gamma)$

subject to $f(\alpha,\gamma) = \frac{1}{n}\sum_{t=1}^{n}\left(\left|\frac{\alpha\upsilon_t + (1-\alpha)(\hat{\upsilon}_{t-1} + b_{t-1}) + \gamma(\hat{\upsilon}_t - \hat{\upsilon}_{t-1}) + (1-\gamma)b_{t-1} - \upsilon_t}{\upsilon_t}\right| \times 100\%\right)$

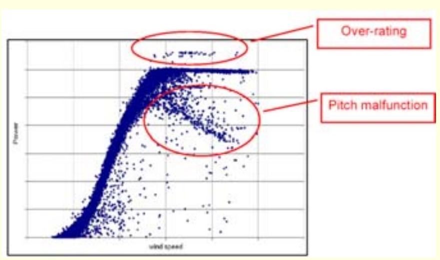
$0 \le \alpha \le 1$

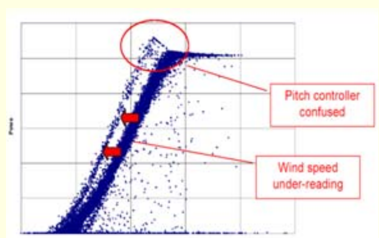
$0 \le \gamma \le 1$

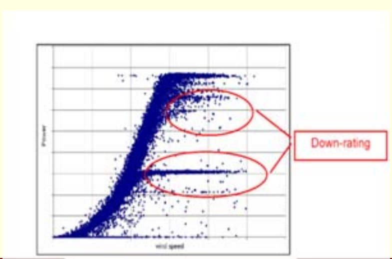
Derivative of this equation or Evolutionary Strategy Algorithm both can be applied to estimate the best value of the smoothing constant

A8

Power Curve Monitoring (1)



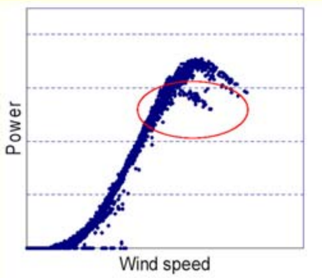




Slide 23

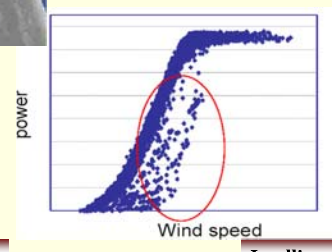
A8 If you could find actual picture of malfunctions on the web, then you could have one curve per page.
I amnot sure if this is possible though.
Andrew, 1/25/2009

Power Curve Monitoring (2)



Dirt or bugs on blades

Power Curve Monitoring (3)



Icing on blades

Power Curve Control Chart

Monitoring mean errors

$$UCL_1 = \mu_{Train} + 3\frac{\sigma_{Train}}{\sqrt{N_{test}}}$$

$$CenterLine_1 = \mu_{Train}$$

$$LCL_1 = \mu_{Train} - 3\frac{\sigma_{Train}}{\sqrt{N_{test}}}$$

μ_{Train} average training errors

σ_{Train} standard deviation of training errors

N_{Test} number of sample data points

Power Curve Control Chart

Monitoring error variation

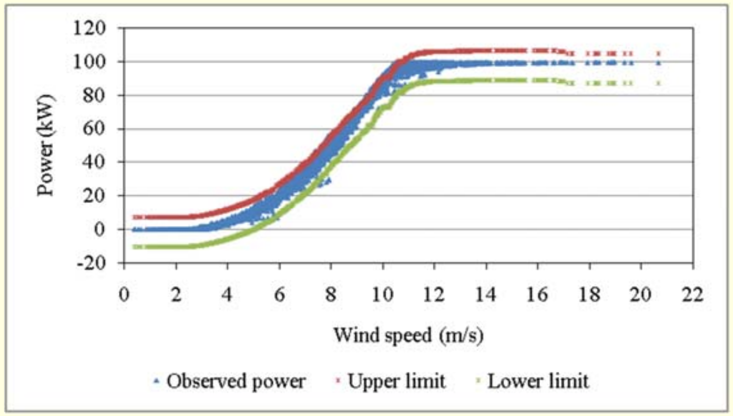
$$UCL_2 = \frac{\sigma^2_{Train}}{N_{test} - 1} \times \chi^2_{\alpha/2, N_{test}-1}$$

$$CenterLine_2 = \sigma^2_{Train}$$

$$LCL_2 = 0$$

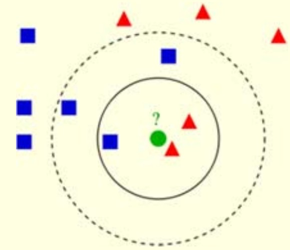
$\chi^2_{\alpha/2, N_{test}-1}$ chi-square distribution

Power Curve Control Chart



Data Mining and Power Curves

- k-NN (k nearest neighbors) algorithm



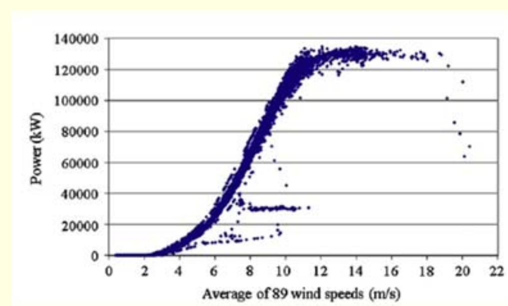
Build Wind Farm Power Curve

- Wind farm data

Time Stamp	Wind Speed Turbine 1	Wind Speed Turbine 2	…	Wind Speed Turbine N	Wind Farm Power
1/22/2008 10:00	6	5	…	5.5	20000
1/22/2008 10:10	6	9	…	9	40000

Build Wind Farm Power Curve

- *k*-NN for learning wind farm power curve

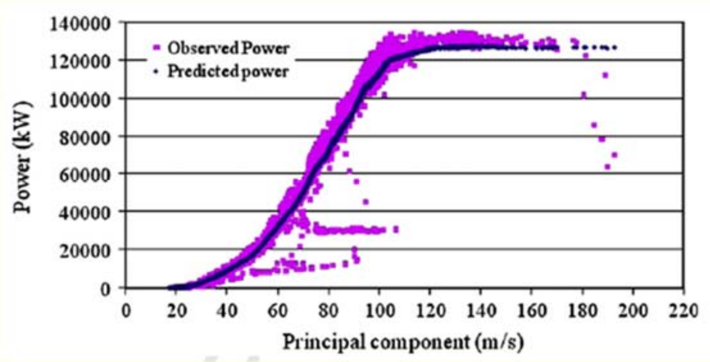


Wind Farm Data Preprocessing

- Remove bad data points
  - Turbine down time
  - Sensor errors
- Principal component analysis
  - Reduce dimensions
  - Reduce noises in the data

$$PCA = \alpha_1 v_{turbine1} + \ldots + \alpha_N v_{turbineN}$$

k-NN Extracted Wind Farm Power Curve



Evaluation of Model Performance

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

$$\text{SDofMAE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|\hat{y}_i - y_i| - \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|)^2}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}(|\frac{\hat{y}_i - y_i}{y_i}|)\times 100\%$$

$$\text{SDofMAPE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|\frac{\hat{y}_i - y_i}{y_i}| - \frac{1}{n}\sum_{i=1}^{n}|\frac{\hat{y}_i - y_i}{y_i}|)^2} \times 100\%$$