Big Data in Wind Energy Generation and Control

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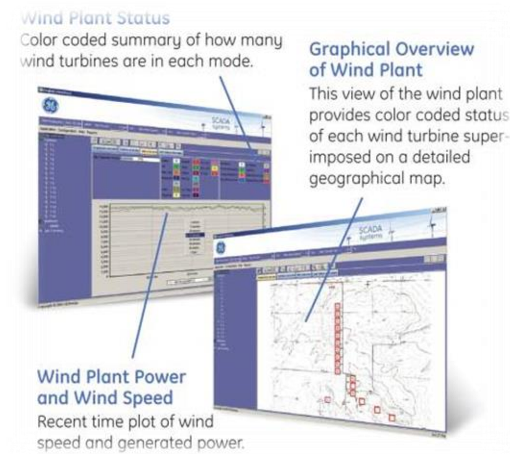
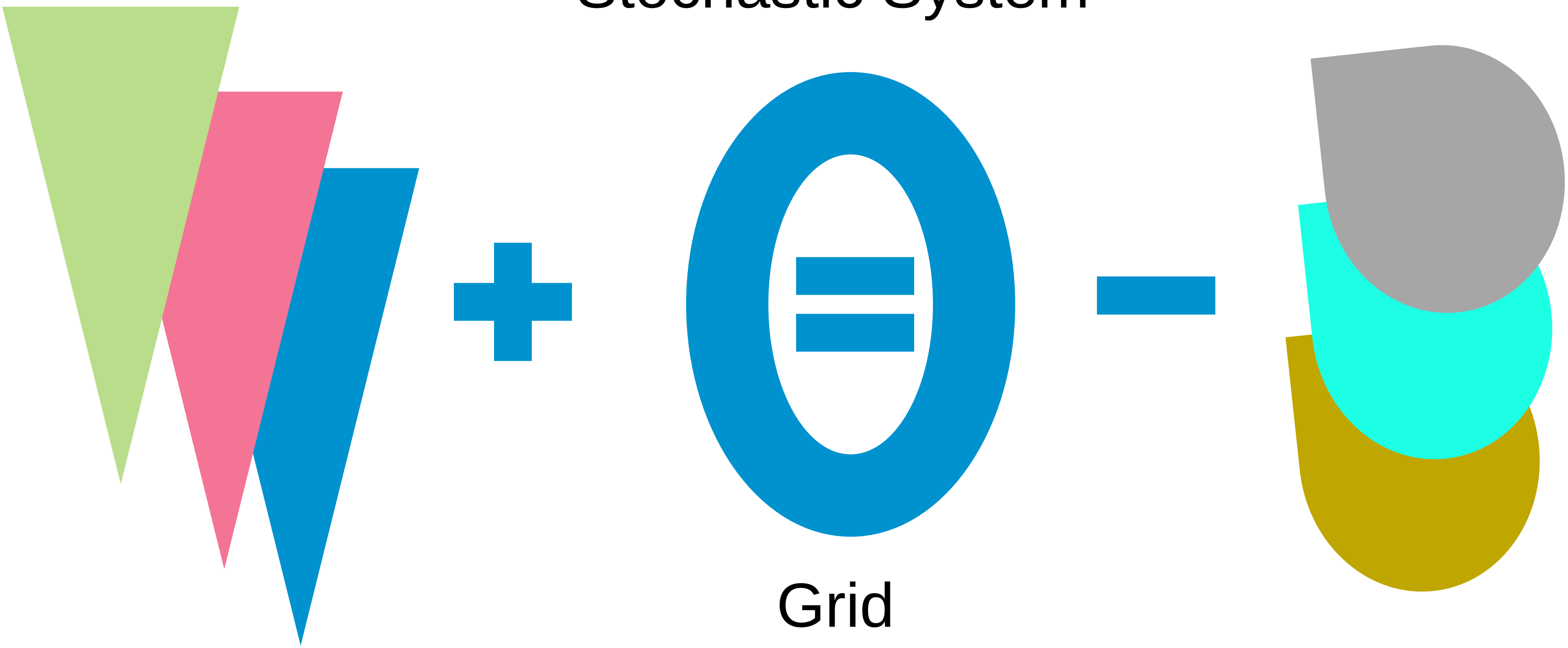
Outline

- Introduction
- Modeling from data
- Big data applications
  - ✓ Control of energy generation
  - ✓ Power prediction
  - ✓ Health monitoring
  - ✓ Innovation in energy
- Summary



Big Picture Energy Management

Stochastic System



Grid
- AC/DC
- Smart

Generation

Consumption

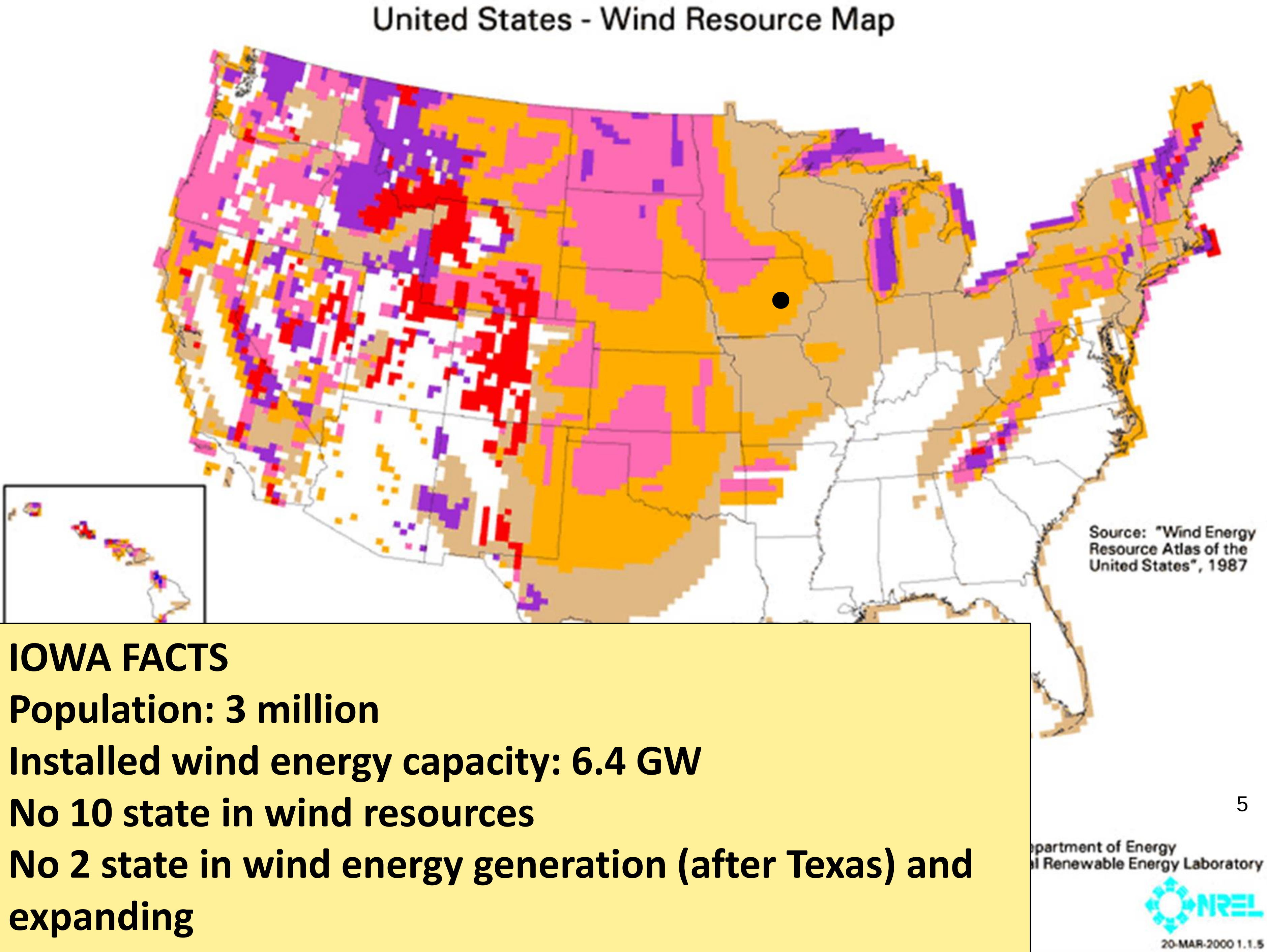
Wind Energy Headlines

Iowa #1 in wind energy

March 1, 2016: Gov. Terry Branstad announced that Iowa generates more than **31%** of its energy from the wind.

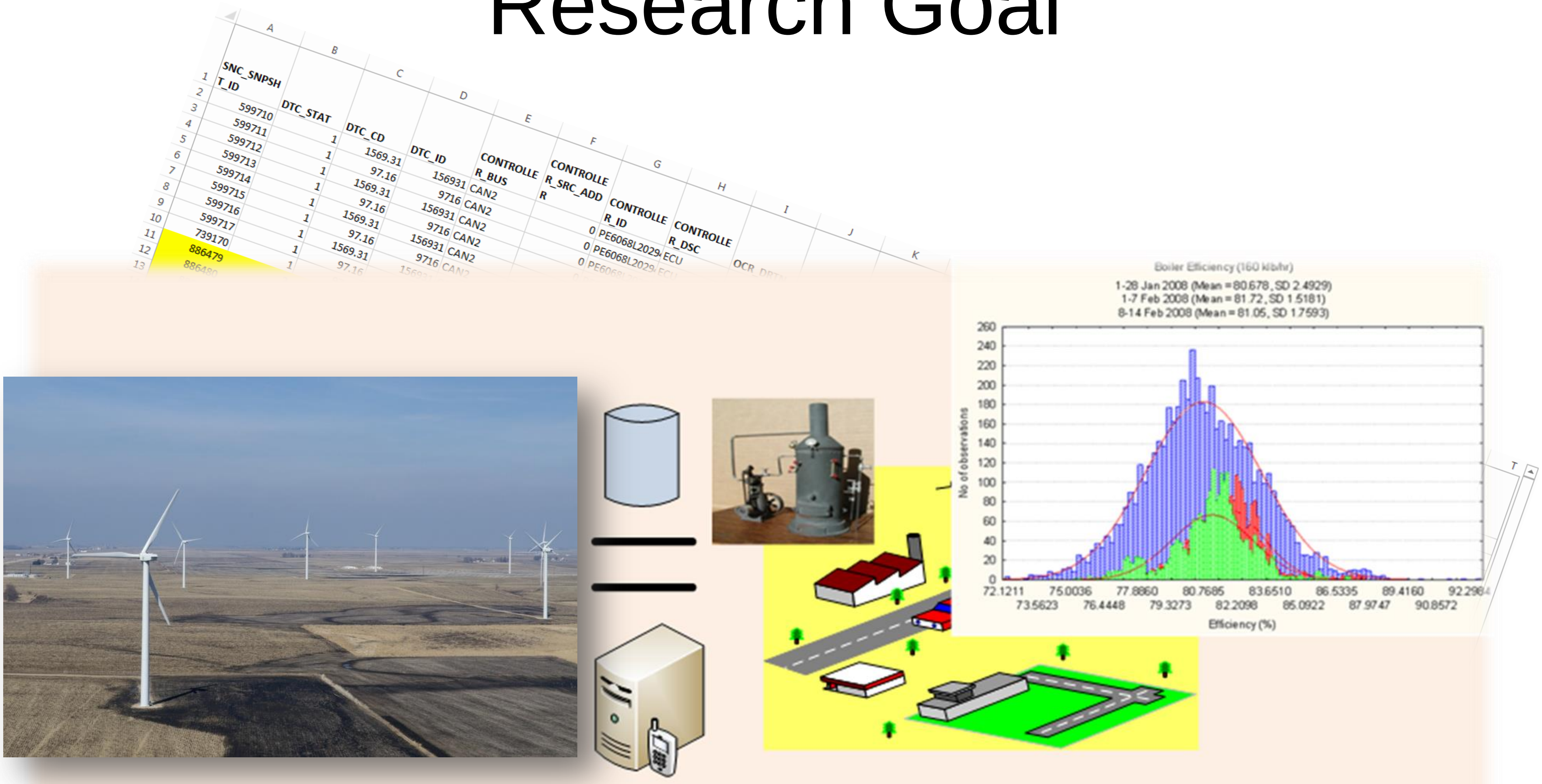
April 14, 2016: MidAmerican Energy will invest US$ 3.6 billion to install additional wind turbines in Iowa by 2019.

http://www.awea.org/resources/statefactsheets.aspx?itemnumber=890



IOWA FACTS
Population: 3 million
Installed wind energy capacity: 6.4 GW
No 10 state in wind resources
No 2 state in wind energy generation (after Texas) and expanding

Research Goal



Wind farm → Wind power plant

Why Modeling from Data?

✓ Bottom up modeling

✓ No limits on the type and number of parameters

✓ Model accuracy

Data Mining → Decision Making/ Optimization

~½ Solution ~½ Solution

How Big is Energy Data?

Characteristics of big data:

- ✓ Volume: size
- ✓ Velocity: speed, frequency
- ✓ Variety: multiple forms and characteristics
- ✓ Veracity: accuracy and truthfulness
- ✓ Value: benefits

Nature, January 2016

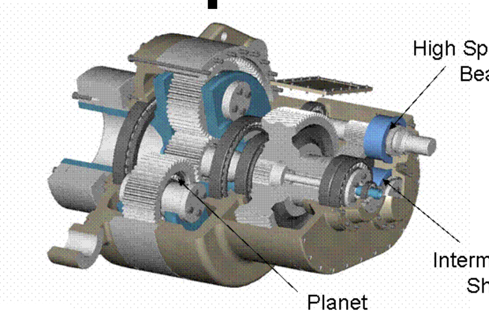
How Difficult is Wind Modeling?

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

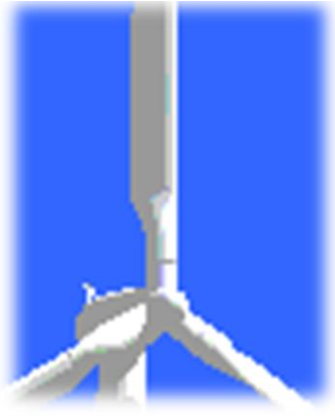
10 second data

Wind Turbine Control: Power Equilibrium

Process equilibrium



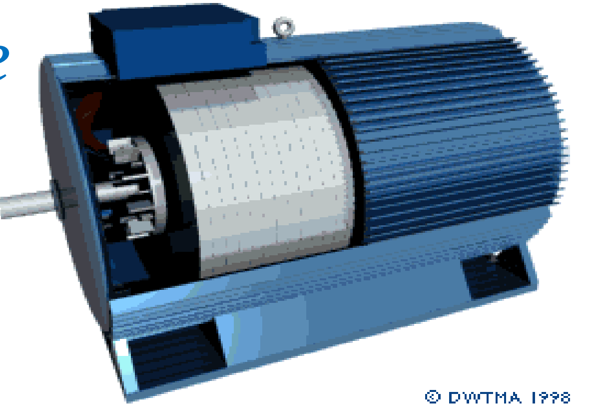
$$P_a = \frac{1}{2}\rho\pi R^2 C_p(\lambda,\beta)v^3 \quad = \quad P_a = \omega_r T$$



Classical science

=

Data science



Pictures courtesy of Danish Wind Energy Association

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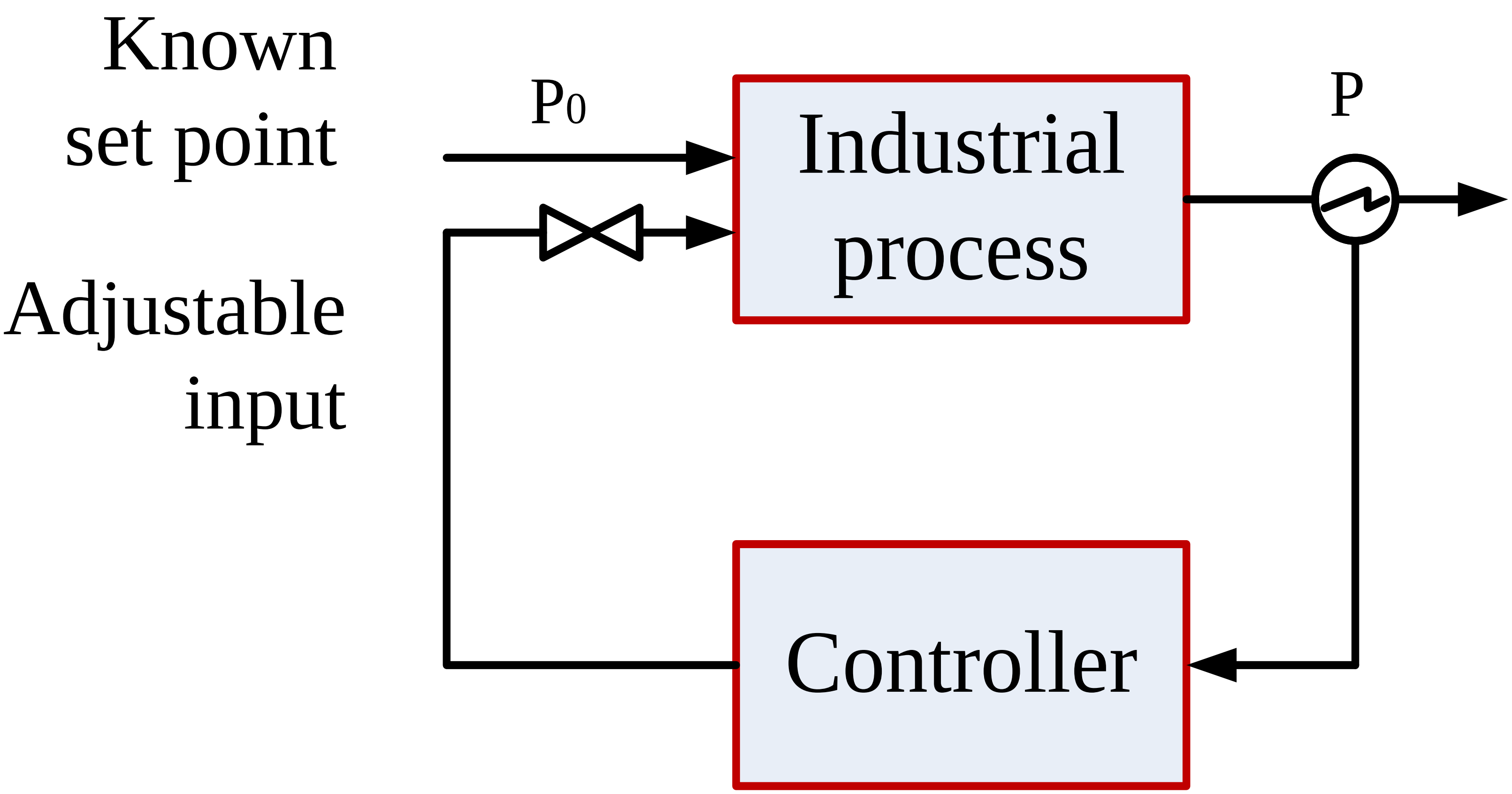
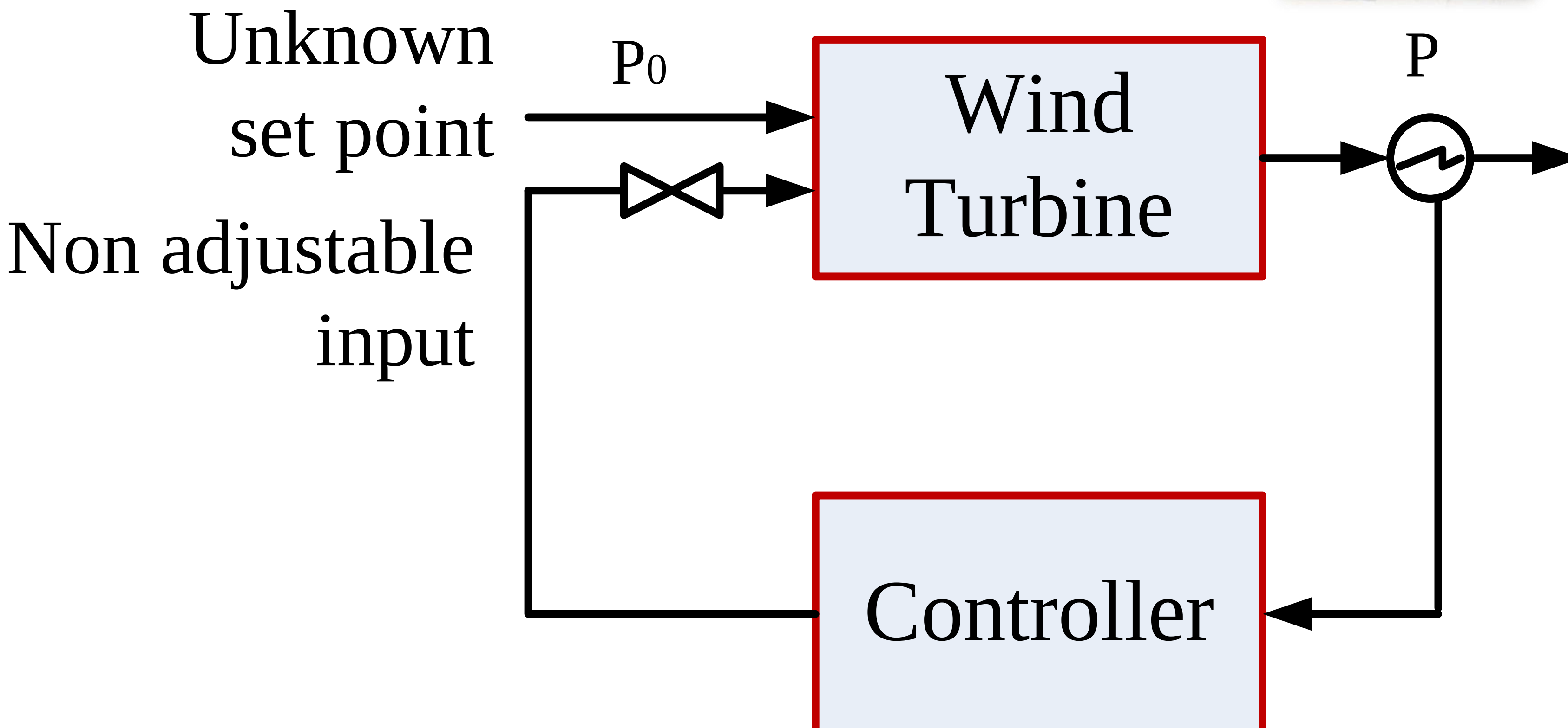
Classical Control

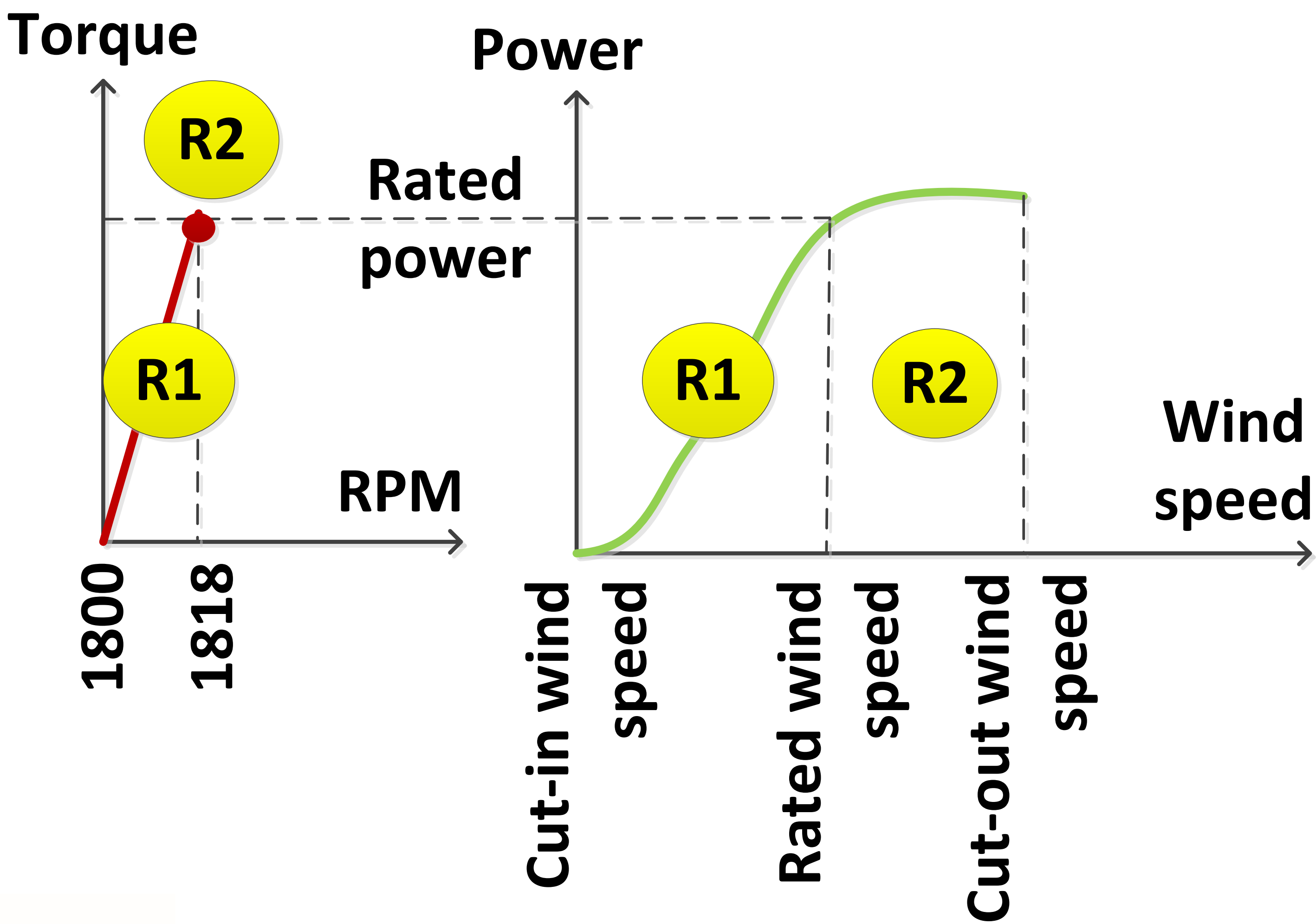


Wind Turbine Control

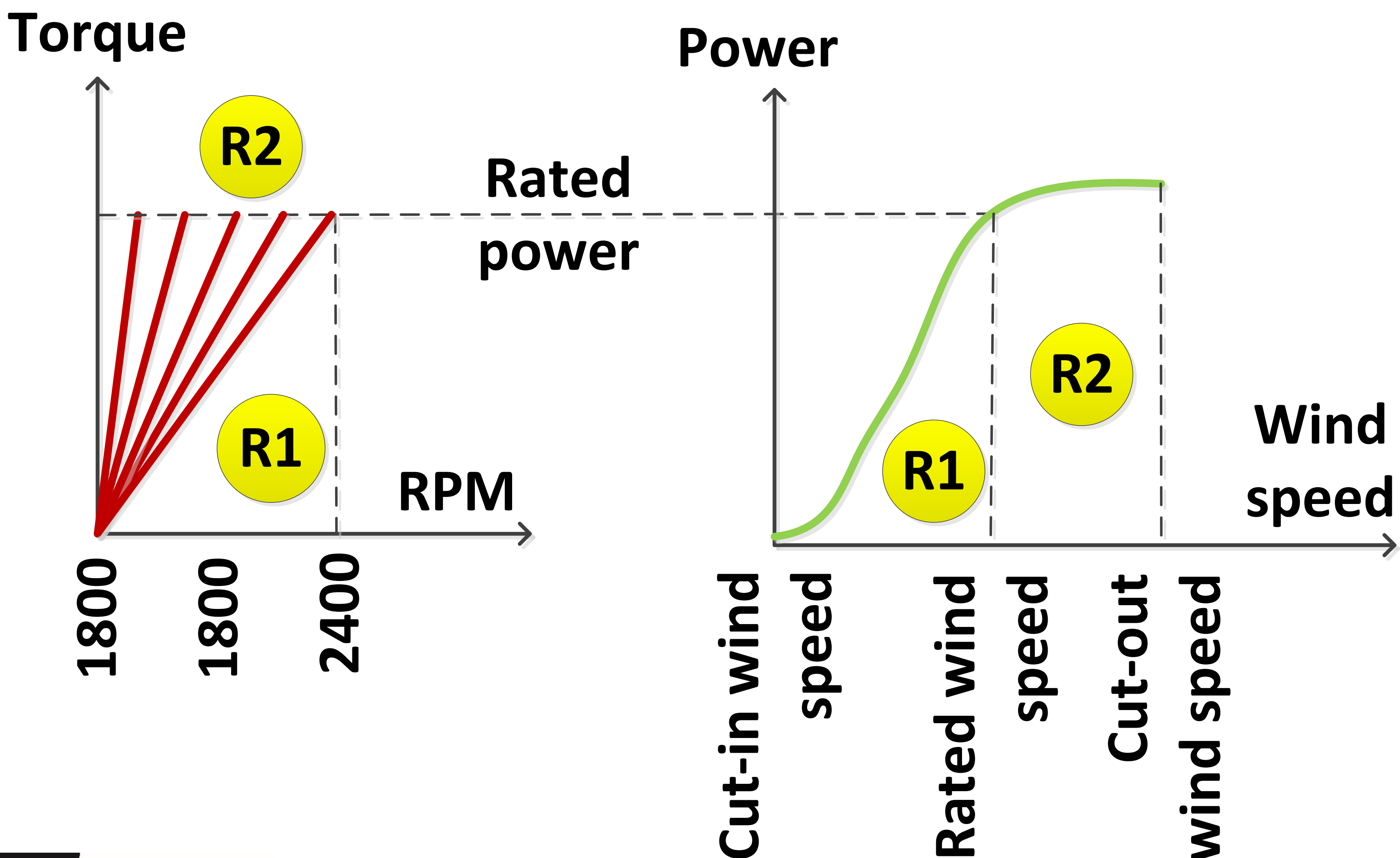
Anticipatory Control



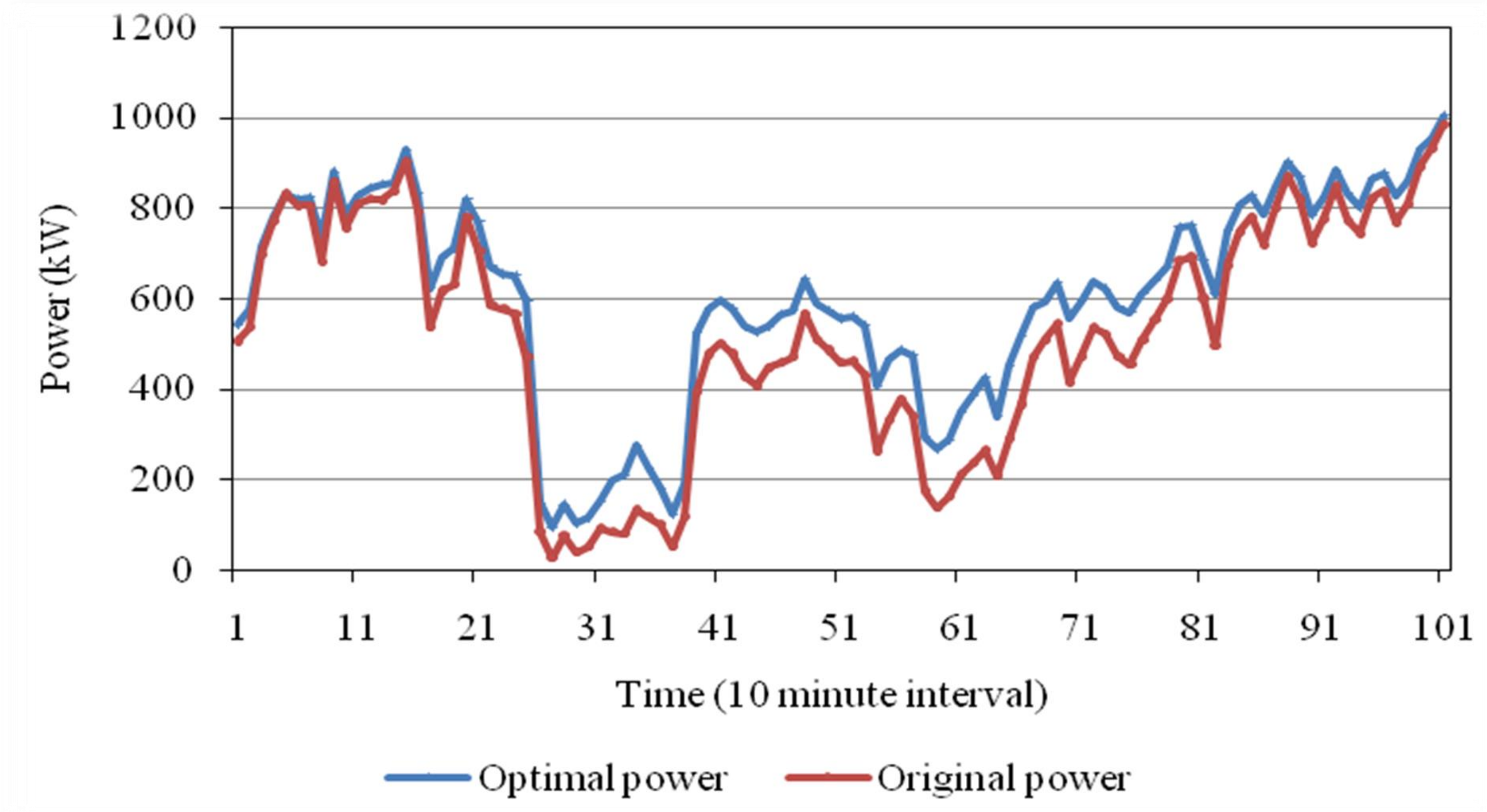
Fixed Speed Generator



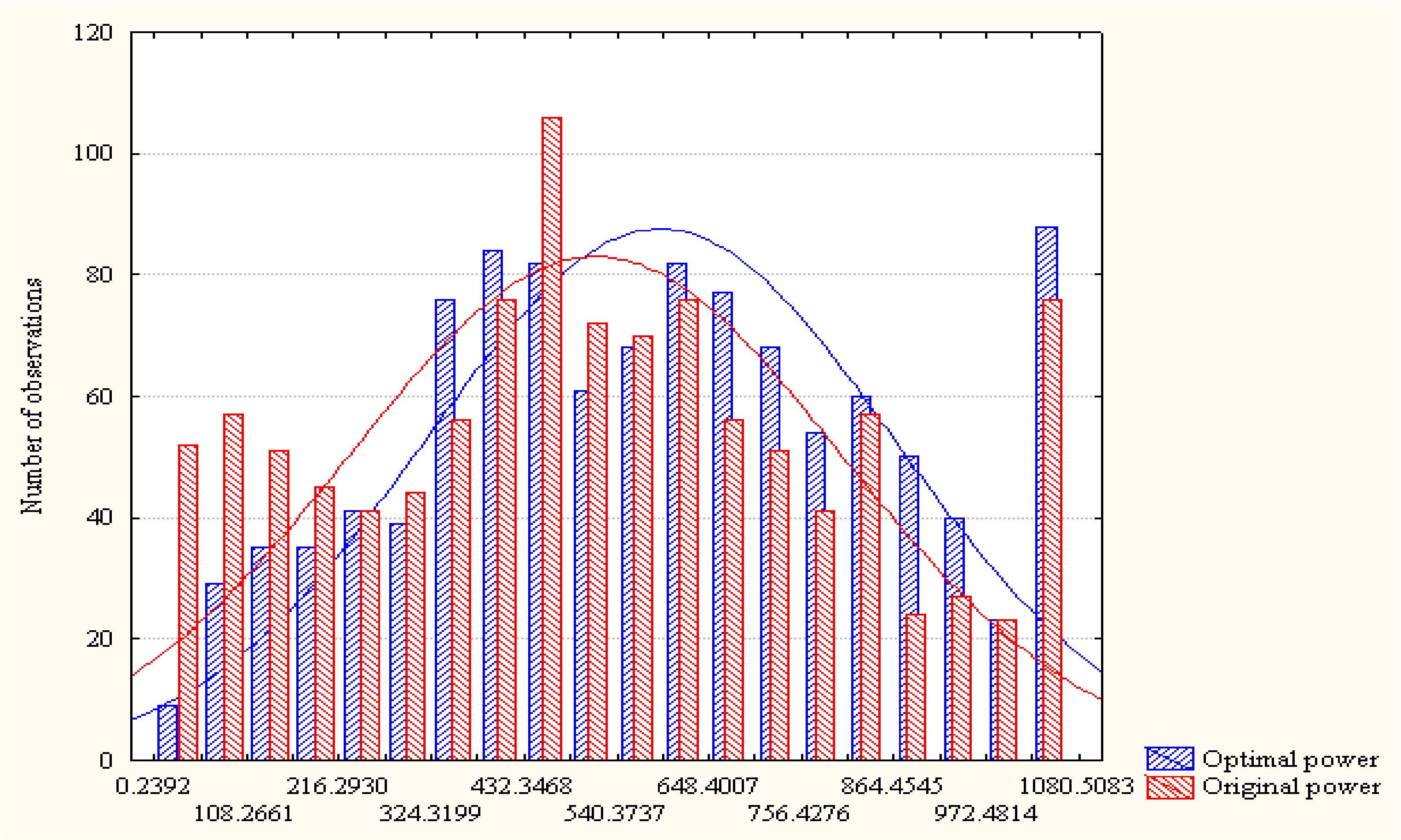
Variable Speed Generator



Optimized Pitch Control

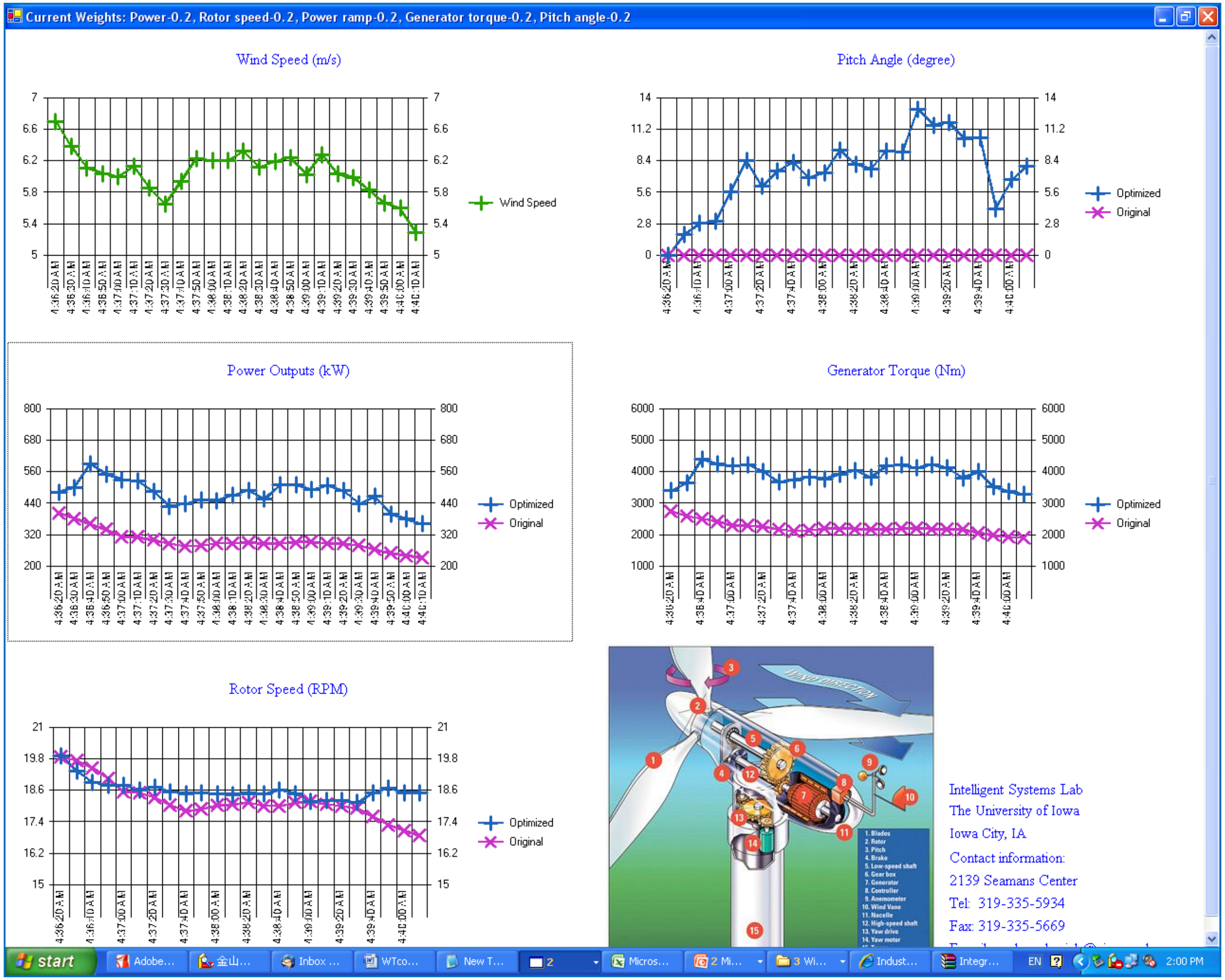


Optimal vs Original Power



Original power: Normal (513.1, 283.7)
Optimal power: Normal (588.3, 270.9)

Multi-Criteria Control



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Multi-Criteria Optimization Model

$$\min_{\tau(t)^*,\beta(t)^*,\tau(t+\mathrm{T})^*,\beta(t+\mathrm{T})^*} C(\cdot)$$

subject to

$$A_d(t)^* = f(v(t), v(t-2\mathrm{T}), v(t-3\mathrm{T}), \beta(t-\mathrm{T}), \beta(t-3\mathrm{T}), \tau(t)^*, \tau(t-\mathrm{T}), \tau(t-3\mathrm{T}), w_d(t-3\mathrm{T}), A_d(t-\mathrm{T}))$$

$$A_d(t+\mathrm{T})^* = f(v(t+\mathrm{T}), v(t-\mathrm{T}), v(t-2\mathrm{T}), \beta(t)^*, \beta(t-2\mathrm{T}), \tau(t+\mathrm{T})^*, \tau(t)^*, \tau(t-2\mathrm{T}), w_d(t-2\mathrm{T}), A_d(t)^*)$$

$$A_t(t)^* = f(v(t), v(t-\mathrm{T}), v(t-2\mathrm{T}), v(t-3\mathrm{T}), \beta(t-\mathrm{T}), \tau(t)^*, \tau(t-2\mathrm{T}), \tau(t-3\mathrm{T}), A_t(t-\mathrm{T}))$$

$$A_t(t+\mathrm{T})^* = f(v(t+\mathrm{T}), v(t), v(t-\mathrm{T}), v(t-2\mathrm{T}), \beta(t)^*, \tau(t+\mathrm{T})^*, \tau(t-\mathrm{T})^*, \tau(t-2\mathrm{T}), A_t(t)^*)$$

$$P(t)^* = f(v(t), v(t-\mathrm{T}), \beta(t)^*, \beta(t-\mathrm{T}), \tau(t)^*, \tau(t-\mathrm{T}))$$

$$P(t+\mathrm{T})^* = f(v(t+\mathrm{T}), v(t), \beta(t+\mathrm{T})^*, \beta(t)^*, \tau(t+\mathrm{T})^*, \tau(t)^*)$$

$$v(t) = f(v(t-\mathrm{T}), v(t-2\mathrm{T}), v(t-3\mathrm{T}), v(t-4\mathrm{T}), v(t-5\mathrm{T}), v(t-6\mathrm{T}), v(t-8\mathrm{T}))$$

$$P_a(t)^* \le \min\{1500, 2.625 v(t)^3\}$$

$$P_a(t+\mathrm{T})^* \le \min\{1500, 2.625 v(t+\mathrm{T})^3\}$$

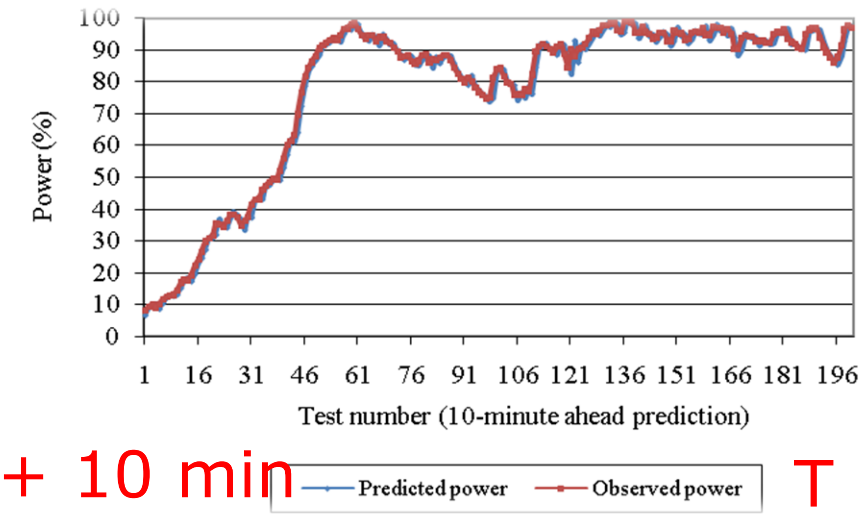
$$\max\{0, \mathrm{currentSetting} - 40\} \le \tau(t)^* \le \min\{100, \mathrm{currentSetting} + 40\}$$

$$\max\{0, \mathrm{currentSetting} - 40\} \le \tau(t+\mathrm{T})^* \le \min\{100, \mathrm{currentSetting} + 40\}$$

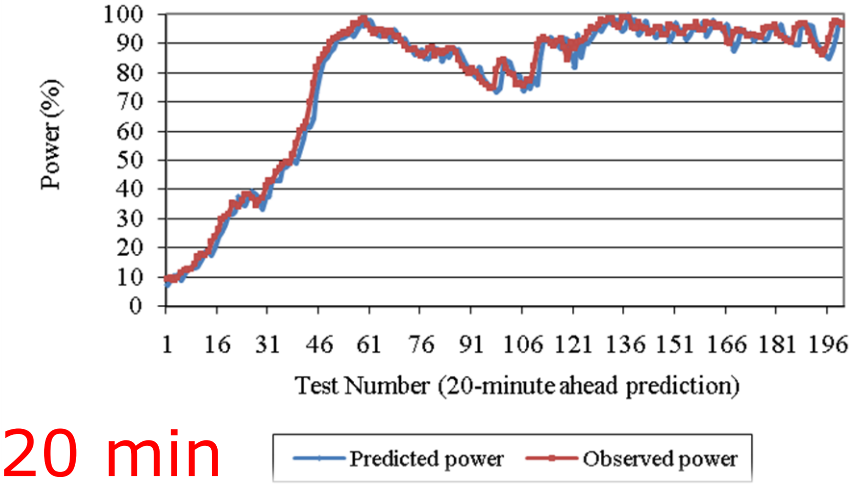
$$\max\{-0.57, \mathrm{currentSetting} - 15\} \le \beta(t)^* \le \min\{90.61, \mathrm{currentSetting} + 15\}$$

$$\max\{-0.57, \mathrm{currentSetting} - 15\} \le \beta(t+\mathrm{T})^* \le \min\{90.61, \mathrm{currentSetting} + 15\}$$

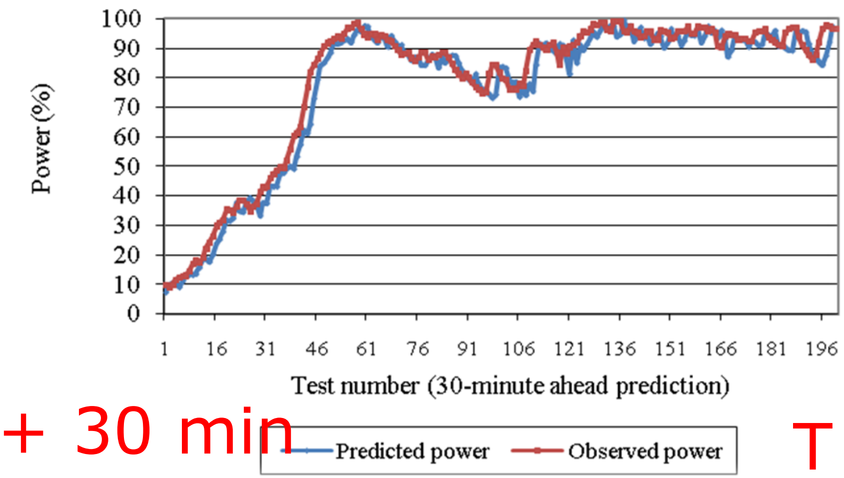
T + 10*n* Minute Power Predictions



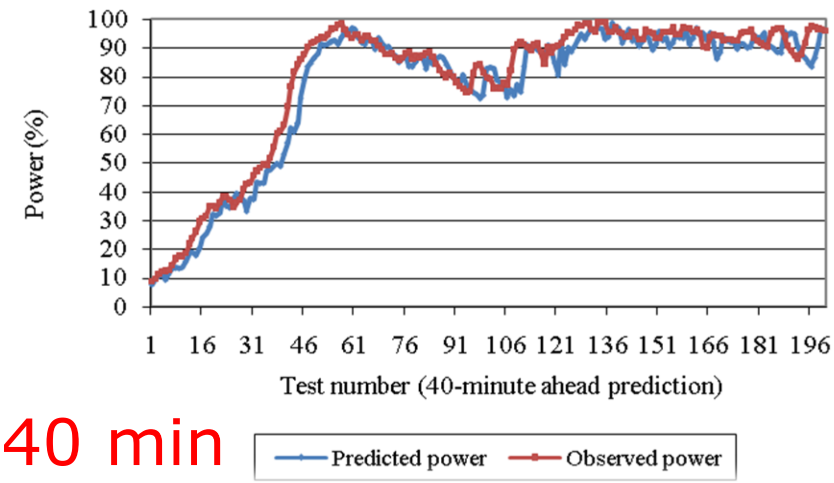
T + 10 min



T + 20 min



T + 30 min



T + 40 min

T + 10*n* Minute Predictions

Time	MAPE (%)	Std (%)
T + 10 min	2.21	2.50
T + 20 min	3.91	4.08
T + 30 min	5.14	5.14
T + 40 min	6.06	5.91
T + 50 min	6.72	6.56
T + 60 min	7.38	6.98
T + 70 min	8.02	7.51

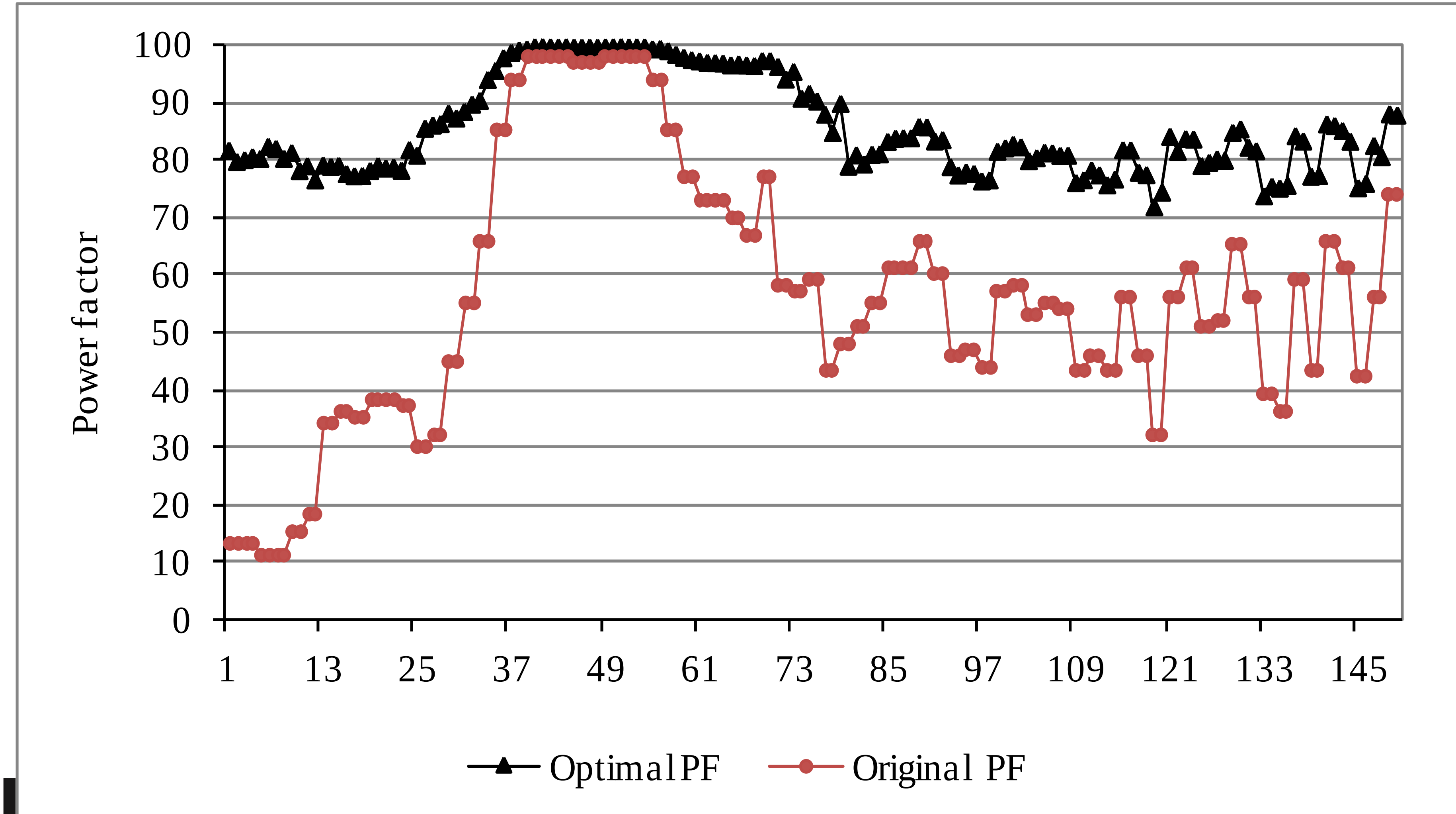
Short Term Predictions

Time	MAPE (%)	Std (%)	Time	MAPE (%)	Std (%)
T + 1	9.28	8.12	**T + 7**	9.82	9.19
T + 2	9.35	8.21	**T + 8**	10.57	9.91
T + 3	9.76	8.69	**T + 9**	8.41	8.73
T + 4	9.36	8.32	**T + 10**	11.06	10.63
T + 5	9.97	8.93	**T + 11**	11.19	9.08
T + 6	10.49	9.99	**T + 12**	11.49	10.53

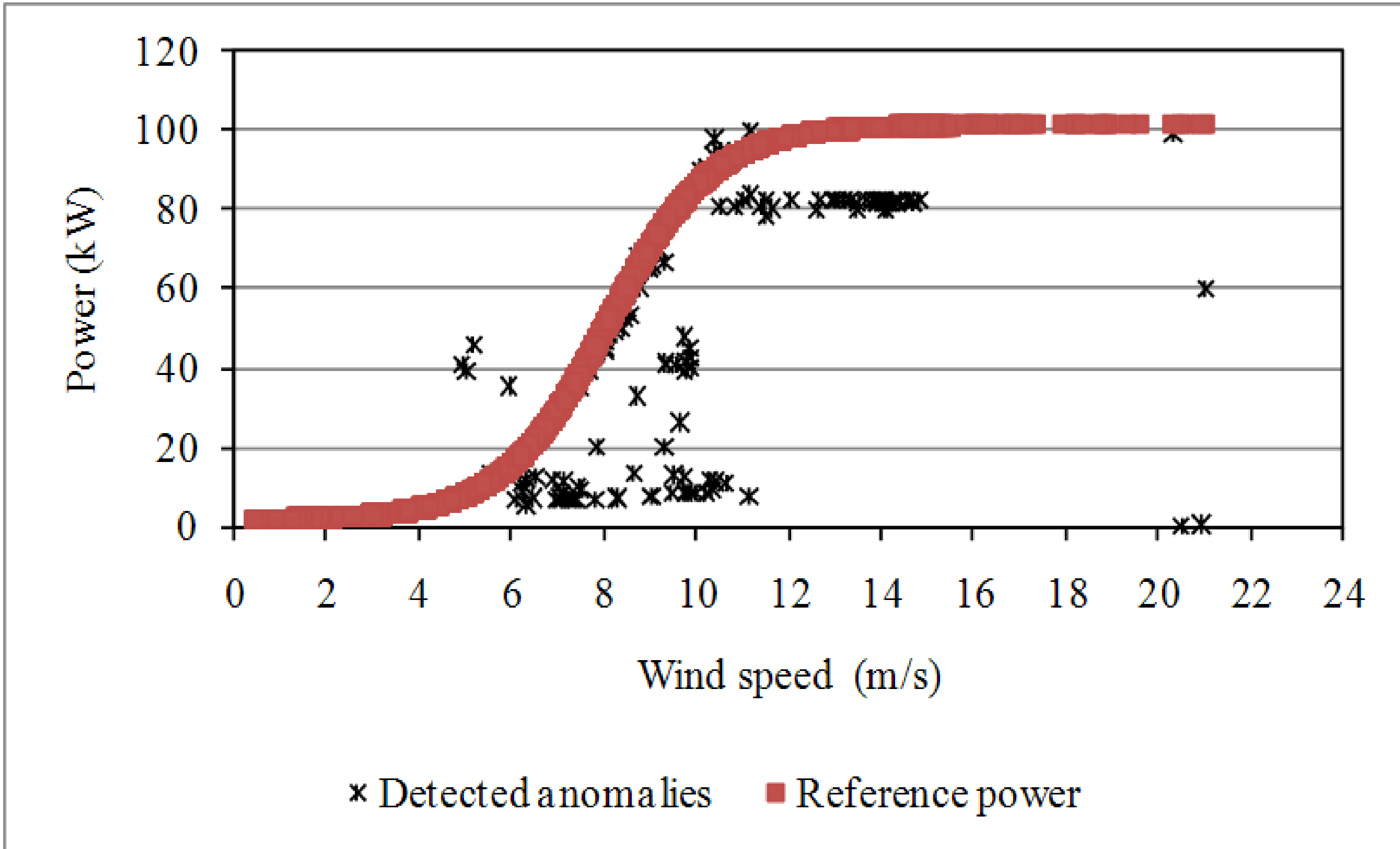
Long Term Predictions

Time	MAPE (%)	Std (%)	Time	MAPE (%)	Std (%)
T + 3	5.93	4.23	**T + 45**	12.87	10.23
T + 9	9.12	8.91	**T + 51**	10.97	10.92
T + 15	9.92	8.04	**T + 57**	13.82	9.61
T + 21	9.39	7.28	**T + 63**	11.88	9.95
T + 27	10.35	6.41	**T + 69**	9.56	7.68
T + 33	11.81	12.24	**T + 75**	10.83	9.32
T + 39	11.63	7.79	**T + 81**	6.37	6.19
T + 42	11.49	10.06	**T + 84**	10.57	8.78

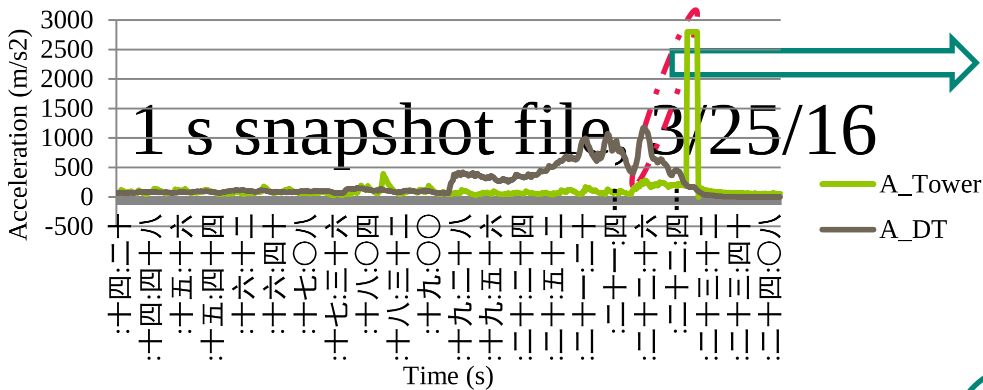
Optimization of Reactive Power



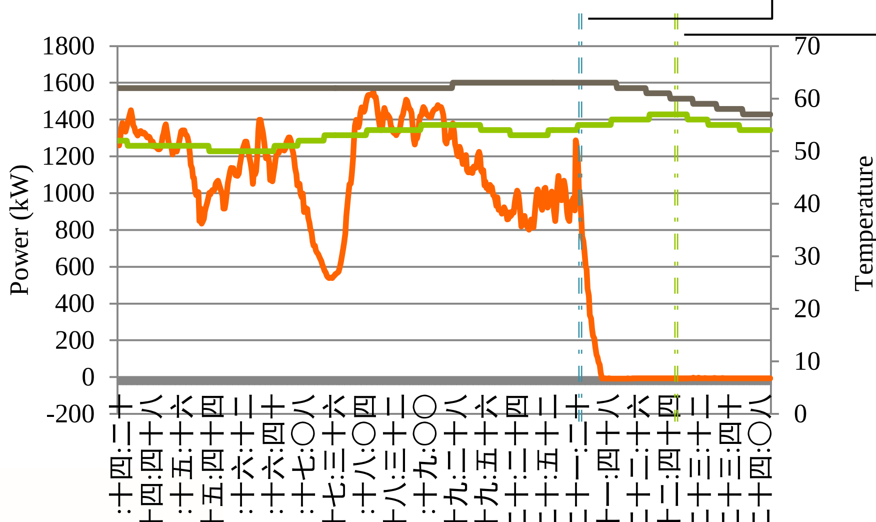
Anomaly Detection



Catastrophic Gearbox Failure



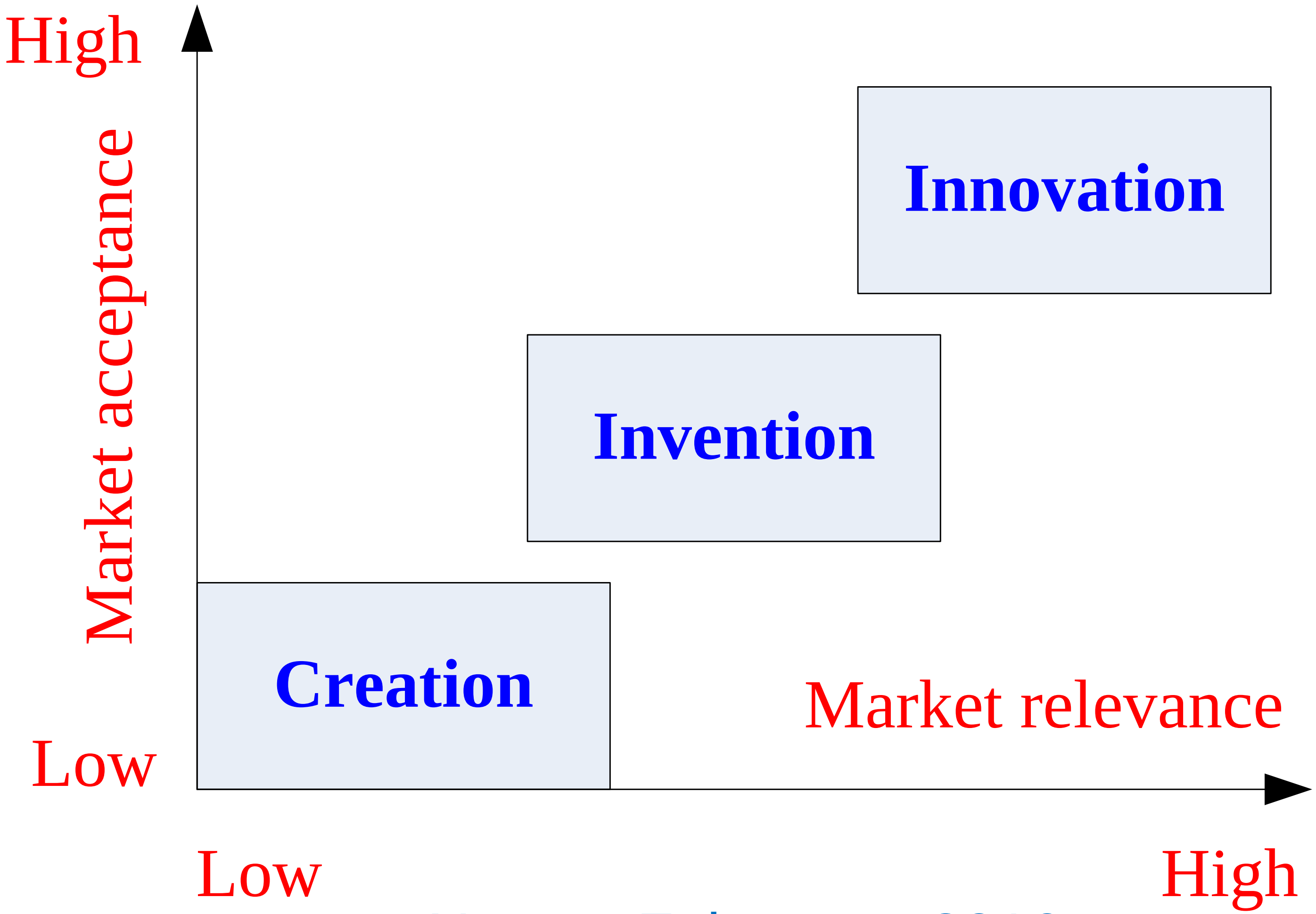
Gearbox failure reflected by high acceleration of the drive train and tower



Fault indication

Actual fault

Innovation Solution



Nature, Febrauary 2016

Summary

- Growing role of data in wind energy
- Data mining and computational intelligence key to novel solutions
- Data offers new ways of discovery of disruptive technologies