Data Analytics Application Series I: Wind Energy Part II

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Parts of contents from Prof. Andrew Kusiak's wind power course

Characterizing Wind Variations

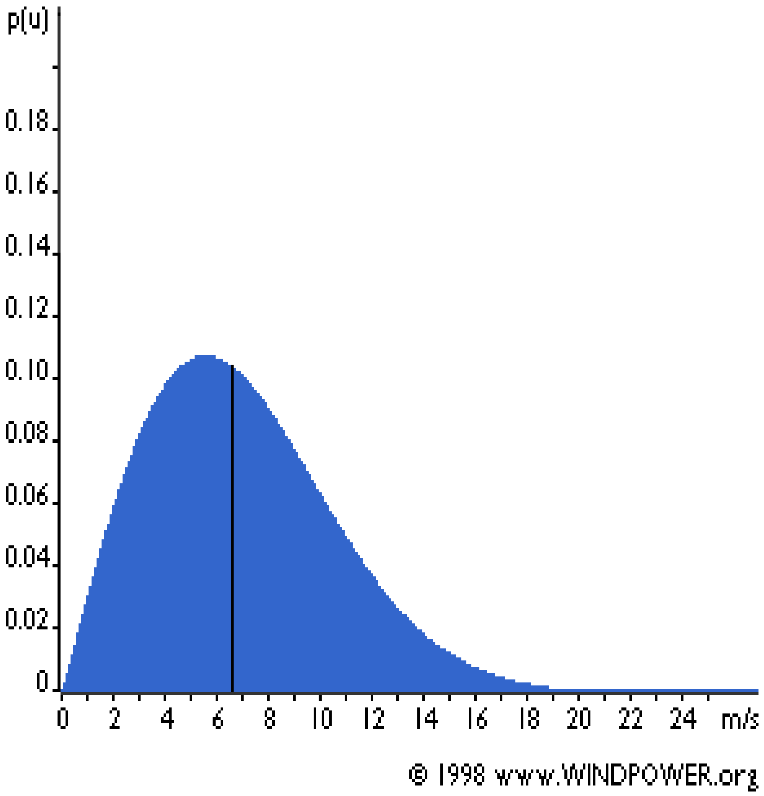
✓ Characterization of the variation of wind speed of importance to the wind industry

✓ Designers use it to optimize the design of the turbines, e.g., by minimizing the energy generation cost

✓ Wind farm designers use it to locate wind farms and select turbines

✓ Investors use it to estimate the income from electricity generation

Wind Variations: Weibull Distribution



The General Pattern of Wind Speed Variations

- ✓ Weibull distribution describes the wind variation for a typical site
- ✓ The site has the mean wind speed of 7 m/s
- ✓ The shape parameter of the function is $k = 2$
- ✓ The data has been collected over a year period

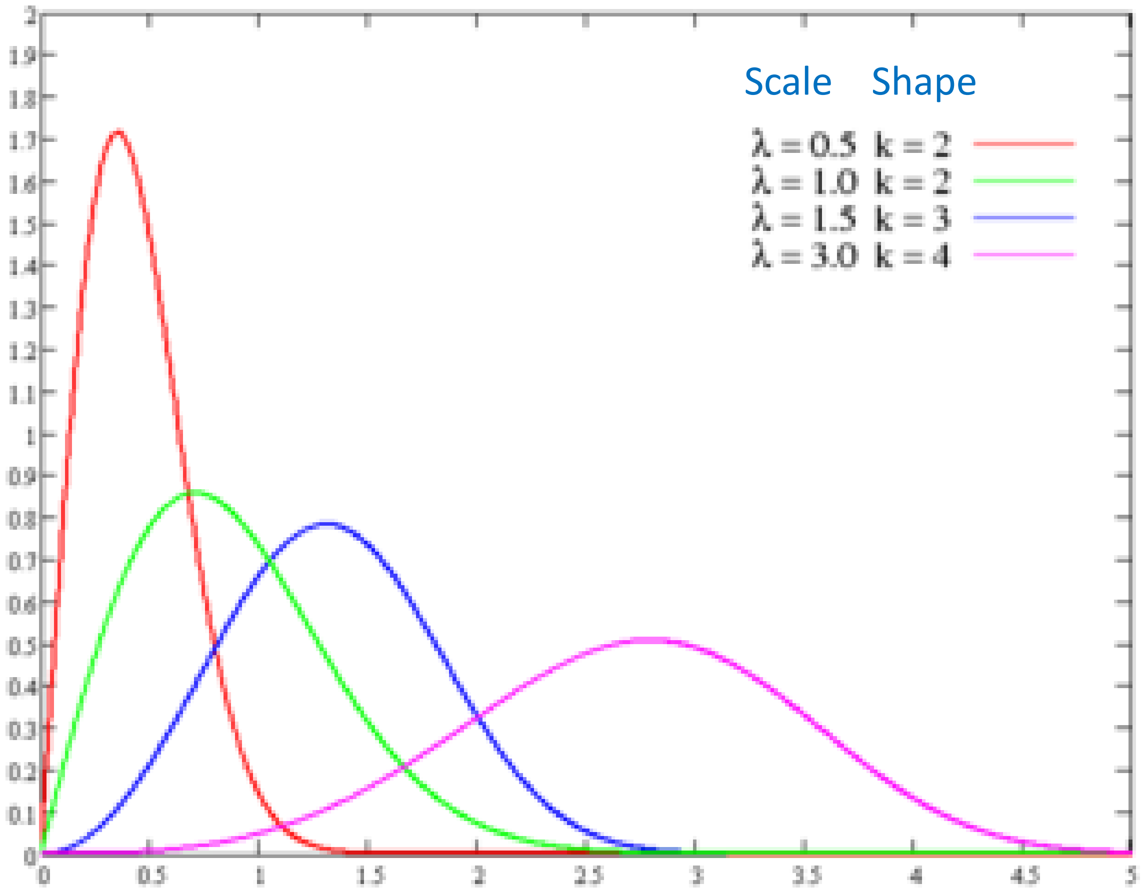
Weibull Distribution

$$f(x; k, \lambda) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}$$

where:
$\lambda > 0$ is the scale parameter
$k > 0$ is the shape parameter of the distribution

For $k = 3.4$, the Weibull distribution appears similar to the normal distribution
For $k = 1$, the Weibull distribution becomes the exponential distribution

Weibull Distribution



$$f(x;k,\lambda) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}$$

Median

$$\lambda \ln(2)^{1/k}$$

Mode

$$\lambda\left(\frac{k-1}{k}\right)^{\frac{1}{k}}$$

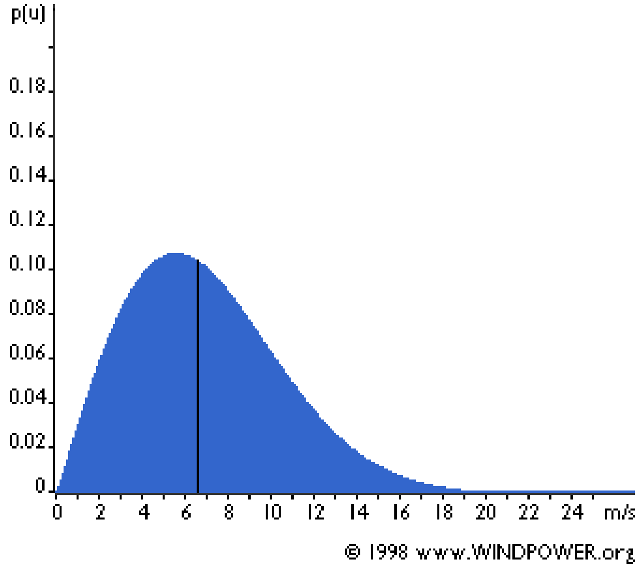
Mean

$$\lambda\Gamma\left(1+\frac{1}{k}\right)$$

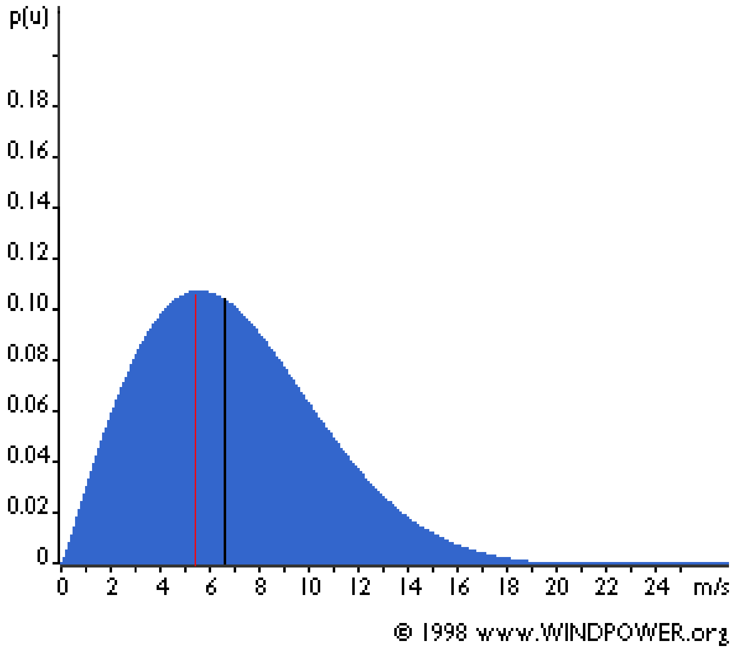
where the gamma function is

$$\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}\,\mathrm{d}t$$

Description of Wind Speeds

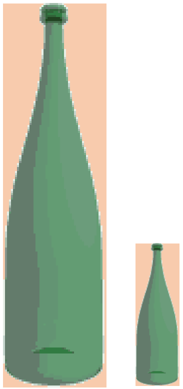


- ✓ The area under the pdf curve is always exactly 1 (the probability that the wind is blowing at some wind speed including 0 is 100 %)
- ✓ Median = 6.6 m/s (Half of the blue area is to the left)
- ✓ This means that 50% of the time the wind speed is less than 6.6 m/s, the other 50% of the time it is greater than 6.6 m/s
- ✓ Note: The median 6.6 m/s is not equal the mean 7m/s due to asymmetry of the pdf



Description of Wind Speeds

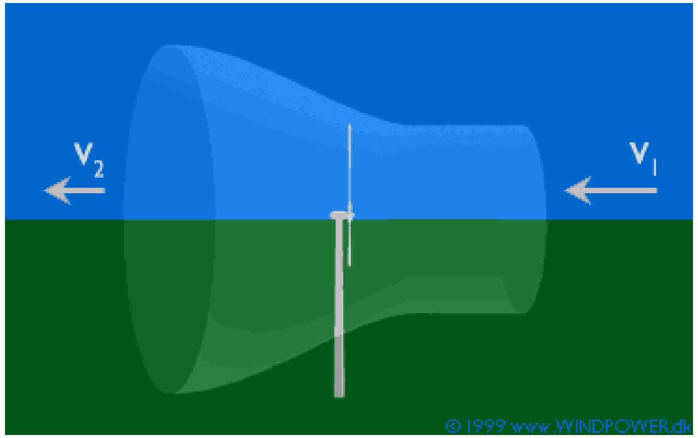
- ✓ Mode = 5.5 m/s (The most common wind speed)
- ✓ The statistical distribution of wind speeds depends on location climate conditions, the landscape, and its surface
- ✓ The Weibull distribution may thus vary in its shape, determined by the pdf parameters



The Average Bottle Fallacy

- ✓ The average energy content of the wind at a turbine site can not be determined from the average wind speed, rather the Weibull distribution is needed
- ✓ How large (in volume) is the average bottle, one is 0.24m and the other is 0.76m tall and both are of same shape?
- ✓ Though one is only only 3.17 taller than the other, its volume is actually 3.17^3 = 32 times larger than the small bottle (bottle V = cube of its size)

Betz' Law

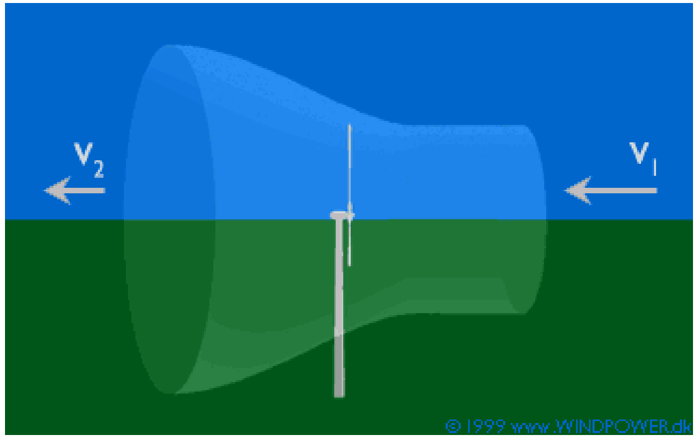


The Ideal Braking of the Wind

- ✓ The more kinetic energy a wind turbine extracts from the wind, the more the wind will be slowed down (as it leaves the left side of the turbine in the tunnel)

- ✓ An attempt to extract all the energy from the wind, would reduce the speed to zero, i.e., the air could not leave the turbine
- ✓ In that case we would not extract any energy at all, as the new air would obviously be prevented from entering the rotor of the turbine
- ✓ Passing air without speed change would lead to zero extracted energy

Betz' Law

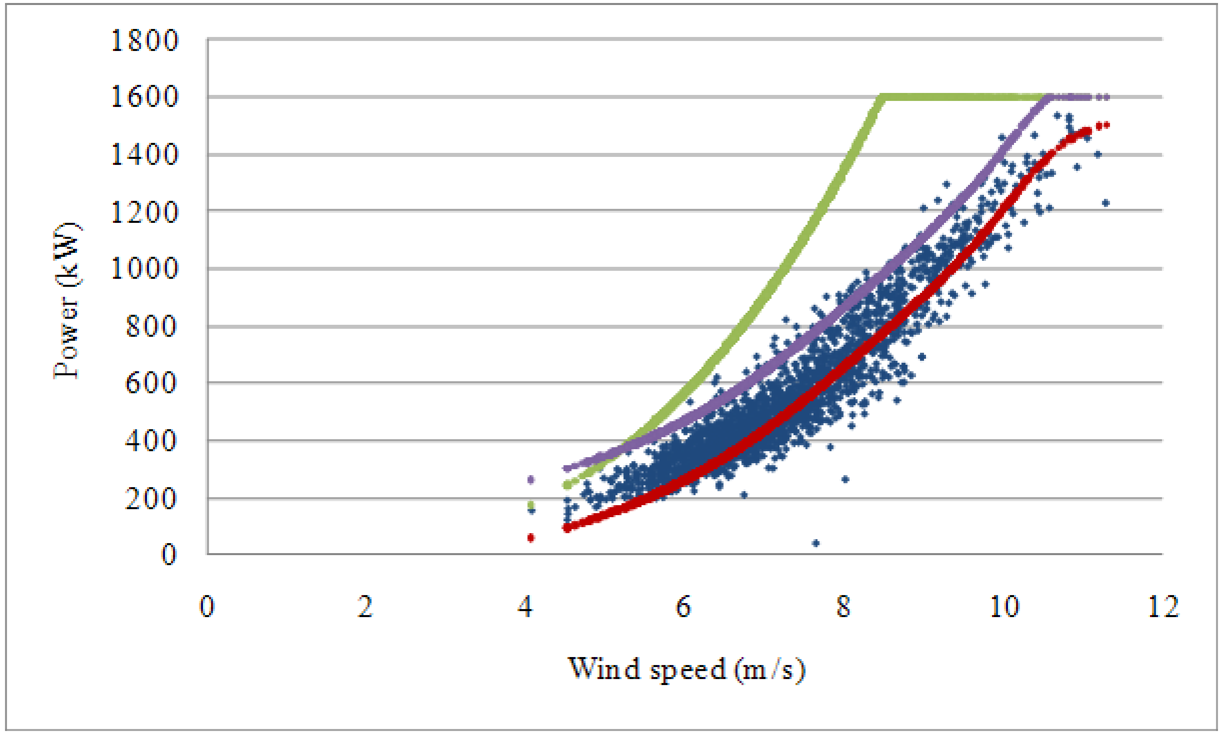


- ✓ The optimal point is: An ideal wind turbine slows down the wind by 2/3 of its original speed ($v_2 = 1/3 v_1$)

- ✓ Betz' law (Year 1919) says that one can only convert not more than 16/27 (or 59%) of the kinetic energy in the wind to mechanical energy using a wind turbine.
  (Albert Betz, German Physicist)

Modern rotors achieve values of the coefficient of performance C_p = 0.4 - 0.5, which is 70% to 80% of the theoretically possible value of C_{pmax} = 0.59

Drawback of Betz' Law

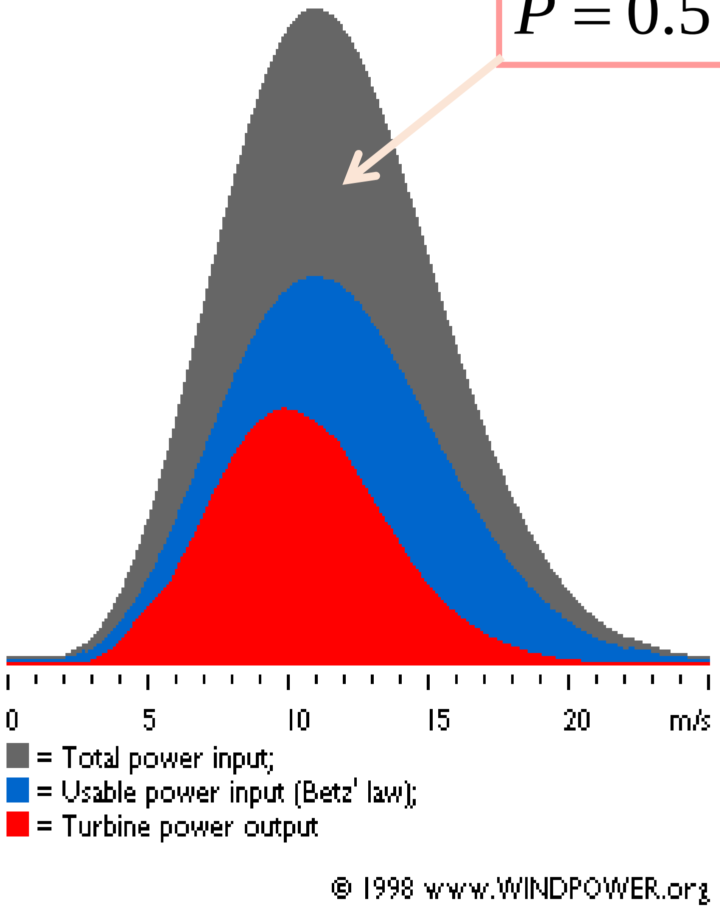


The green line is the power optimization boundary estimated based on Betz' Law

Power Density Function

$$P = 0.5 \times \rho \times A \times v^3$$

The Power of the Wind



- ✓ The area under the blue curve shows theoretical power that can be extracted (Betz' law says, 16/27 of the total power in the wind)
- ✓ The total area under the red curve represents the electrical power a certain wind turbine could produce
- ✓ Turbine's power curve determines the actual power produced

$$E = E_{rot} \times E_{ger} \times E_{gen} \times E_{p\text{-}conv}$$

where: E = Wind Turbine System Efficiency

= E*Rotor* x E*Gearbox* x E*Generator* x E*PowerConverter*

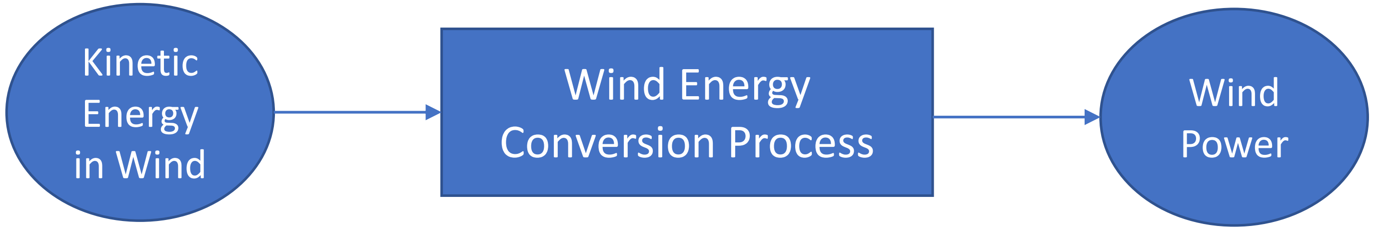
Wind Turbine Modeling

Majorly talk about modeling wind power conversion process.

There are a number of ways for modeling the wind power conversion process:

- Computational Fluid Dynamics (More for design stage)
- Power Curve Model (Easy to compute)
- Data-driven Model (For tracking real dynamics in operations)

Computational Fluid Dynamics Model



Aerodynamics Model

$$P_a = \frac{1}{2}\rho \pi R^2 C_p(\lambda , \beta) v^3$$

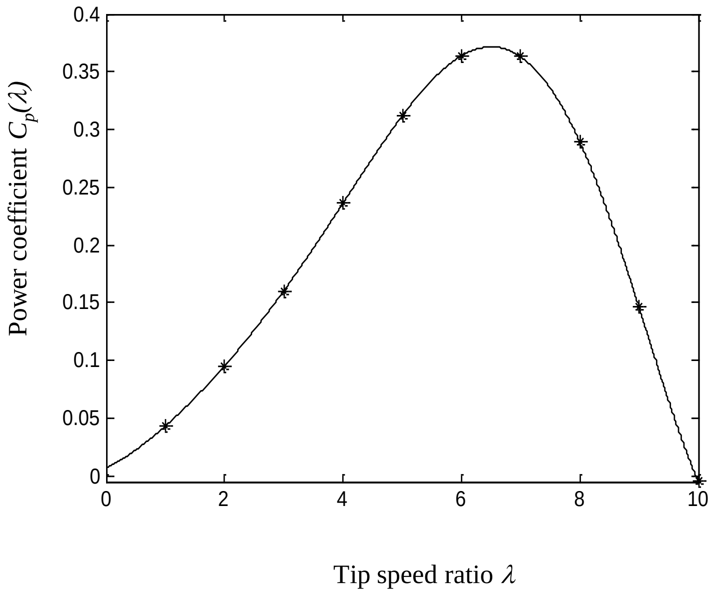
$$\lambda = \frac{\omega_r R}{v}$$

Tip-speed ratio

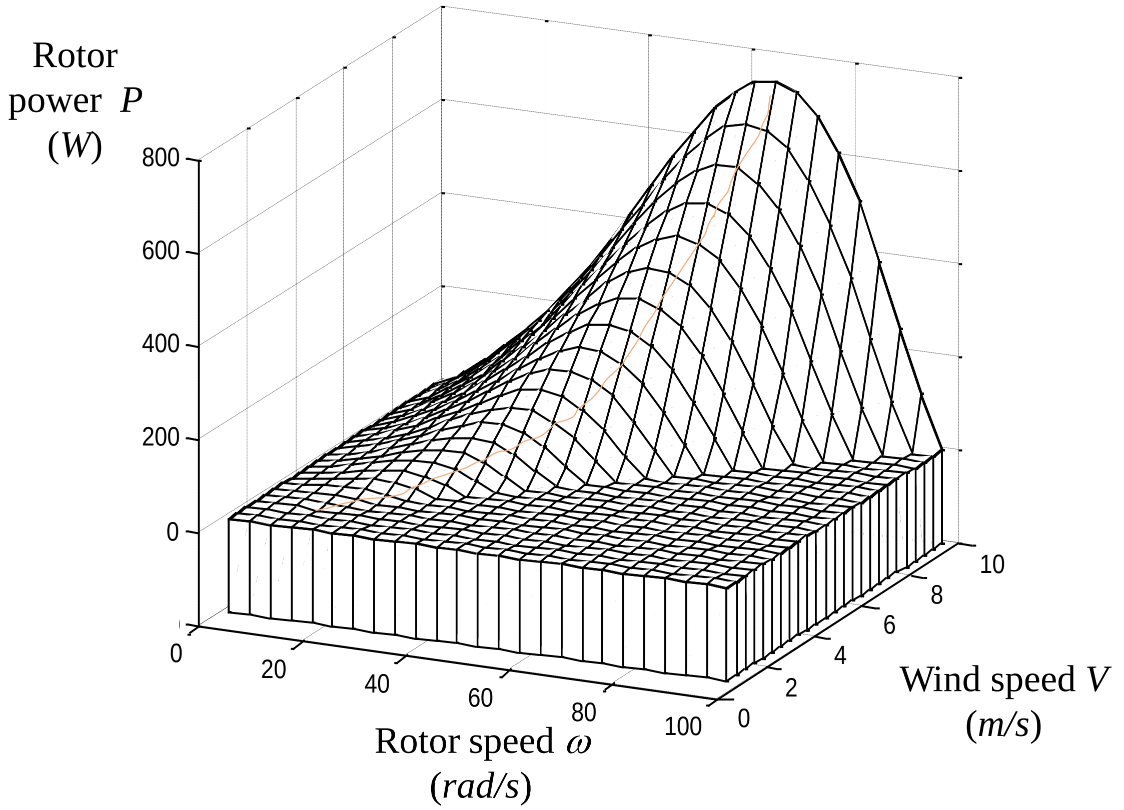
Mechanical Power: Summary 1

$$P = \frac{1}{2}\rho A C_p(\lambda) V^3 \qquad \lambda = \frac{r\,\omega}{V}$$

P	Mechanical power produced by the rotor
ρ	Air density
A	Rotor swept area
V	Wind speed
λ	Tip speed ratio
C_p	Power coefficient
r	Rotor radius
ω	Rotor speed



Mechanical Power: Summary 2



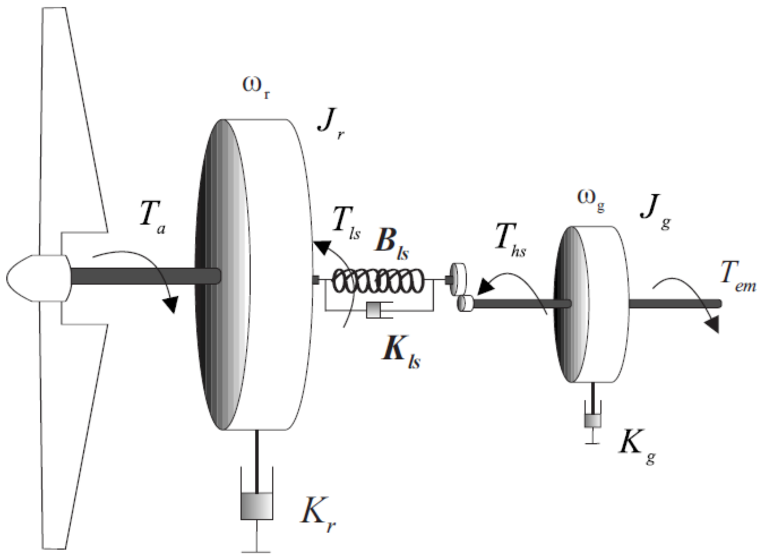
Summary 3

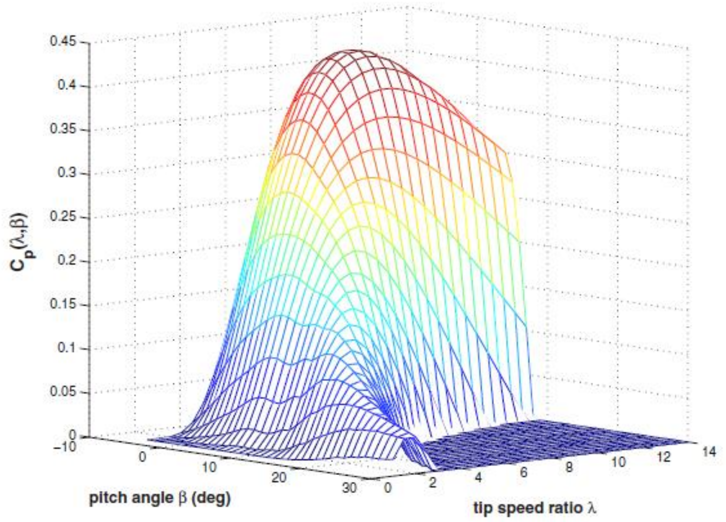
- ✓ It is important to notice is that the bulk of wind energy is extracted at wind speeds above the average wind speed
- ✓ This is due to the fact that that the energy content of high wind speeds is much higher than energy content of low wind speeds
- ✓ Basically, the non-linear (cube) relationship between the power and wind speed

$$\boxed{P = 0.5 \times \rho \times A \times v^3}$$

Computational Fluid Dynamics Model

- The challenging point - Cp(·) in the aerodynamics model is highly nonlinear and does not have exact form.

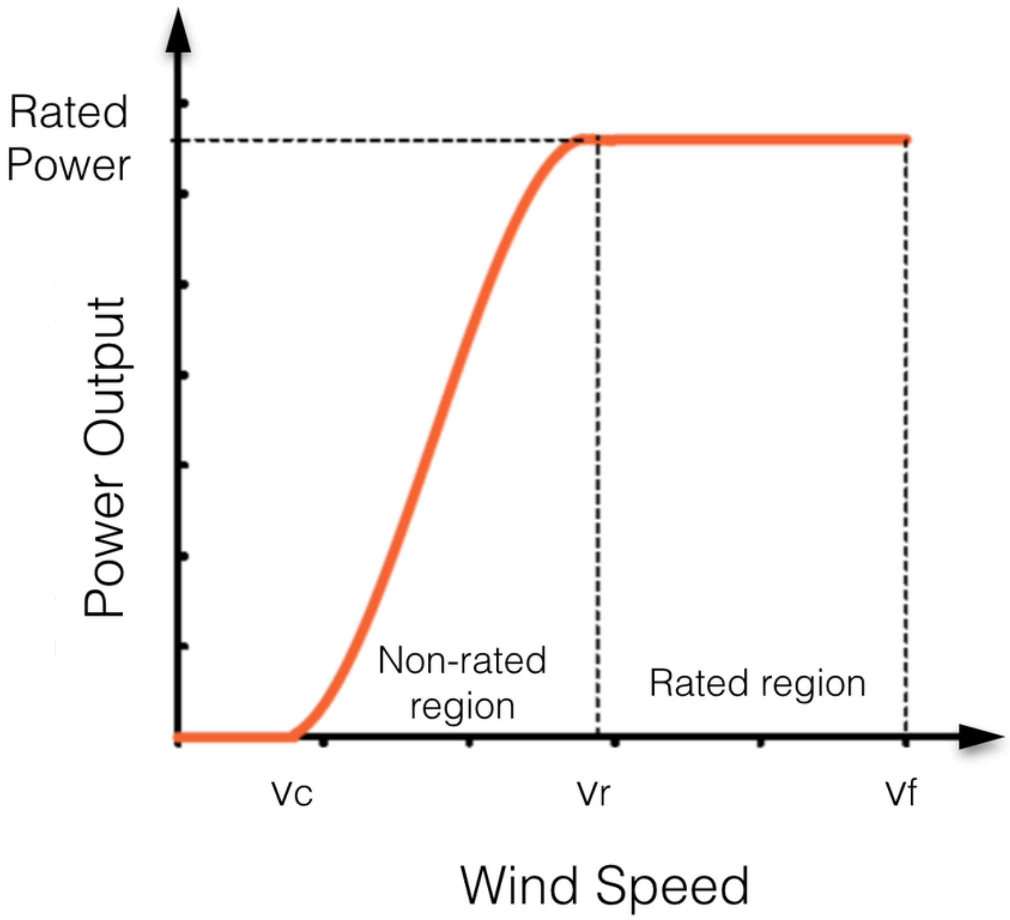




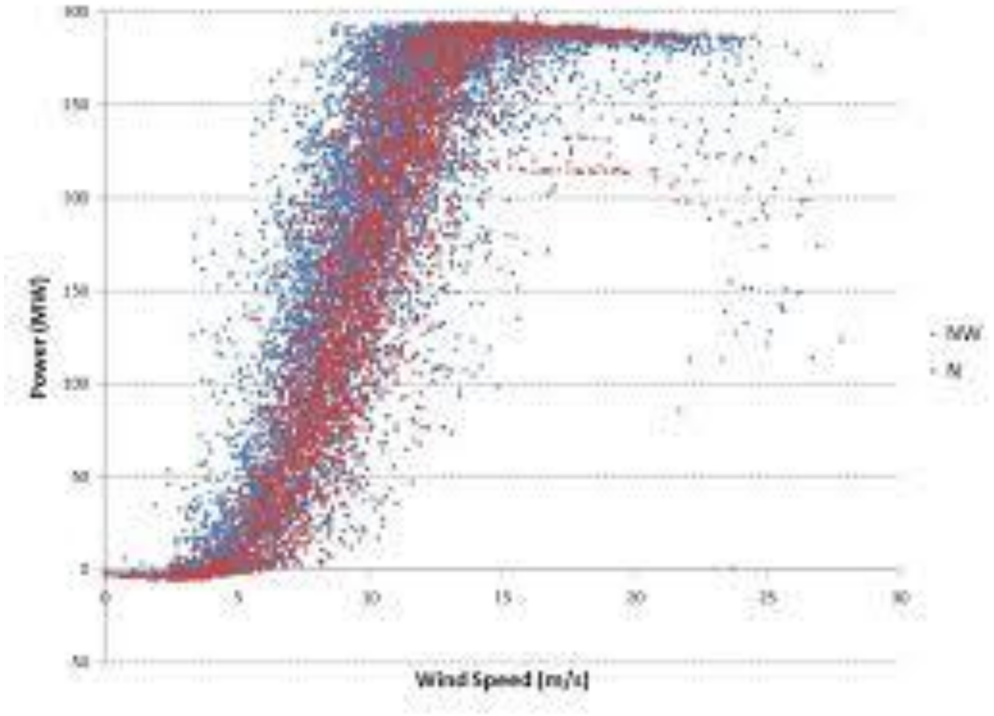
Computational Fluid Dynamics Model

- Cp(·), the power coefficient, needs to be estimated
- Estimation based on data
- Estimation based on control theory
- Estimation based on stochastic process

Power Curve Model

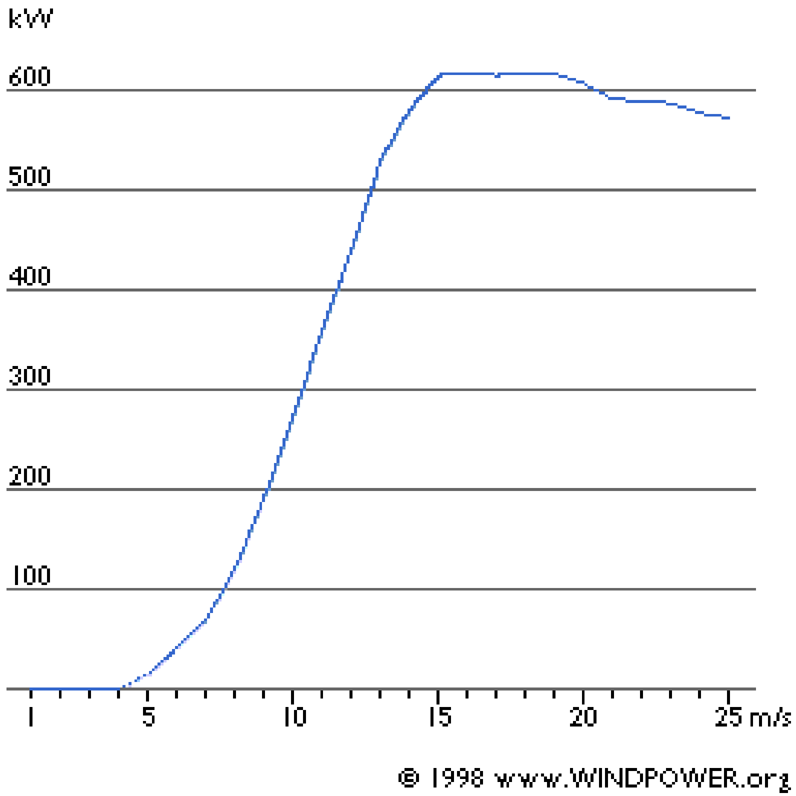


Ideal Power Curve Model



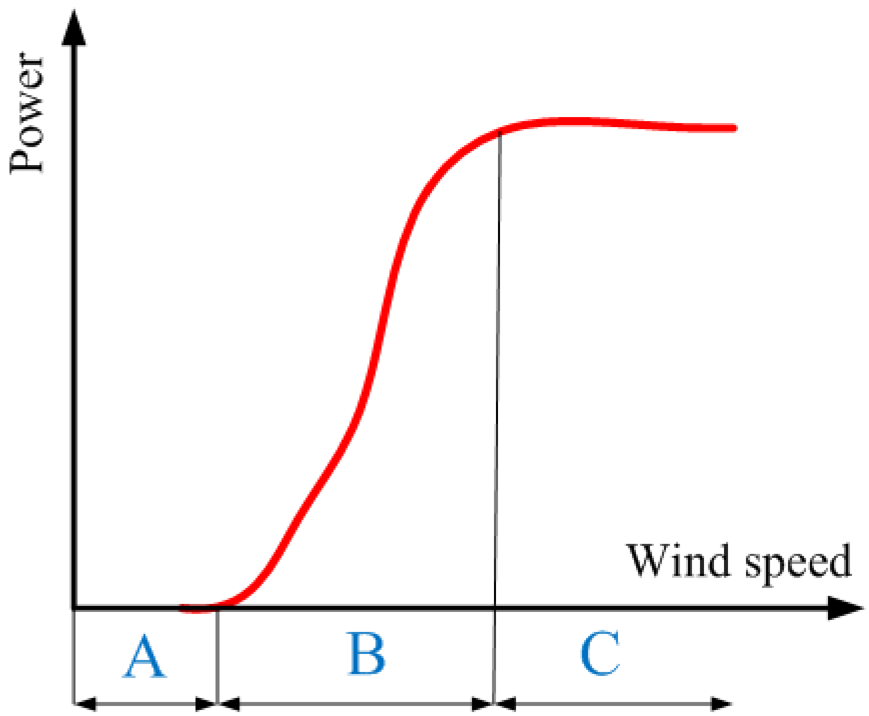
Real Power Curve Model

The Power Curve of a Wind Turbine



- ✓ The power curve of a wind turbine plots large the electrical power output at different wind speeds
- ✓ The cut-in wind speed: Turbines are designed to start running at wind speeds, e.g., 3 to 5 m/s
- ✓ The cut-out wind speed: Turbines are programmed to stop at high wind speeds, e.g., above 25 m/s to avoid damaging the turbine

Power Curve



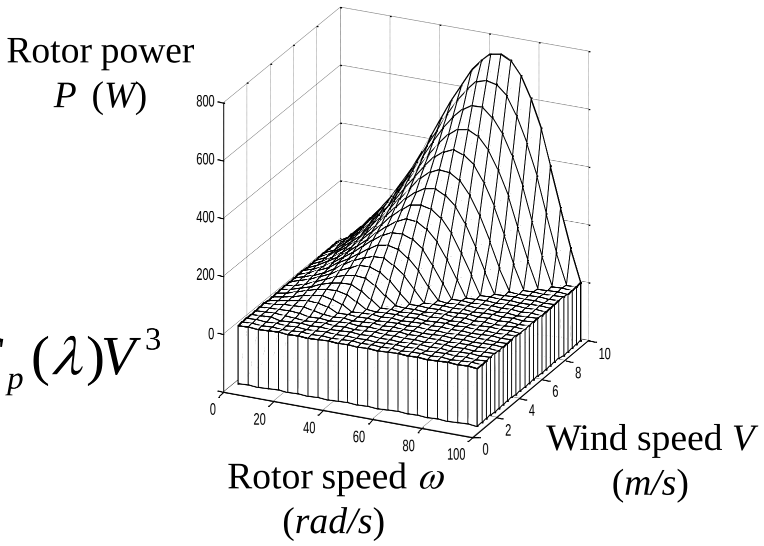
A: Insufficient power to overcome friction and initial torque

B: Turbine operates to maximize efficiency

C: Fixed (rated) power operation

$$P = \frac{1}{2}\rho A C_p(\lambda) V^3$$

$$\lambda = \frac{r\,\omega}{V}$$

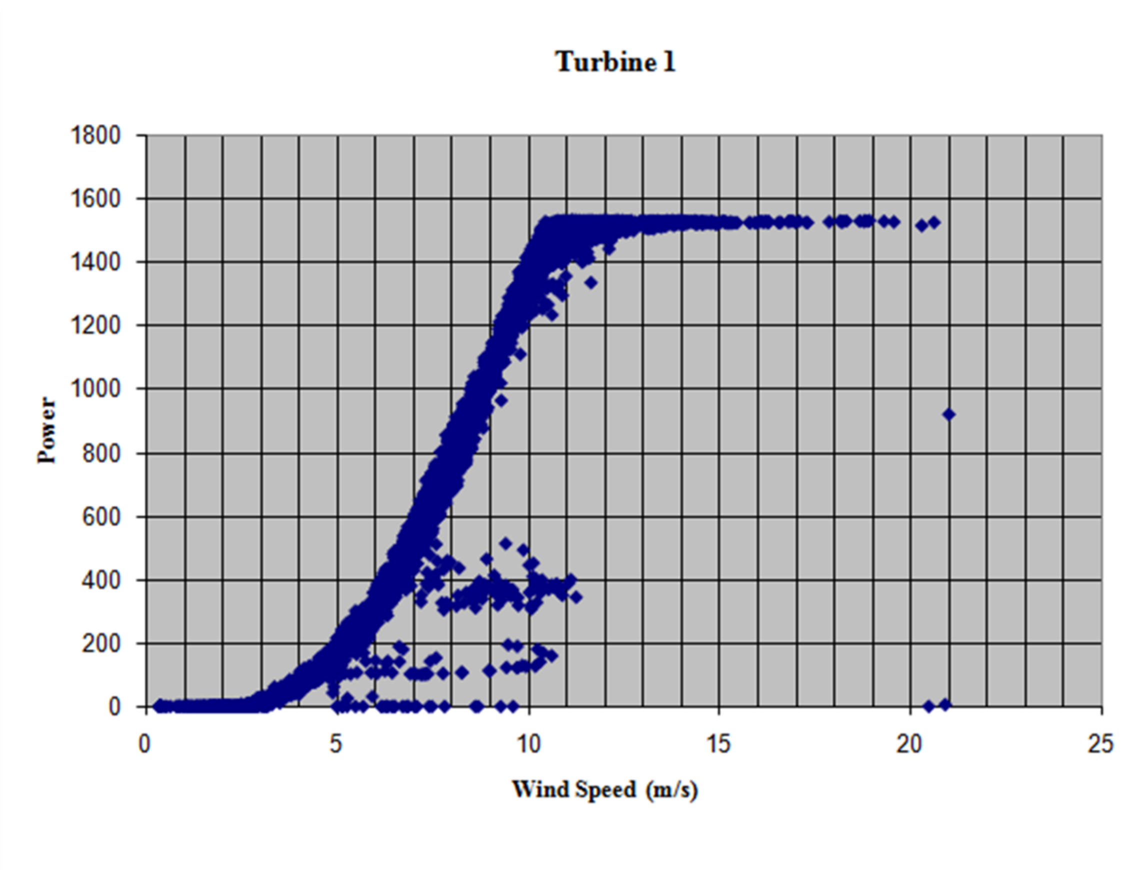


Plotting Power Curves

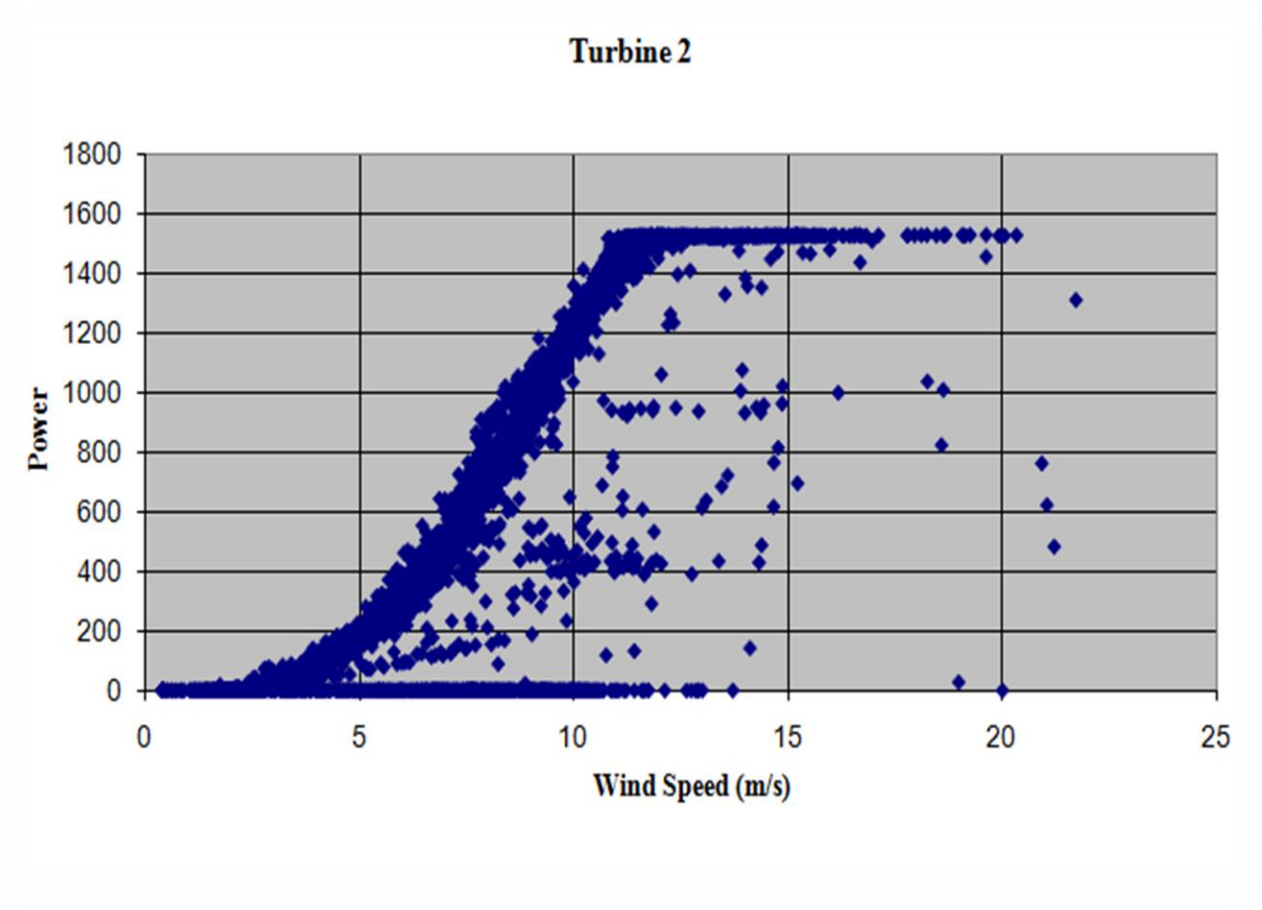
- ✓ If the wind speed is not fluctuating too rapidly, then one may use the wind speed measurements from the anemometer and read the electrical power output from the wind turbine and plot the two values in the form of the power curve
- ✓ In practice the wind speed always fluctuates, one cannot measure exactly the column of wind passing and therefore one will see a swarm of points dispersed around
- ✓ Furthermore, the actual anemometer error can be 3% , thus leading to 9% (or even 10%) error of the certified power curves

? $$\boxed{P = 0.5 \times \rho \times A \times v^3}$$

Actual Power Curve



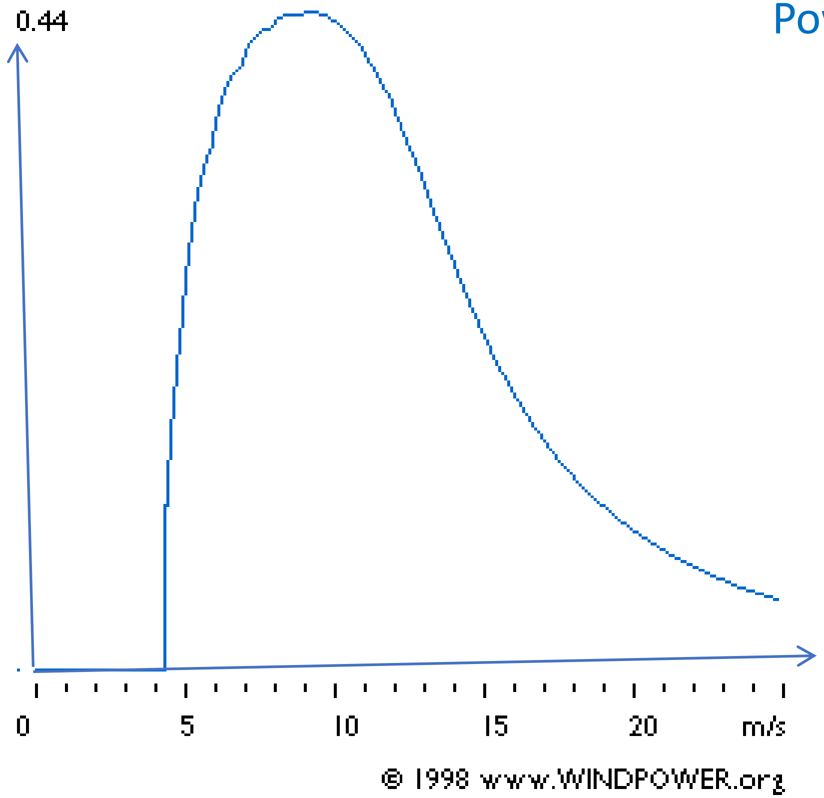
Actual Power Curve



Verifying Power Curves

- ✓ Power curves are constructed using measurements in areas with low turbulence intensity, and with the wind coming directly towards the front of the turbine
- ✓ Local turbulence and complex terrain (e.g., turbines placed on a rugged slope) may mean that wind gusts hit the rotor from varying directions
- ✓ It may therefore be difficult to reproduce the power curve exactly at any given location

The Power Coefficient



Illustrative power efficiency curve

Power coefficient = Turbine efficiency

- ✓ The power coefficient indicates how efficiently a turbine converts the wind energy into electricity

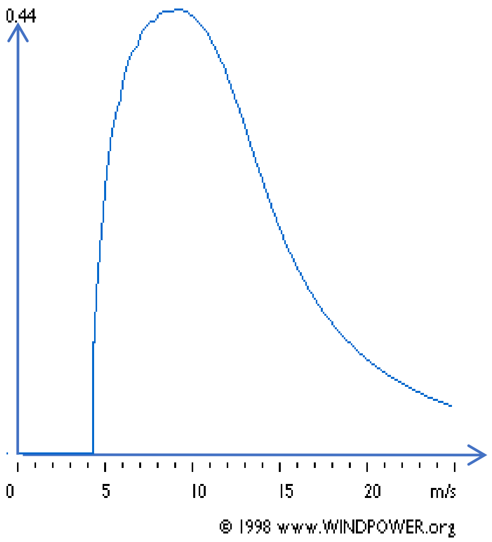
$$E = E_{rot} \; x \; E_{ger} \; xE_{gen} \; x \; E_{p\text{-}conv}$$

- ✓ Power coefficient = $\dfrac{\text{The electrical power output}}{\text{The wind energy input}}$ (From the power equation)

- ✓ The efficiency varies with the wind speed

$$\boxed{P = 0.5 \times \rho \times A \times v^3}$$

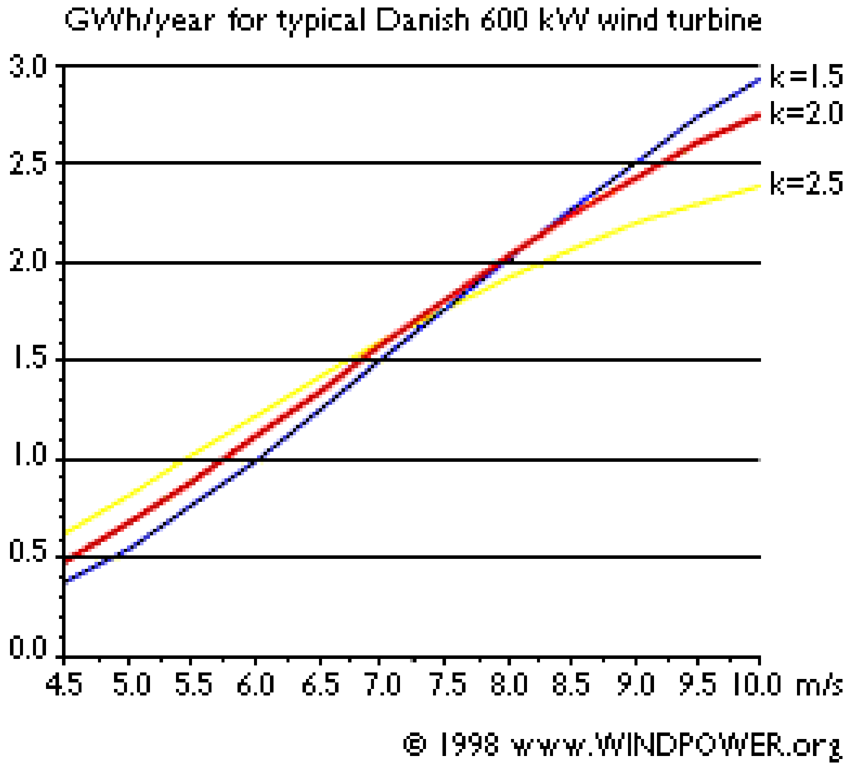
The Power Coefficient



Power coefficient = Turbine efficiency

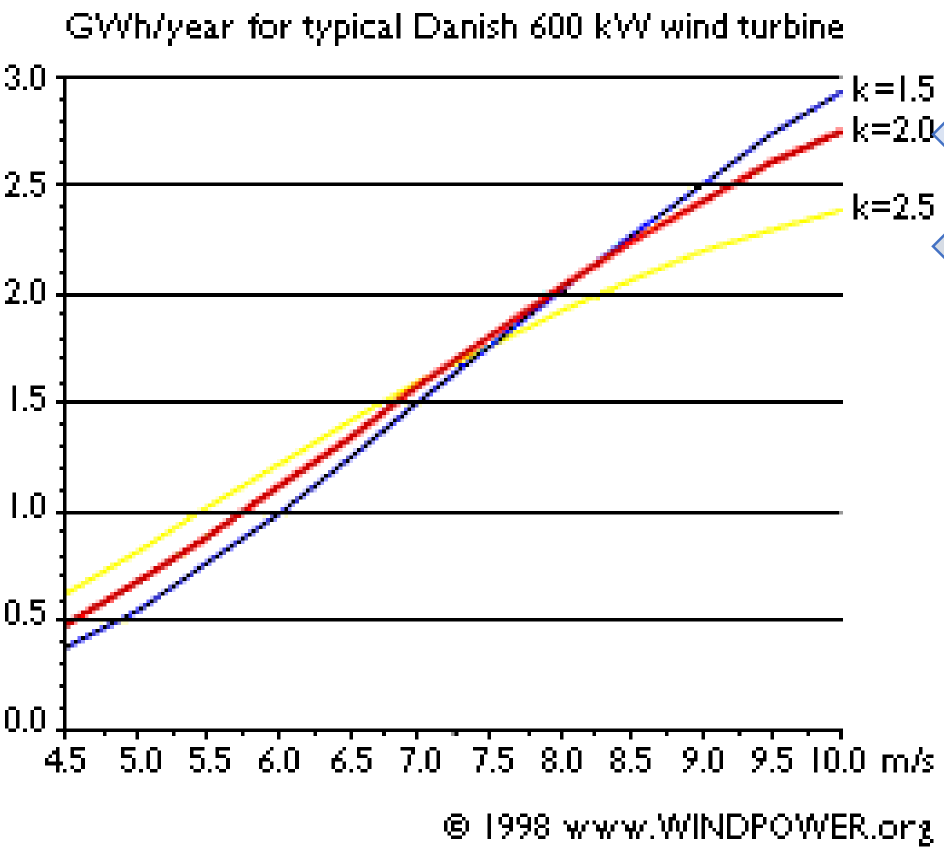
- ✓ Example: A turbine was designed for the max efficiency of 44% at a wind speed of about 9 m/s
- ✓ The efficiency is not as important at low wind speeds as there is not much energy to harvest
- ✓ At high wind speeds the turbine wastes the excess energy above the cut out speed
- ✓ Efficiency therefore matters most in the regions of wind speeds (i.e., high) where the most of energy is to be found

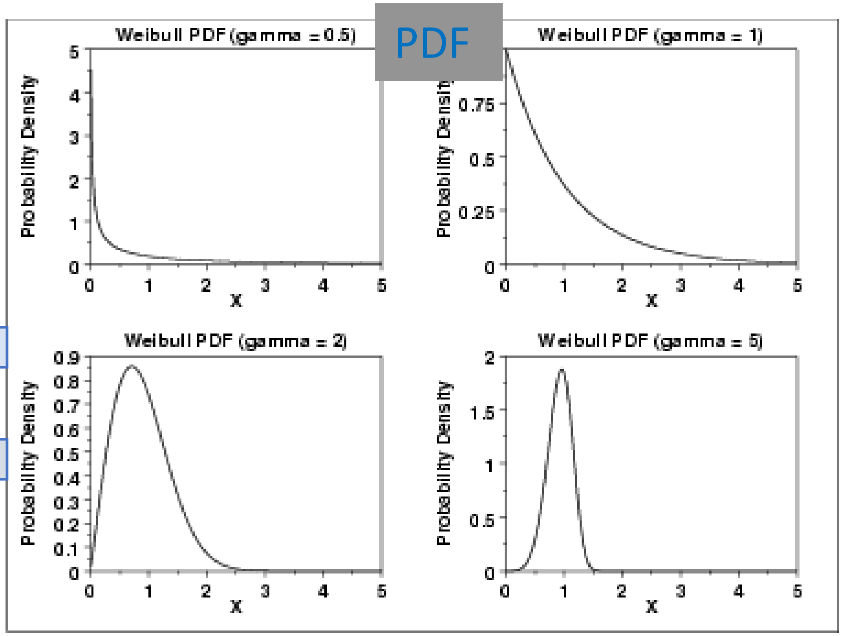
Annual Energy Output from a Wind Turbine

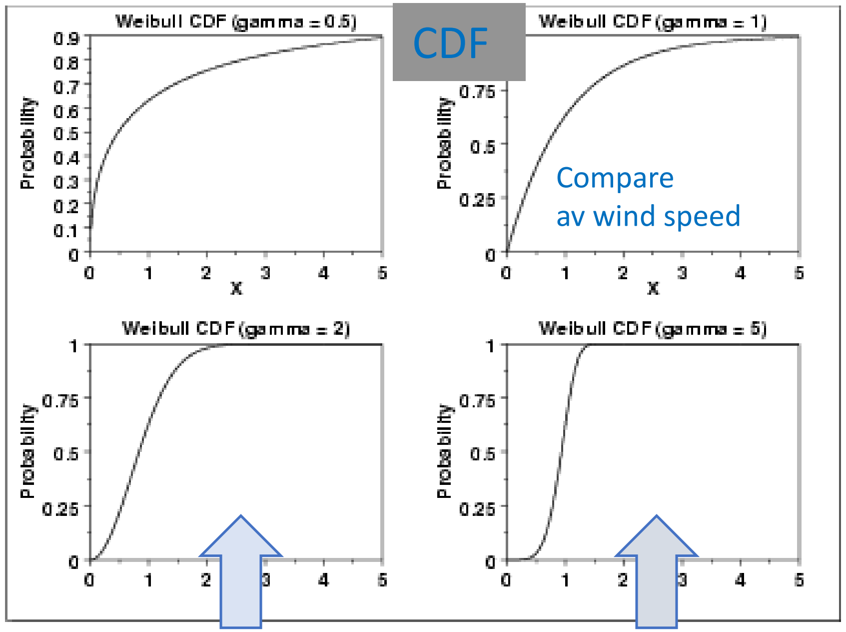


- ✓ The relationship between the average wind speed and the annual energy output from a wind turbine
- ✓ Standard atmosphere with air density of 1.225 kg/m3
- ✓ For each of the Weibull shape parameters k = 1.5, 2.0, and 2.5, the annual energy output is computed at different average wind speeds at the turbine hub height

The Impact of *k*

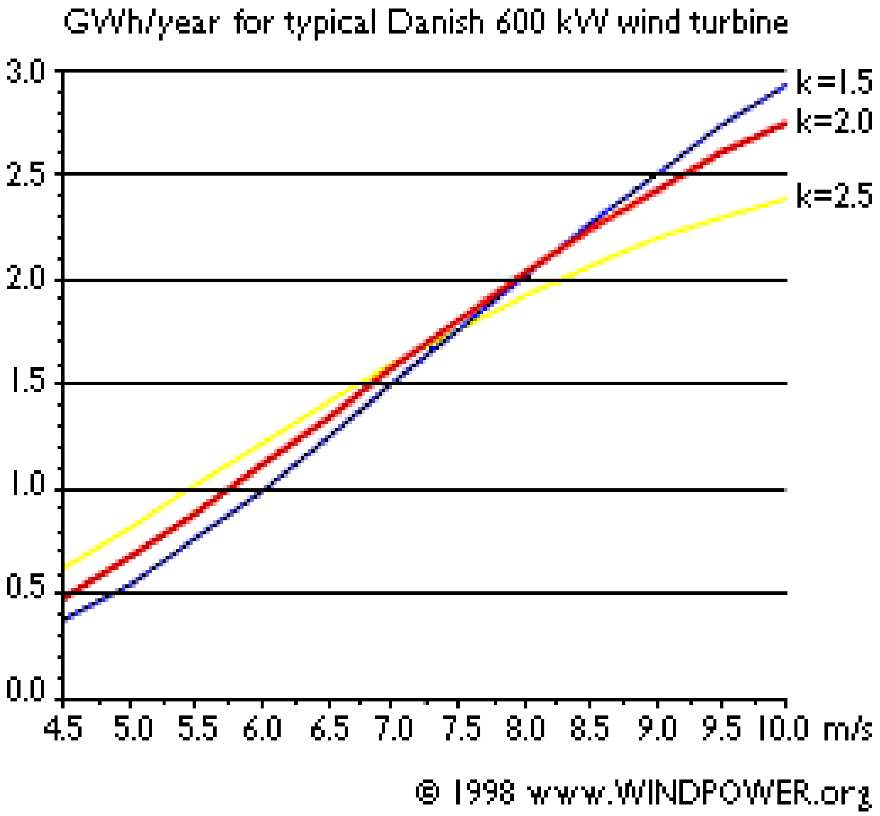






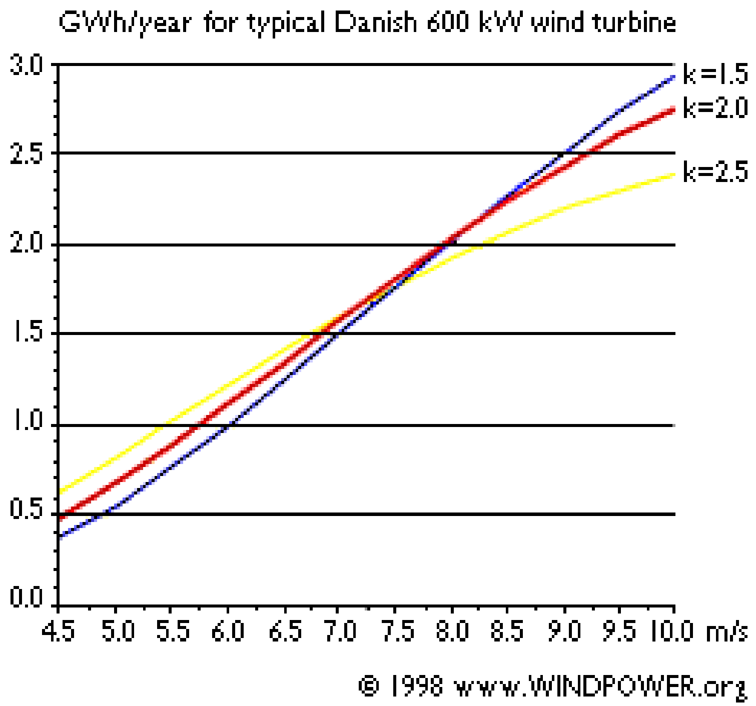
Shape parameter gamma = *k*
Scale parameter λ = 1
(Location parameter = 0)

Annual Energy Output from a Wind Turbine



- ✓ Depending on the value of shape parameter *k* the energy output may vary up to 50% at a low average wind speed of 4.5 m/s, and some 30% at a higher average wind speed of 10m/s

Output Varies with the Average Wind Speed



- ✓ Consider the red curve with the shape parameter $k = 2$, normally shown by manufacturers
- ✓ For an average wind speed of 4.5 m/s the turbine generates about 0.5 GWh per year
- ✓ For an average wind speed to 9 m/s 2.4 GWh/year it generated
- ✓ Thus, doubling the average wind the energy output increased 4.8 times

Output Varies with the Wind Speed

- ✓ For the average speeds 5 and 10 m/s (the same speed ratio of 2), energy output would differ by the factor of 4 (rather than 4.8)
- ✓ The reason for the difference, is that the efficiency of the wind turbine varies with the wind speed (the power curve)
- ✓ Note, that the uncertainty that applies to the power curve also applies to the above result
- ✓ The calculations can be refined by considering that, e.g., in temperate climates the wind tends to be stronger in winter than in summer, and stronger during the daytime than at night

The Capacity Factor

✓ Turbine capacity factor = $\dfrac{\text{The actual annual energy output}}{\text{The theoretical maximum output}}$

Theoretical maximum output = if the turbine was running at its maximum rated power for 8766 hours of the year (=24h*365.25days)

✓ Example: For a 600 kW turbine producing 1.5 million kWh per year, its capacity factor is
= 1,500,000/(365.25*24*600) = 1,500,000/5,259,600
= 0.285 = 28.5%

✓ The capacity factor may theoretically vary from 0 to 100%, but in practice it usually is 20% to 70%

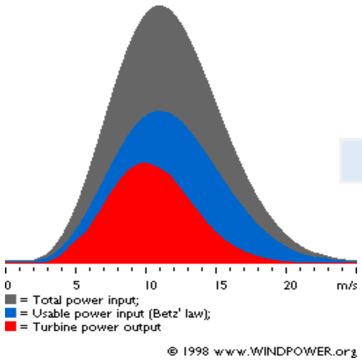
Turbine/Wind Plant Availability Factor

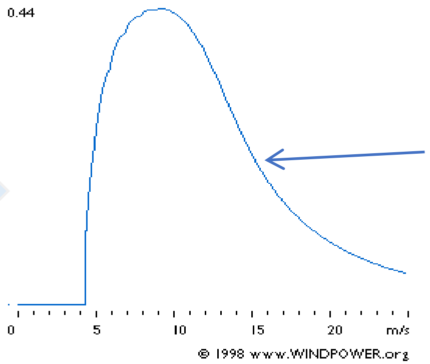
- ✓ Availability factor = $\dfrac{\text{The time turbine/wind plant is available}}{\text{The total time (in a year)}}$

- ✓ Different specific definitions of the availability factor
- ✓ Has improved in recent years
- ✓ Equipment reliability
- ✓ Warranty terms

Comparison

✓ Turbine power coefficient = $$\frac{\text{The electrical power output [KW]}}{\text{The wind energy input [KW]}}$$





Aerodynamic break

✓ Turbine capacity factor = $$\frac{\text{The actual annual energy output [kWh]}}{\text{The theoretical maximum output [kWh]}}$$

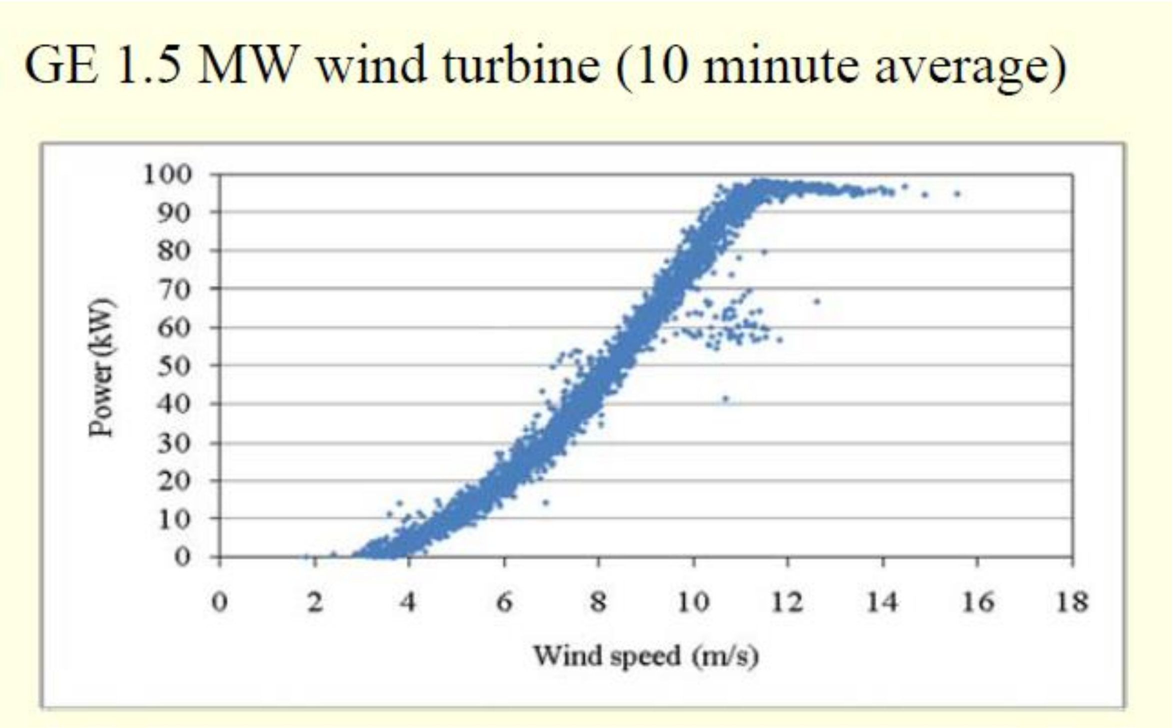
✓ Availability factor = $$\frac{\text{The time turbine/wind plant is available}}{\text{The total time (in a year)}}$$

Power Curve – 10-min 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

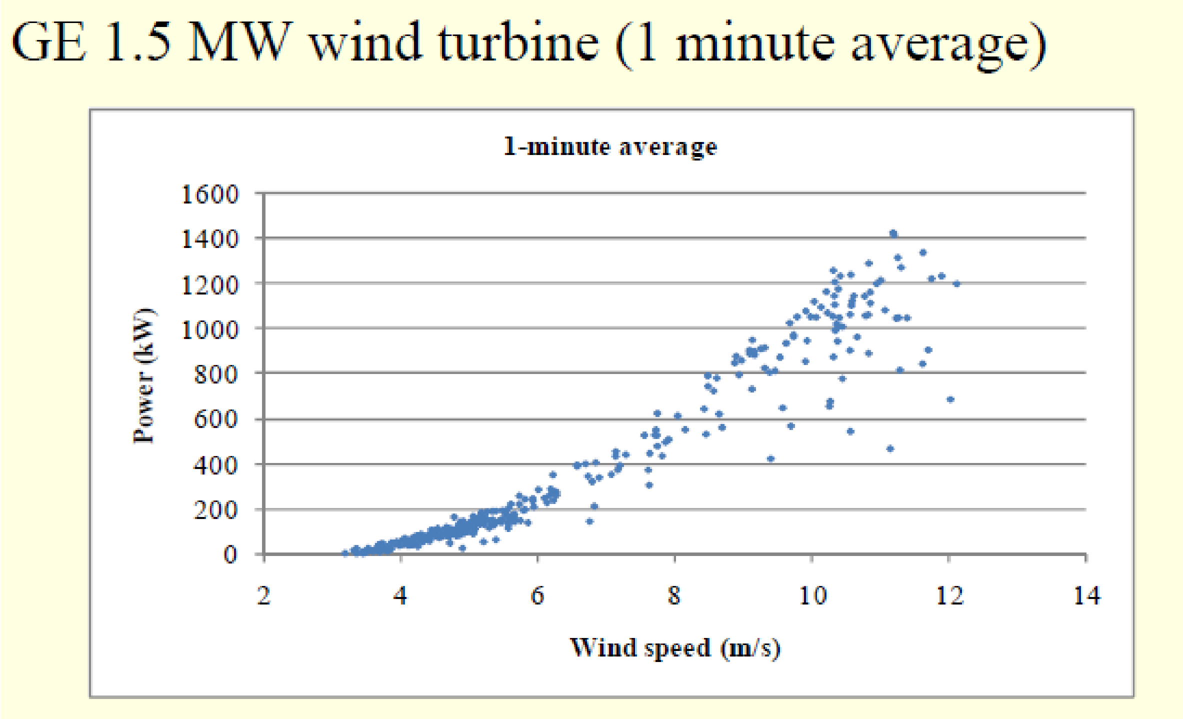


Power Curve – 1-min Data

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

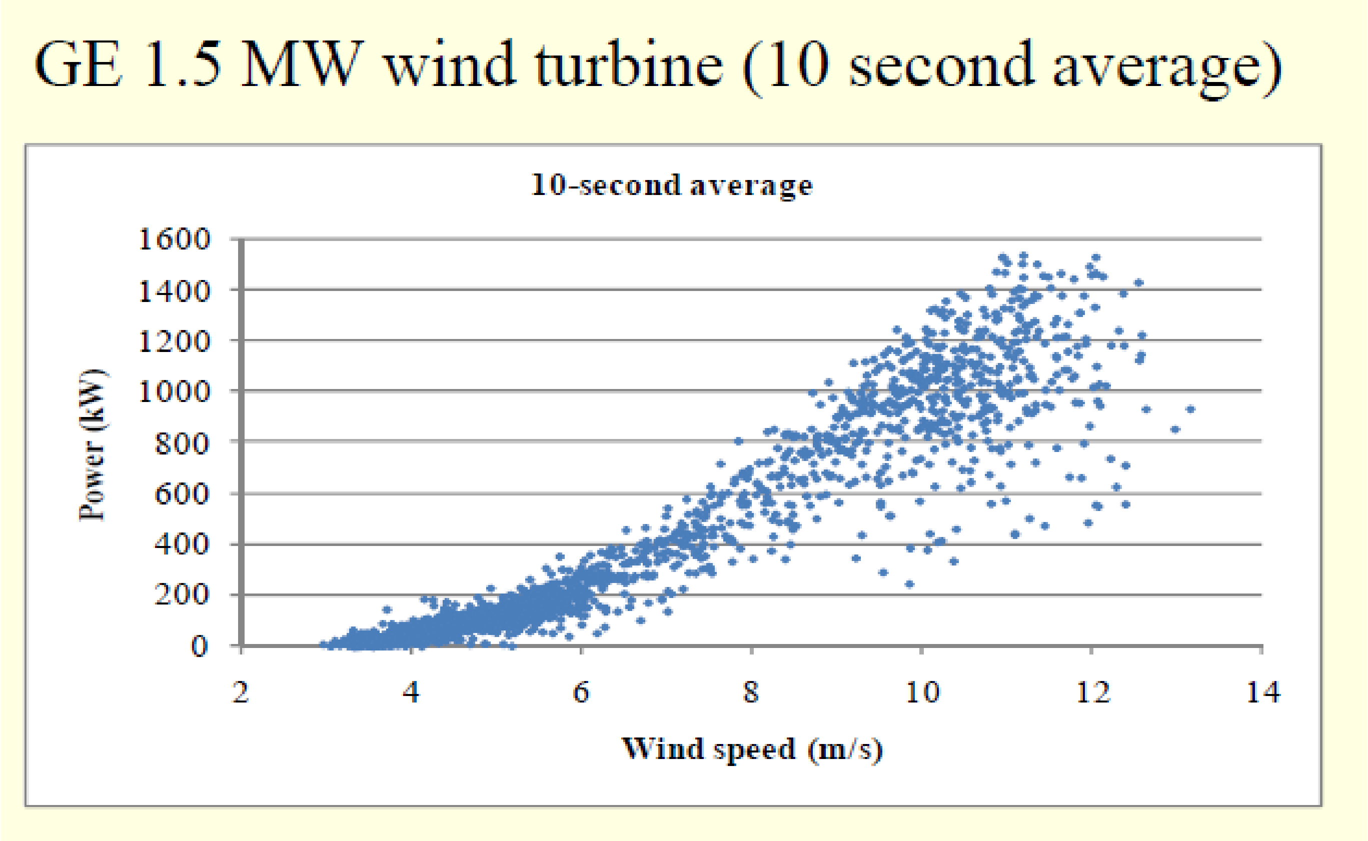


Power Curve – 10-sec Data

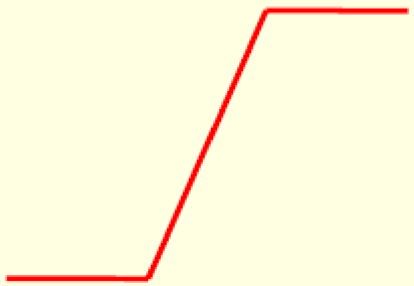
GE 1.5 MW wind turbine (10 second average)

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



Power Curve Model 1



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

Linear power curve function

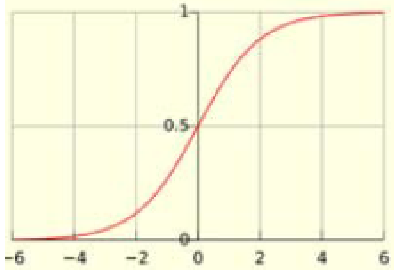
y power output

v wind speed

λ slope, η intercept

P_{rated} rated power

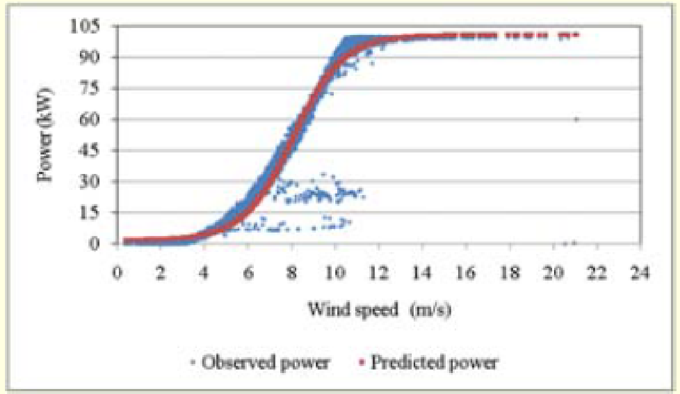
Power Curve Model 2



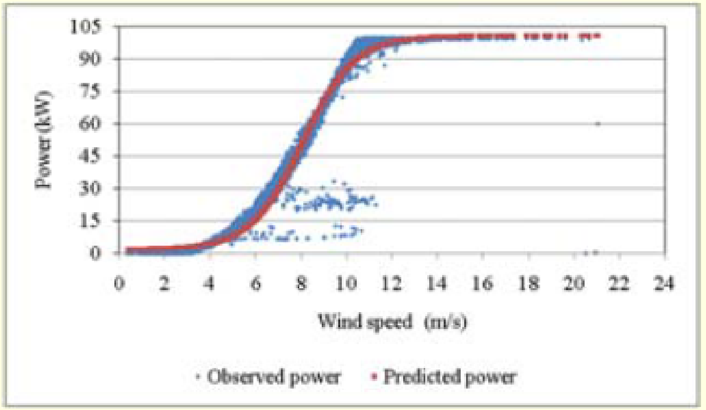
$$y = f(v, \boldsymbol{\theta}) = a\frac{1 + me^{-v/\tau}}{1 + ne^{-v/\tau}}$$

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

Logistic function power curve



Power Curve Model 2



Least square estimation of the power curve

Number of field data points

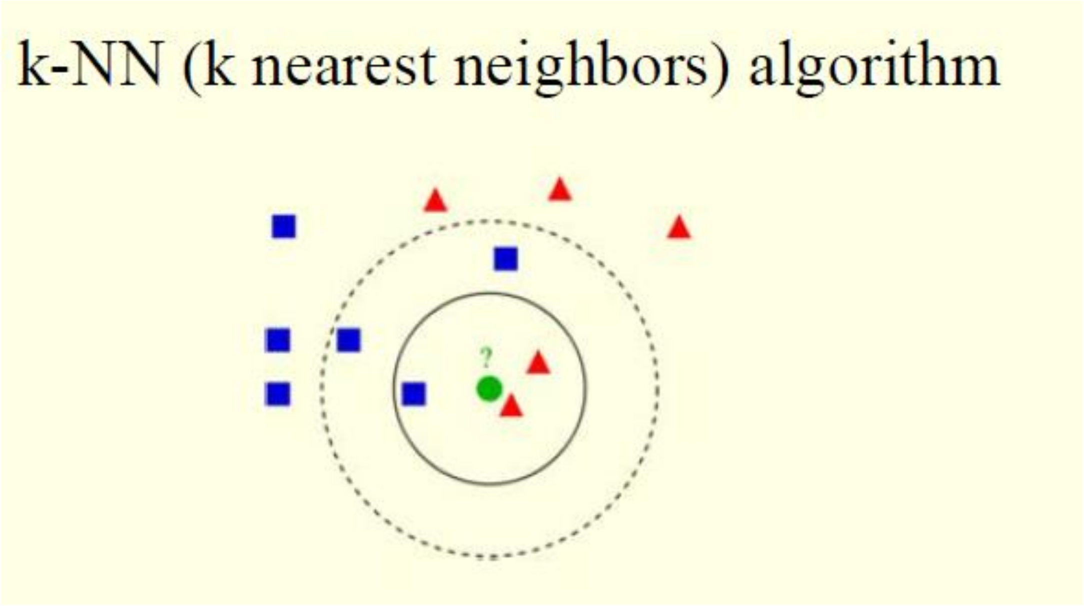
$$\min_{\boldsymbol{\theta}} \sum_{i=1}^{N} (f(v_i, \boldsymbol{\theta}) - y_i)^2$$

Power curve function predicting power output

Change Theta to minimize the squared error

Actual measured power output

Power Curve Model 3



Power Curve Model 3

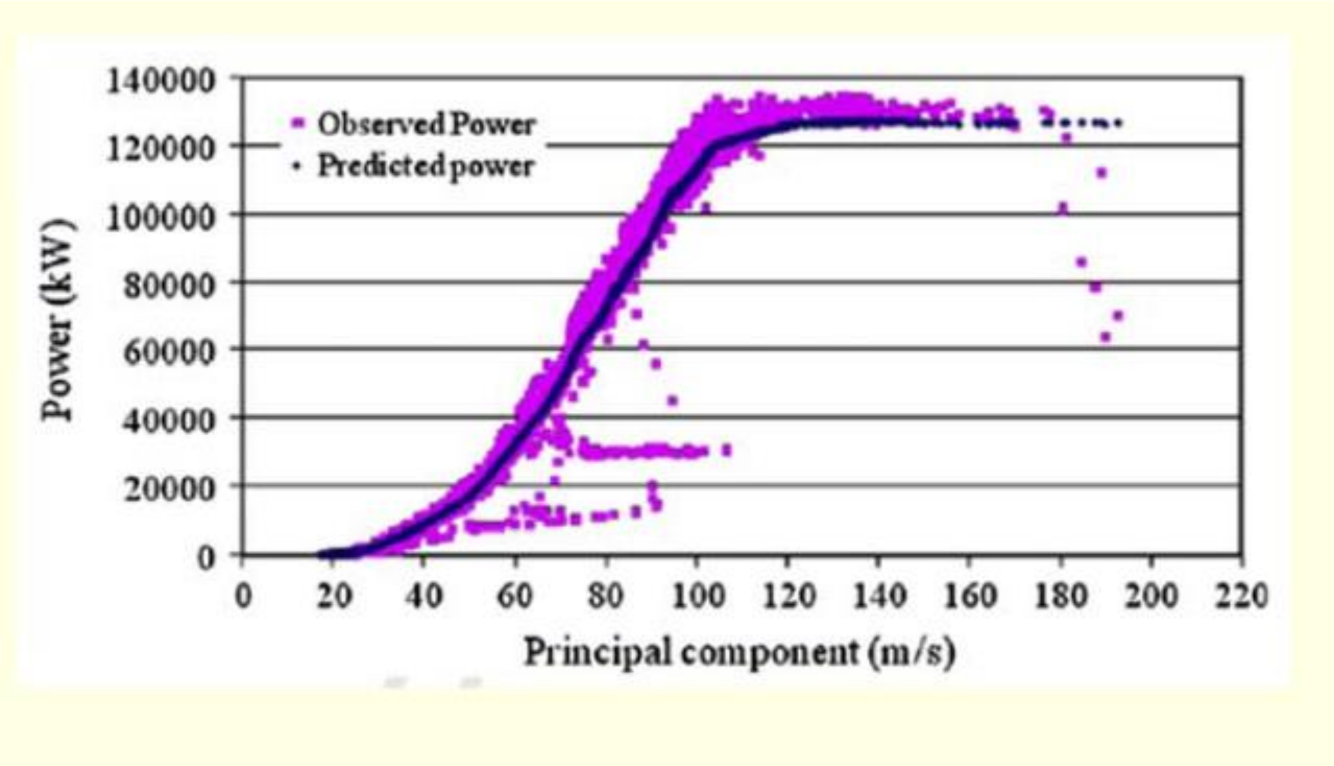
Remove bad data points

- Turbine down time
- Sensor errors

Principal component analysis

- Reduce dimensions
- Reduce noises in the data

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



Data-driven Model 1

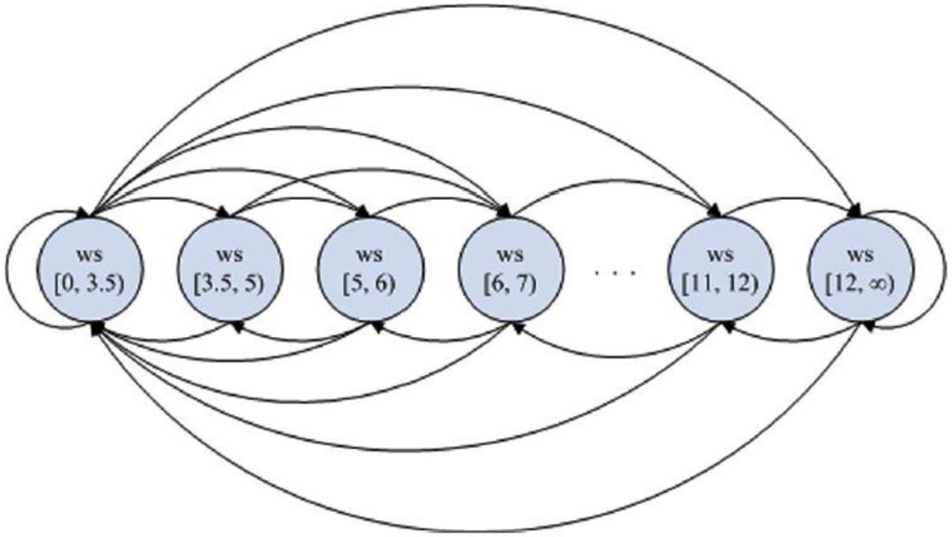
- A Gray-box Model Extended From Aerodynamic Model

$$P_a = \frac{1}{2}\rho\pi R^2 C_p(\lambda, \beta)\upsilon^3$$

$$P_{a(t)} = \frac{1}{2}\rho\pi R^2 f_A \times \left(\omega_{r(t)}, \omega_{r(t-T)}, \upsilon_t, \upsilon_{t-T}, \beta_t, \beta_{t-T}, C_{p(t-T)}\right)\upsilon_t^3$$

$$C_{p(t)} = f_A\left(\omega_{r(t)}, \omega_{r(t-T)}, \upsilon_t, \upsilon_{t-T}, \beta_t, \beta_{t-T}, C_{p(t-T)}\right).$$

Data-driven Model 1



TRANSITION MATRIX OF WIND SPEED CHANGES IN 60 S

WS Interval	[0, 3.5)	[3. 5,5)	[5, 6)	[6, 7)	[7, 8)	[8, 9)	[9, 10)	[10, 11)	[11, 12)	[12, ∞)
[0, 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

Data-driven Model 2

- A direct data-driven model with process engineering

$$P_{a(t)} = f_A(\tau_t, \upsilon_t, \upsilon_{t-T}, \beta_t)$$

Data-driven Model 3

- A data-driven considering system dynamics

$$P_{a(t)} = f(P_{a(t-T)}, \upsilon_t, \omega_{r(t)}, \beta_t)$$

Data-driven Modeling Process

- Feature selection
- Modeling method selection

PERFORMANCE OF FIVE ALGORITHMS FOR MODEL TWO

Algorithm	MAE	SD of MAE	MAPE	SD of MAPE
Neural network	7.3416	5.8452	0.0260	0.3762
Boosting tree	48.0019	58.3010	0.1277	3.3080
Random forest	96.1827	106.6014	0.1834	2.3494
Support vector machine	27.5409	14.5258	0.1440	5.6230
k-nearest neighbor	9.9953	8.8141	0.0342	0.6884

PERFORMANCE OF FIVE ALGORITHMS FOR MODEL ONE

Algorithm	MAE	SD of MAE	MAPE	SD of MAPE
Neural network	1.2877	1.6810	0.0344	0.2230
Boosting tree	5.6543	5.6819	0.1298	0.2920
Random forest	6.9763	6.9643	0.1569	0.3536
Support vector machine	5.8793	3.6885	0.1454	0.2202
k-nearest neighbor	2.9935	3.4315	0.0723	0.2763

PERFORMANCE OF FIVE ALGORITHMS FOR MODEL THREE

Algorithm	MAE	SD of MAE	MAPE	SD of MAPE
Neural network	20.5270	29.8117	0.0442	0.3440
Boosting tree	59.8376	60.5458	0.1507	3.6392
Random forest	94.4690	103.2844	0.1851	3.0446
Support vector machine	45.2412	46.8501	0.1920	5.5457
k-nearest neighbor	28.1062	43.5211	0.0610	0.9422

Data-driven Modeling Process

SUMMARY OF PREDICTION ACCURACY OF THREE MODELS

Model	MAE	SD of MAE	MAPE	SD of MAPE
Model-One	18.3454	28.9566	0.0344	0.2230
Model-Two	7.3416	5.8452	0.0260	0.3762
Model-Three	20.5270	29.8117	0.0442	0.3440

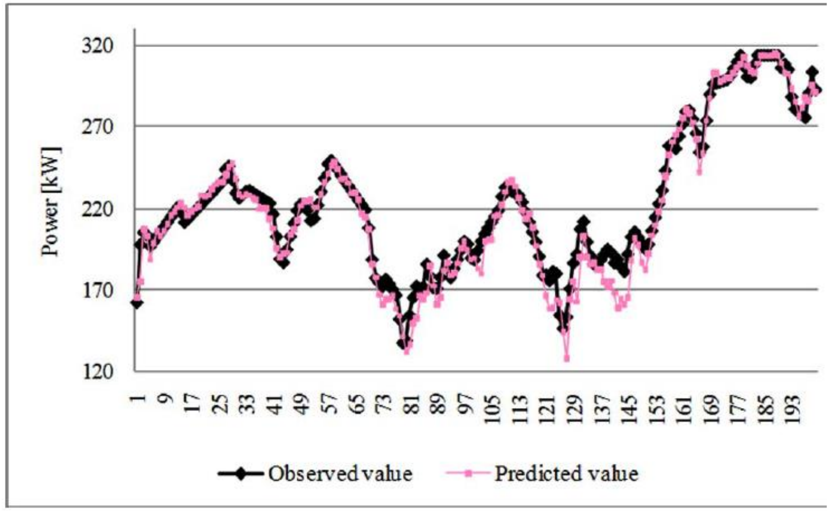


Fig. 10. First 200 test points in predicting power by model one.

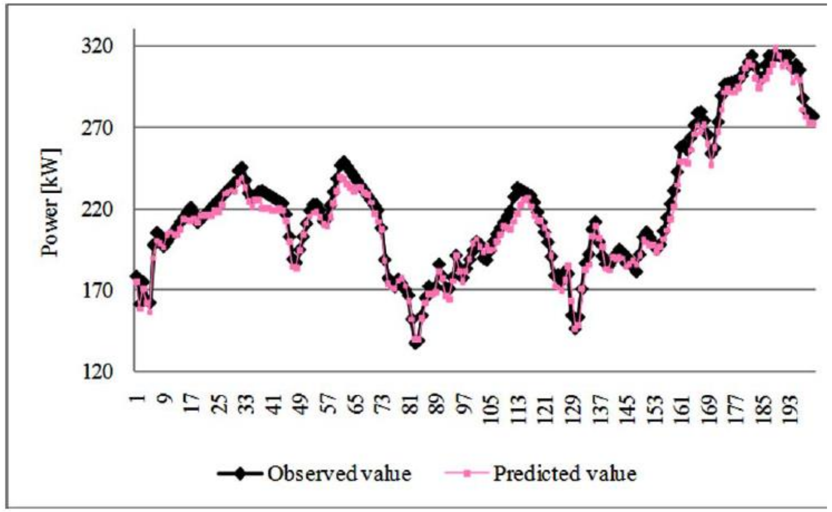


Fig. 11. First 200 test points in predicting power by model two.

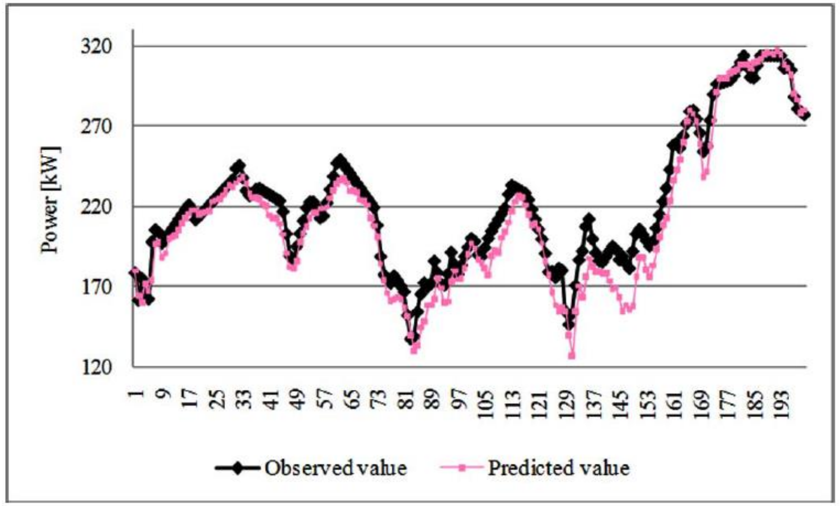


Fig. 12. First 200 test points in predicting power by model three.

Multi-period Prediction

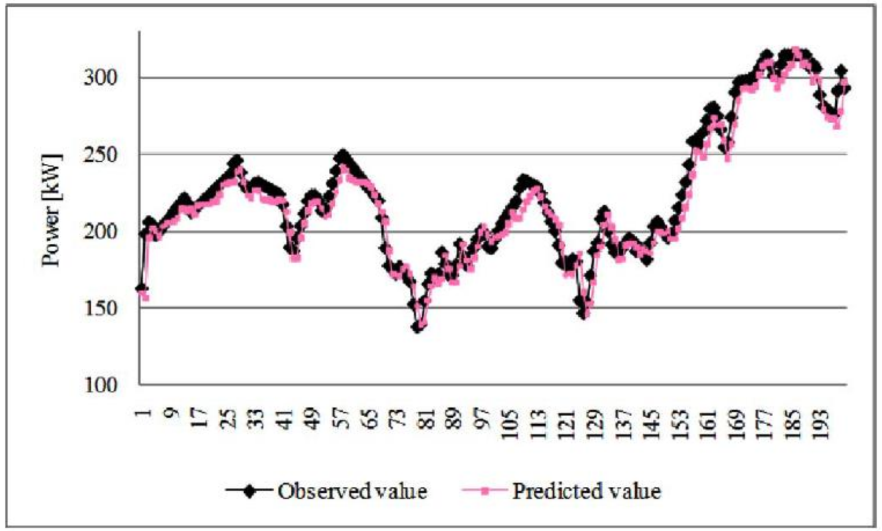


Fig. 13. First 200 points of t +10 s predictions by model two based on dataset 1.

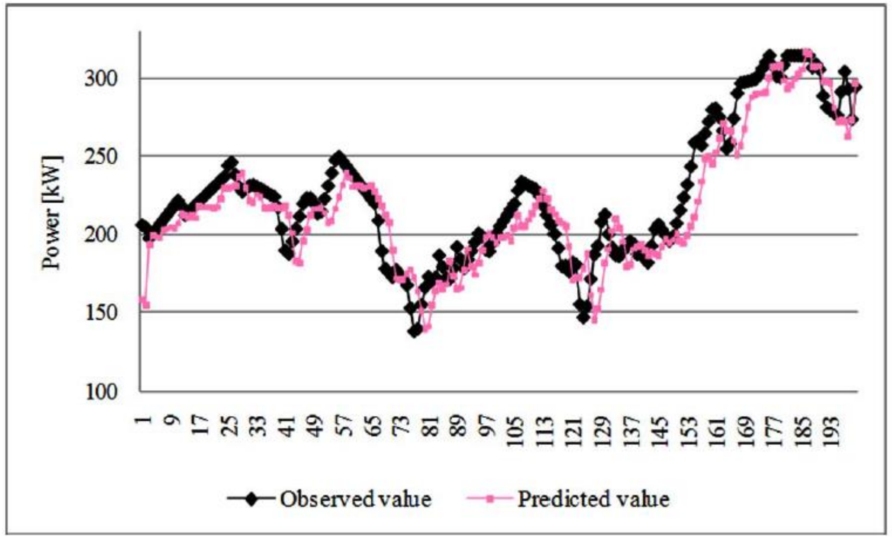


Fig. 15. First 200 points of t + 30 s prediction by model two based on dataset 1.

In-Class Practice

- Use weka to conduct the wind speed prediction
- Datasets have been available in Canvas
- Let us do it together…