Integrated Predictive Analytics and Optimization for Wind Farm Maintenance and Operations

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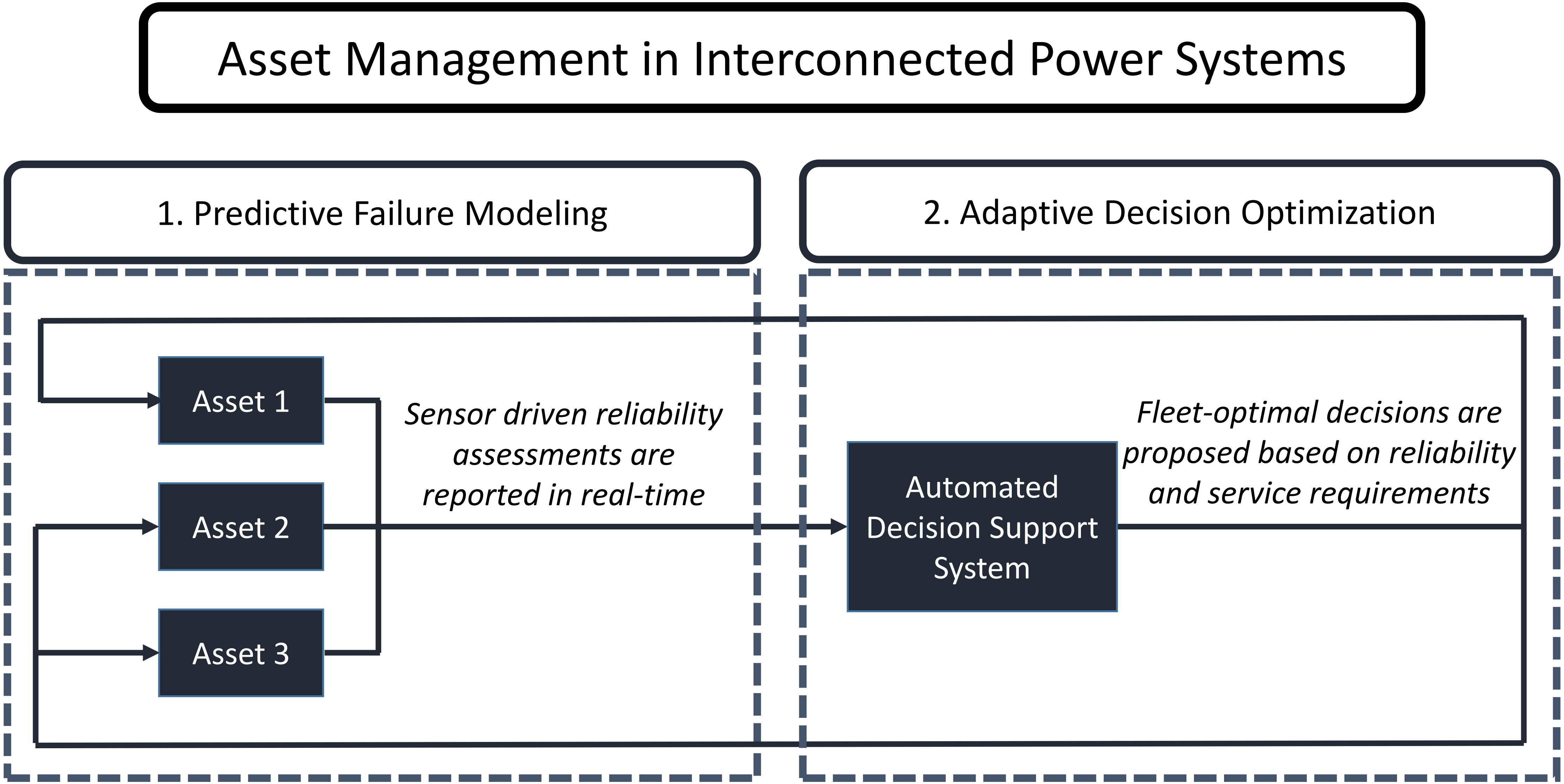
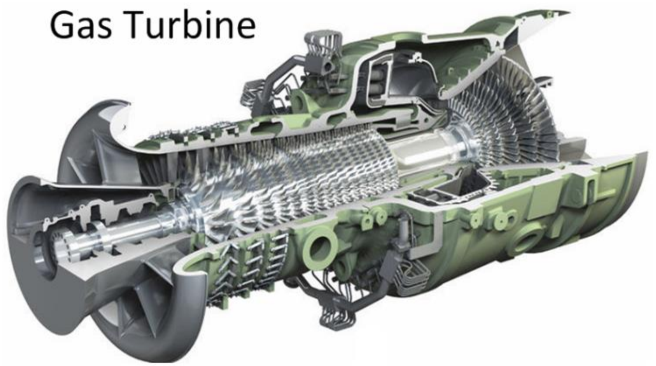
Research Framework

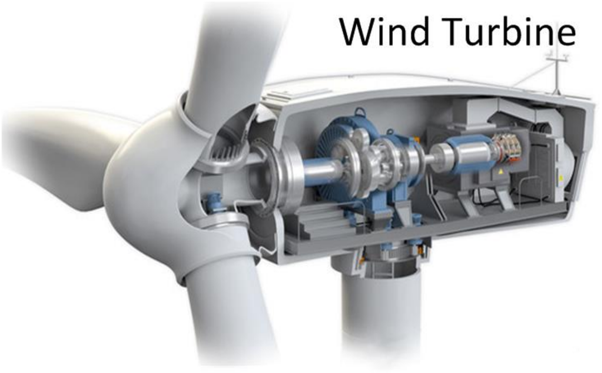


Research Framework

1. Predictive Failure Modeling

Using Real-Time Sensor Data to Predict the Remaining Life Distribution





Methodology:

Data Mining, Bayesian Statistics, Stochastic Degradation Modeling, Accelerated Life Testing

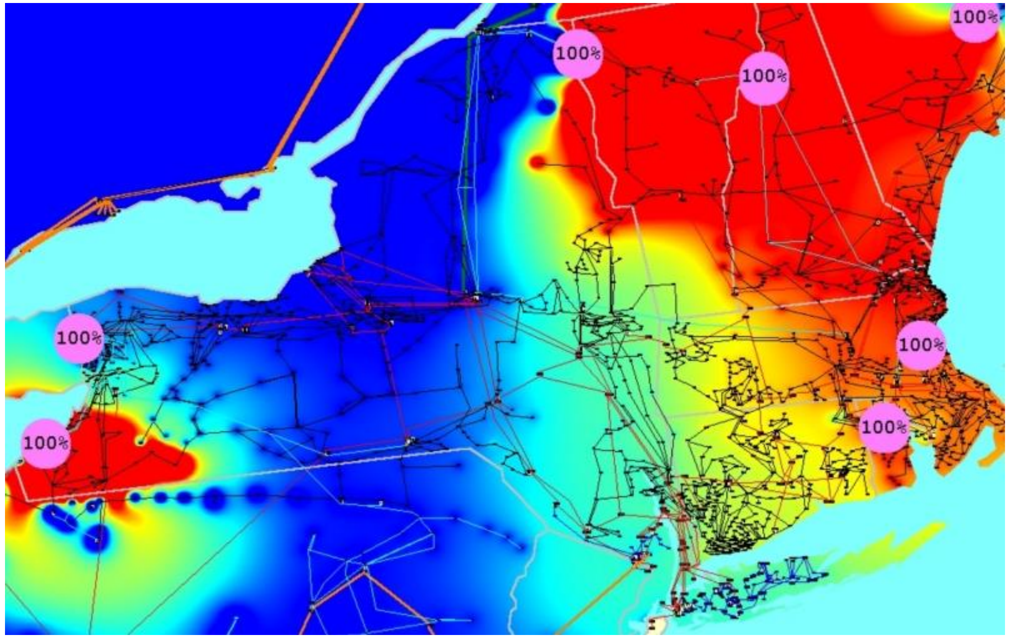
[1] Degradation Modeling Methodology
[2] Accelerated Degradation Experiments

Research Framework

2. Adaptive Decision Optimization

Sensor-Driven Scheduling and Control in Complex Networks

Methodology:
Large-Scale Mixed-Integer Optimization,
Distributed Optimization, Stochastic Optimization



[3] Conventional Generator Maintenance, *IEEE Transactions on Power Systems*
[4] Conventional Generator Operations, *IEEE Transactions on Power Systems*
[5] Opportunistic Wind Farm Operations, , *IEEE Transactions on Power Systems*

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Agenda

- Part I. Introduction
  - Current Practice
  - Motivation and Objectives
- Part II. Predictive Analytics
  - Proposed Framework
  - Predictive Analytics
  - Dynamic Maintenance Cost
- Part III. Opportunistic Adaptive Maintenance– Wind Farms
- Part IV. Adaptive Predictive Maintenance – Conventional Fleets
- Part V. Conclusion

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Maintenance Basics

Maintenance Objectives:

- **Minimizing** unexpected failures
- **Extending** equipment lifetime
- **Reducing** early and/or unnecessary maintenances
- **Alleviating** the consequences of interruptions

(IEEE/PES Task Force on Impact of Maintenance Strategy on Reliability)

Literature Review

Approach 1: Opportunistic Periodic Maintenance Policies

Disadvantage: does not use the sensor information

Besnard et. al (2009), Ding et. al (2012),…

Approach 2: Reliability Based Maintenance (RBM)

Disadvantage: does not use the sensor information

Abiri-Jahromi et. al (2012)

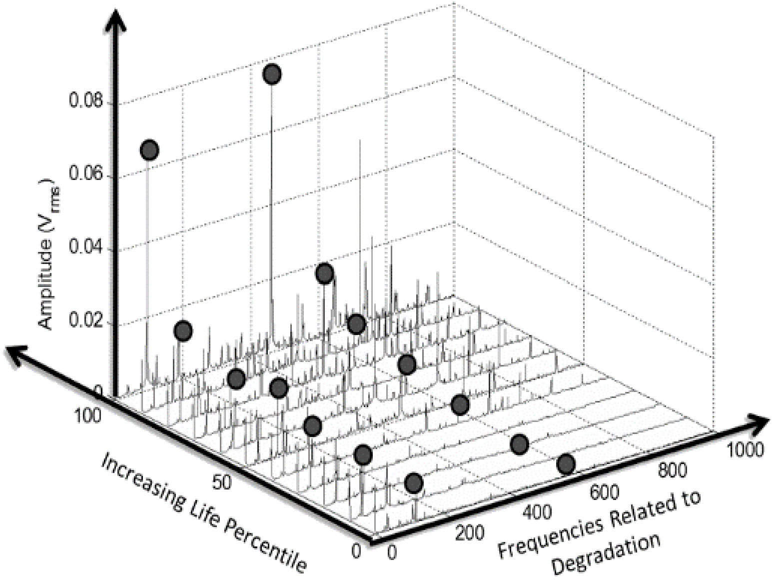
Approach 3: Sensor-Driven Maintenance for Single Turbine Systems

Disadvantage: does not consider the complex interdependencies between turbines

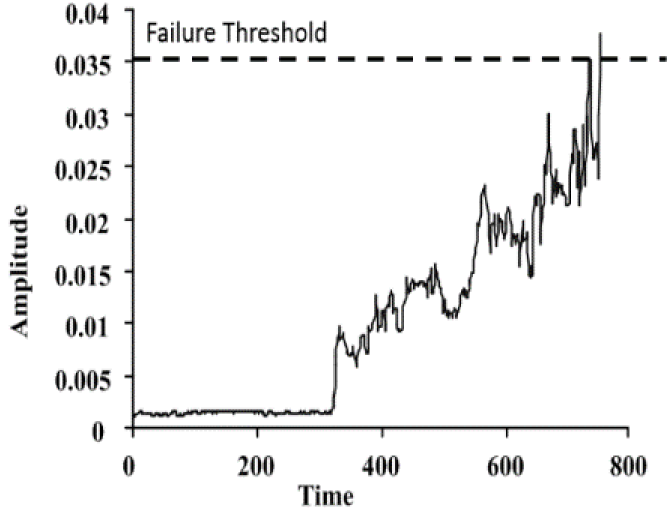
Byon et. al (2010 A,B), Tian et. al (2011),…

Single Turbine: Degradation Analysis

- Gradual accumulation of damage: **degradation process.**
- Sensor driven estimate on the state of health: **degradation signals**.



Extracting Signal Features



Vibration Spectra and its Degradation Signal Transformation

Ciarapica et. al (2006), McMillan et. al (2007), Li et. al (2009), Yang et. al (2012)
Commercial Packages: VibraSyst, Siemens, GE

Single Turbine: Degradation Analysis

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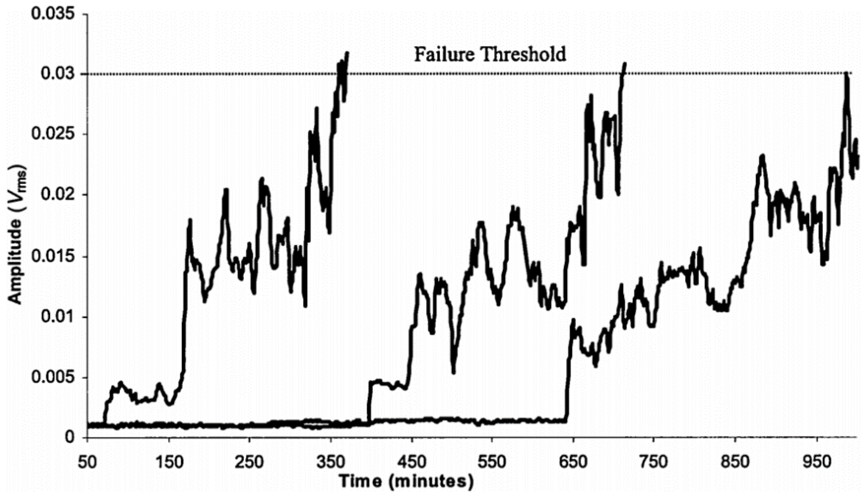

We focus on using this data to improve:

- Remaining life predictions of every turbine
- Risk assessments of all maintenance policies
- Optimization of the turbine fleet maintenance

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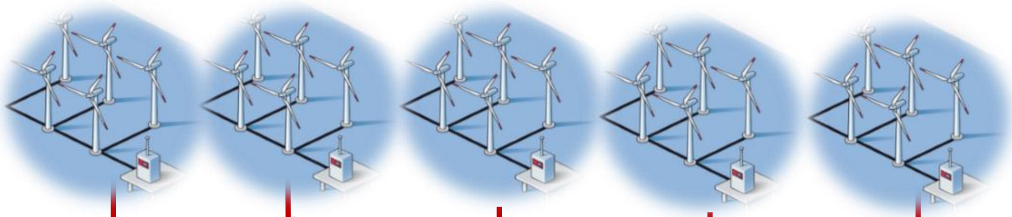
Proposed Framework

Maintenance

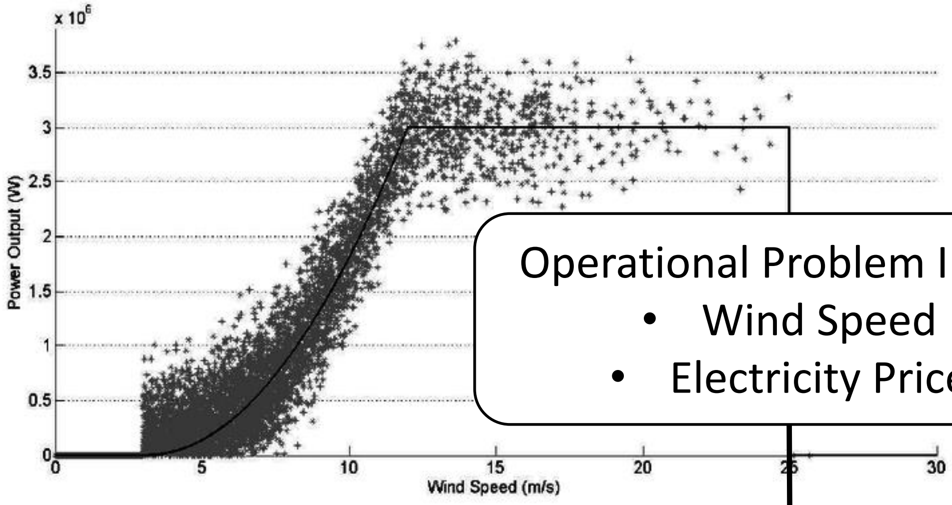


real-time sensor observations

Predictive Analytics

Maintenance Cost Estimation

Operations



Operational Problem Inputs

- Wind Speed
- Electricity Price

<u>Maintenance and Operations Scheduling For Fleets of Generating Units</u>

Outline of Adaptive Predictive Maintenance

New Sensor Observation

Predictive Analytics

- Updating the degradation parameters
- Reevaluating the remaining life estimates

Updated Remaining Life Distribution

Dynamic Maintenance Cost

- Deriving the new predictive cost

Updated Predictive Cost

Updates from other turbines

Adaptive Predictive Maintenance

- Minimizing the maintenance and operational costs by incorporating the sensor information

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<u>Adaptive Predictive Maintenance</u>

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Degradation Modeling

Degradation signal of turbine i at time t

Deterministic degradation characteristic

Stochastic degradation characteristic of turbine i

$$D_i(t) = \phi_i(t; \kappa, \theta_i) + \epsilon_i(t; \sigma)$$

Inherent stochasticity of the degradation

Parametric degradation function

- We assume that the generator's time of failure corresponds to the first time its degradation signal $D_i(t)$ crosses failure threshold Λ_{i}.

$$\tau_i = \min\{t \geq 0 \,|D_i(t) \geq \Lambda_i\}$$

Characterizing the Failure Distribution

- If we had perfect information on the degradation parameter θ_i

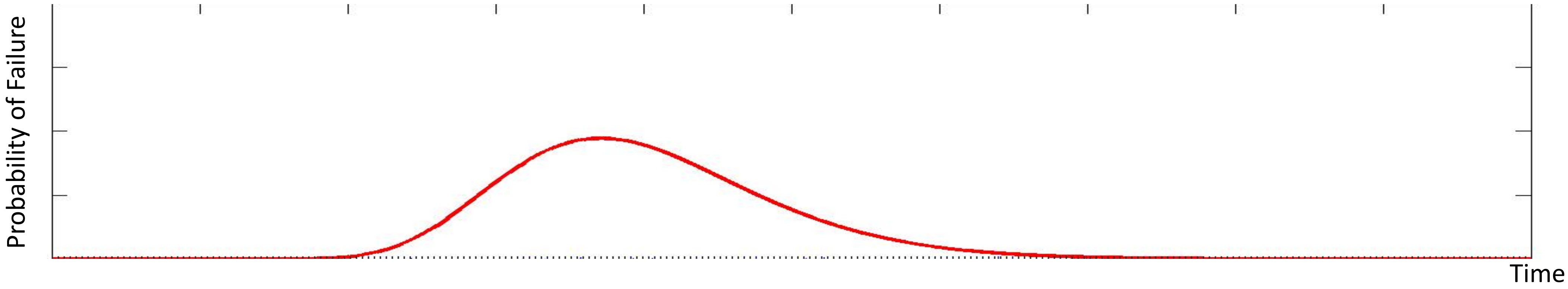
$$P(\tau_i > t|\theta_i) = P(\sup_{0 \le s \le t} D_i(s) < \Lambda_i|\theta_i)$$
$$= P(\sup_{0 \le s \le t} \{\phi_i(s;\kappa,\theta_i) + \epsilon_i(s;\sigma)\} < \Lambda_i|\theta_i)$$

Prior Estimate on the Remaining Life

Given the prior distribution of parameters $\pi(\theta_i)$:

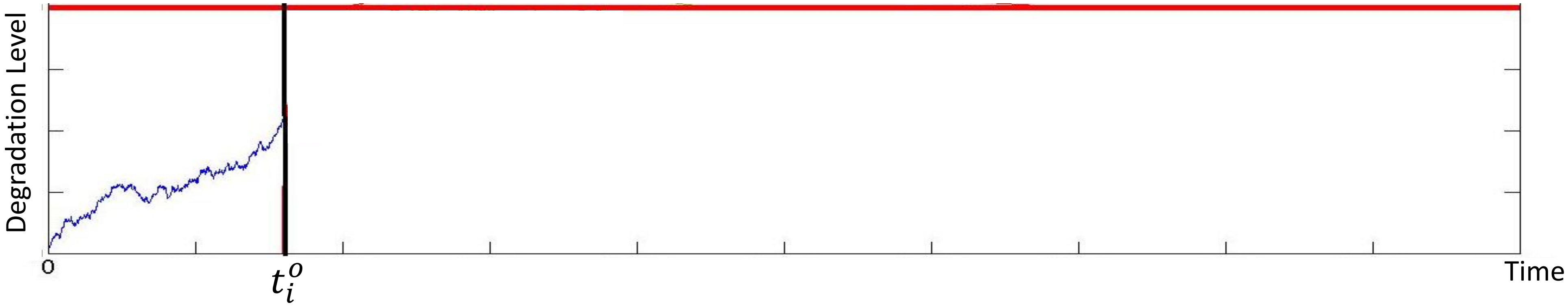
$$P(\tau_i > t) = \int P(\sup_{0\leq s\leq t} D_i(s) < \Lambda_i|\theta_i)\pi_i(\theta_i)d\theta_i$$
$$= \int P\left(\sup_{0\leq s\leq t} \{\phi_i(s;\kappa,\theta_i) + \epsilon_i\,(s;\sigma)\} < \Lambda_i|\theta_i\right)\pi(\theta_i)d\theta_i$$

Remaining Life Distribution Based on Prior Information



Next challenge is to use the sensor-data to improve the estimates on degradation parameter θ_i

Sensor Driven Bayesian Learning



- Given real time sensor data $\boldsymbol{d_i^o} = (d_i^1, d_i^2, \ldots, d_i^{t_o})$, posterior distribution of the degradation parameter θ_i can be determined:

Probability of observing the real time sensor data given parameters θ_i

$$\upsilon(\theta_i) = P(\theta_i | \boldsymbol{d}_i^o) = P(\boldsymbol{d}_i^o | \theta_i)\pi_i(\theta_i)$$

Sensor-updated, posterior distribution of parameter θ_i

Prior distribution of parameter θ_i

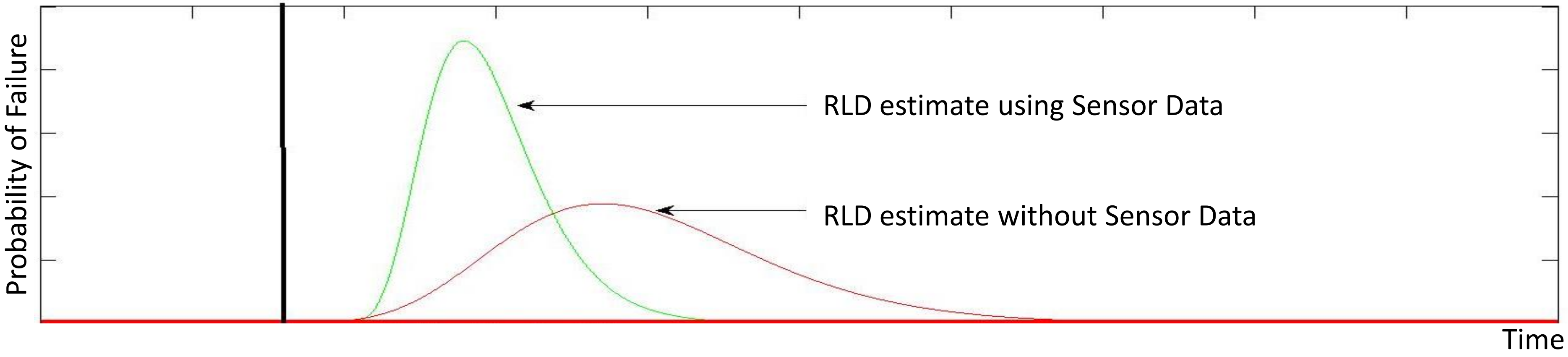
Sensor Driven Estimate on the Remaining Life

- Given $\upsilon(\theta_i)$, the remaining life of generator i can be updated as follows:

$$P(R^i_{t^o_i} > t) = \int P\left(\sup_{t_o \leq s \leq t_o + t} D_i(s) < \Lambda_i | \theta_i \right) \upsilon(\theta_i) d\theta_i$$

Remaining life of generator i at time t

Comparing the Remaining Life Distribution Estimates



Sensor Driven Learning – Notes

- Depending on the prior and posterior distributions, one can find a closed form solution for this update. Otherwise, we may resort to numerical methods for estimation.

- Depending on the form of the degradation model, one can find a closed form solution for the remaining life distribution. Otherwise we resort to numerical methods.
  - e.g. in our studies, we model i) the degradation signal as a Brownian motion with positive drift, and ii) failure threshold as a constant value. The remaining life distribution in this case follows an Inverse Gaussian distribution.

Sensor Driven Learning – Notes

The objective is to predict the distribution of the remaining life, namely $R^i_{t_o}$, given the posterior distribution $u(\boldsymbol{\theta_i})$. The procedure can be outlined as follows:

Step 1. Select a sufficiently large number of realizations M.

Step 2. Simulate M realizations of $\boldsymbol{\theta}_i$ from the distribution $u(\boldsymbol{\theta_i})$. Denote by $\tilde{\boldsymbol{\theta}}_{i,n}$ the n^{th} realization of $\boldsymbol{\theta}_i$. For all n, condition on $\tilde{\boldsymbol{\theta}}_{i,n}$ to simulate the stochastic degradation function $D_{i|\tilde{\boldsymbol{\theta}}_{i,n}}(t)$ for all $t > t_o$, until the simulated signal reaches the failure threshold Λ_i. Register this time t as the time of failure for the n^{th} simulation, and let this realization of remaining life be $\tilde{r}^i_{t_o,n}$.

Step 3. Use the realizations $\tilde{r}^i_{t_o,n}$ from all the simulations to estimate the distribution of $R^i_{t_o}$.

Outline of Adaptive Maintenance

New Sensor Observation

<u>Predictive Analytics</u>

- Updating the degradation parameters
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Updated Remaining Life Distribution

<u>Dynamic Maintenance Cost</u>

- Deriving the new predictive cost

Updated Predictive Cost

Updates from other turbines

<u>Adaptive Maintenance</u>

- Minimizing the maintenance and operational costs by incorporating the sensor information

Dynamic Maintenance Cost

Traditional approach for determining maintenance policies based on renewal theory.

Dynamic cost of conducting maintenance at time t:

Sensor acquisition

Sensor-updated estimation of the degradation parameter θ_i

Sensor-updated probability of survival for generator i

Cost of preventive maintenance

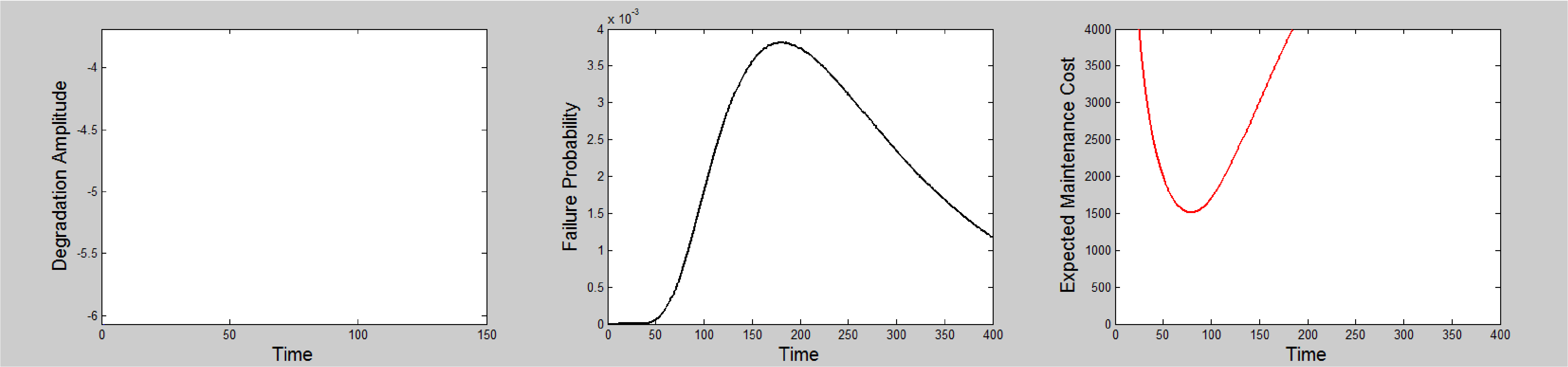
Cost of unexpected failure

$$C_{t,\tau}^{d,i} = \frac{c_i^p \boxed{P(R_t^i > \tau)} + c_i^f \boxed{P(R_t^i \leq \tau)}}{\int_0^\tau \boxed{P(R_t^i > z)} dz + t}$$

Dynamic cost of conducting maintenance at time t

(Armstrong et. al (1996), Alaa et. al (2008))

Asset Level Predictive Analytics



Degradation Signal → Remaining Life Distribution → Dynamic Maintenance Cost

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Outline of Adaptive Maintenance

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- Updating the degradation parameters
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↓ *Updated Remaining Life Distribution*

<u>Dynamic Maintenance Cost</u>

- Deriving the new predictive cost

↓ *Updated Predictive Cost*

Updates from other turbines ↓

<u>Adaptive Predictive Maintenance</u>

- Minimizing the maintenance and operational costs by incorporating the sensor information

Unique Properties of Wind Farm Maintenance

- <u>Significant Cost Reductions from Grouping the Turbine Maintenances</u>

Maintenance cost driven by transport of cranes on onshore sites, and transport of workboats, helicopters on offshore sites.

http://generatingbetter.co.uk/wp-content/uploads/2014/09/leviathan-working-on-sheringham-shoal.jpg

Unique Properties of Wind Farm Maintenance

- Significant Cost Reductions from Grouping the Turbine Maintenances

Maintenance cost driven by transport of cranes on onshore sites, and transport of workboats, helicopters on offshore sites.

- Turbine Failures are not as Catastrophic

Emphasis on the profitability of the wind farms

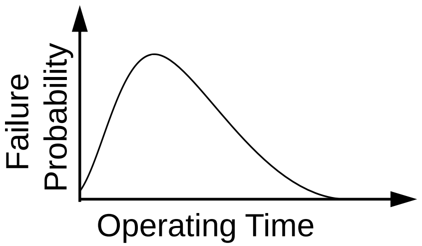
- Instantaneous Reactive Maintenance not Economical

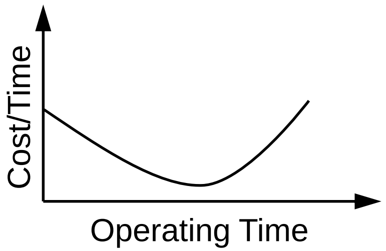
Adaptive Opportunistic Maintenance

Adaptive Opportunistic Maintenance - Concept

Preventive maintenance for two operational turbines with similar RLDs.

Operational





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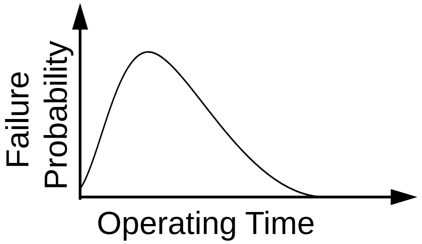
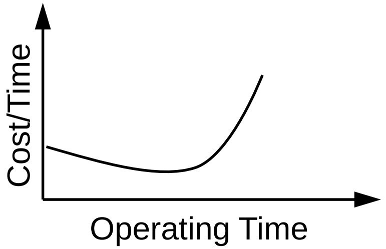
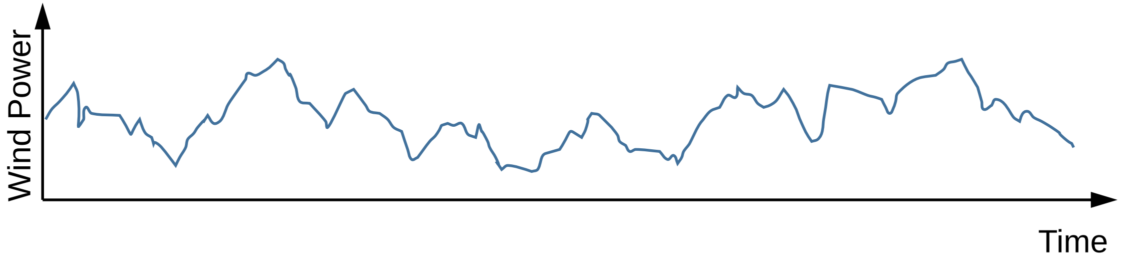
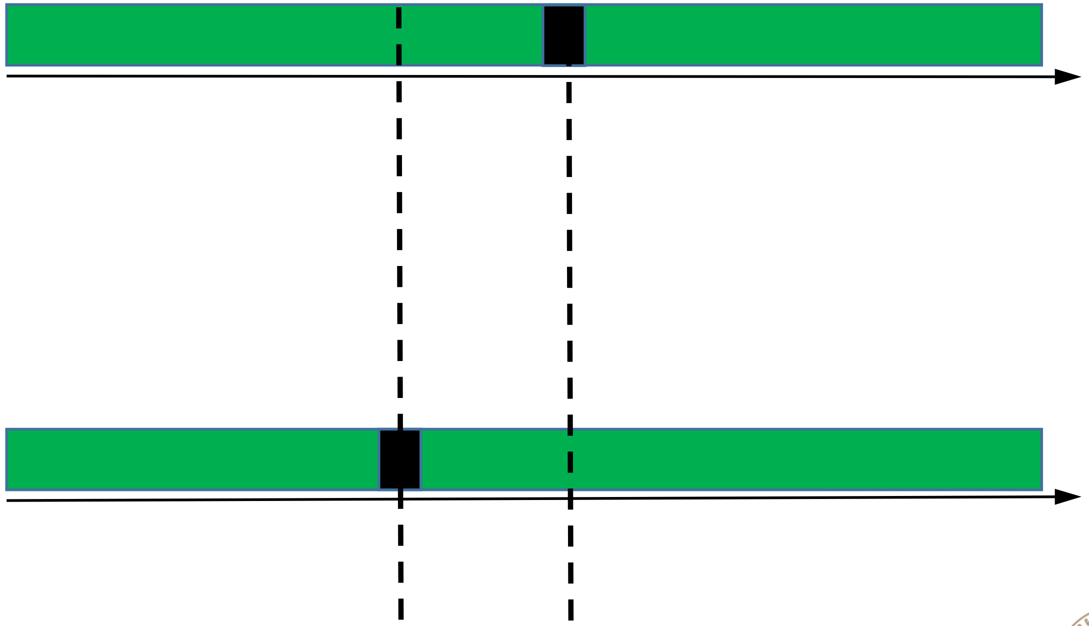




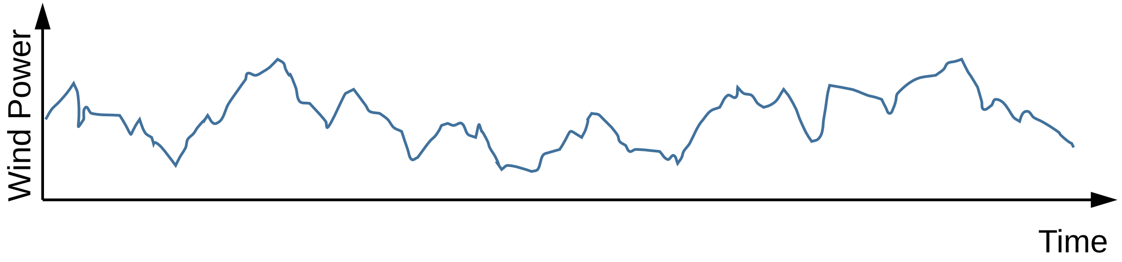




two crew visits

Adaptive Opportunistic Maintenance - Concept

Preventive maintenance for two operational turbines with similar RLDs.



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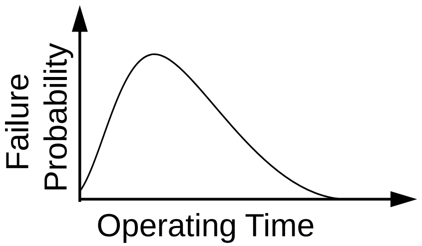

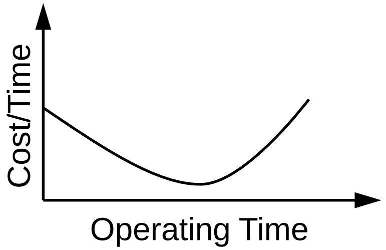

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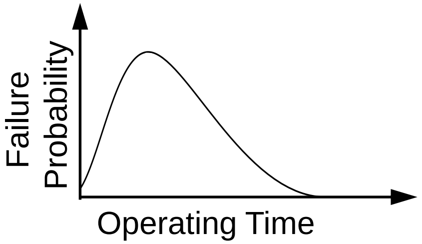
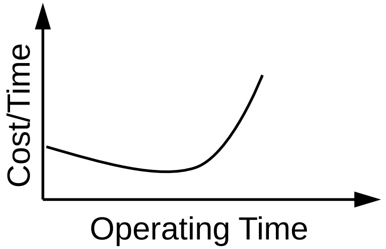
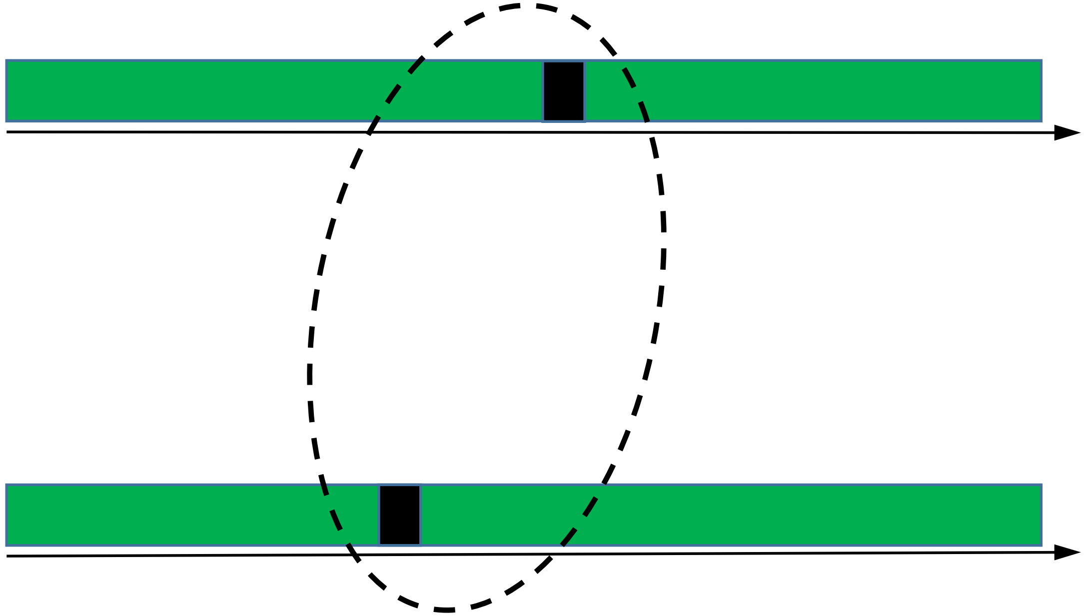




as the crew deployment cost increases…



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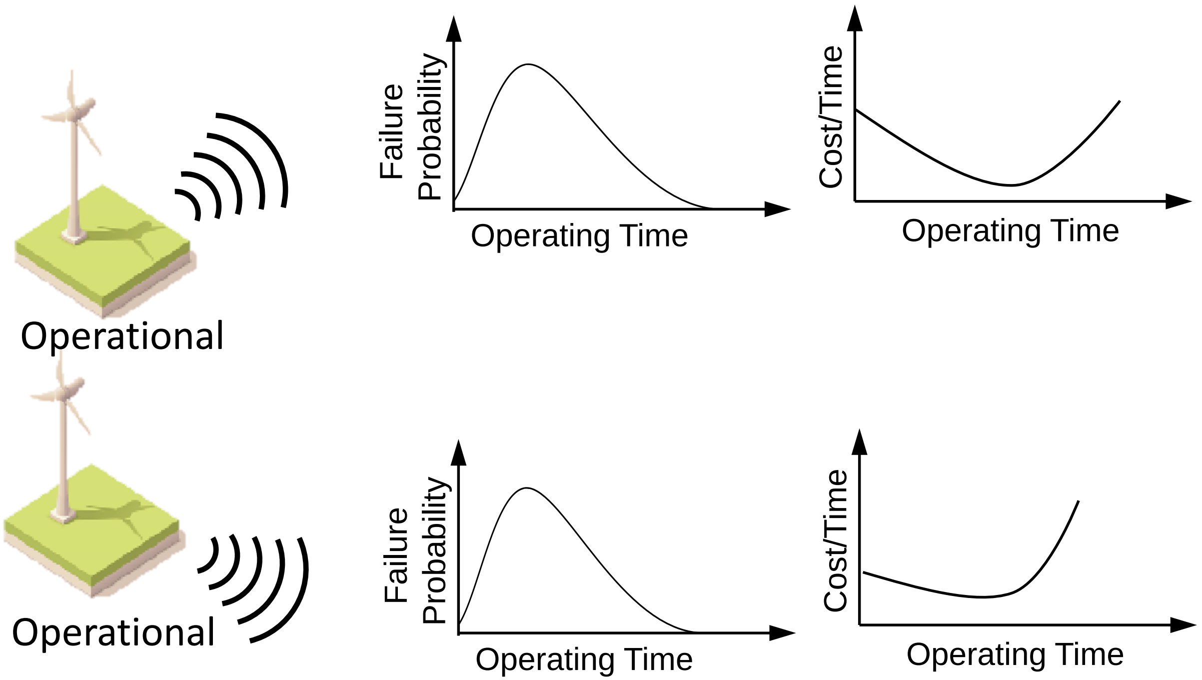

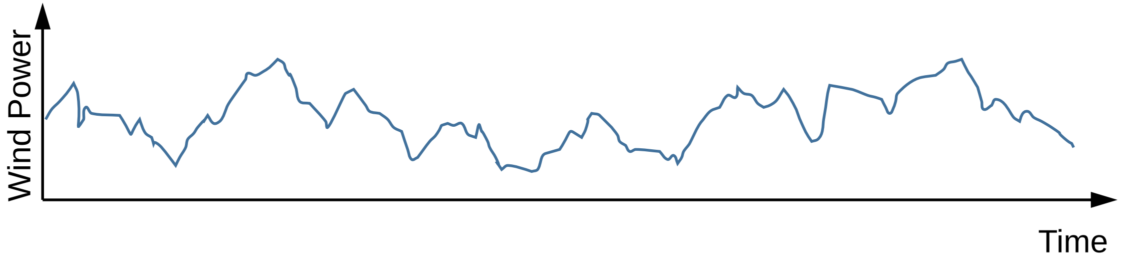

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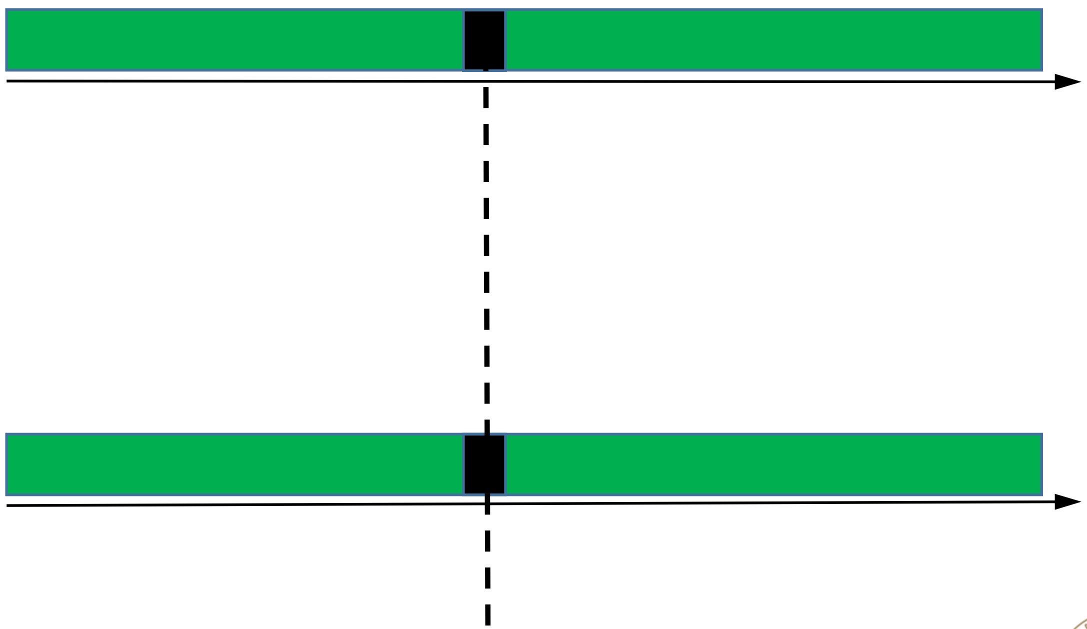
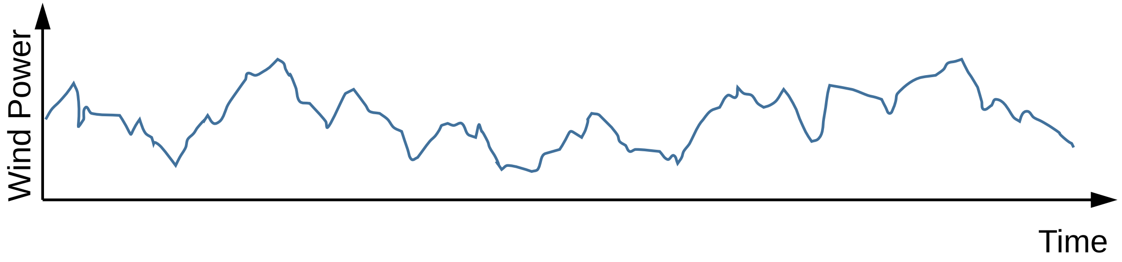


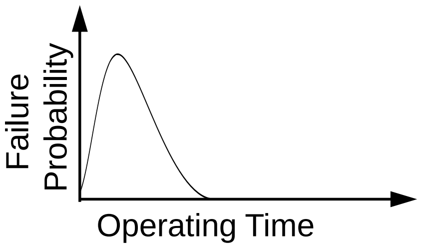
single crew visit

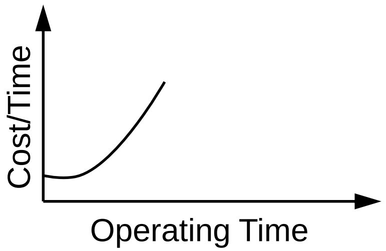
Adaptive Opportunistic Maintenance - Concept

Preventive maintenance for an operational turbines with short life expectancy, and a failed turbine.



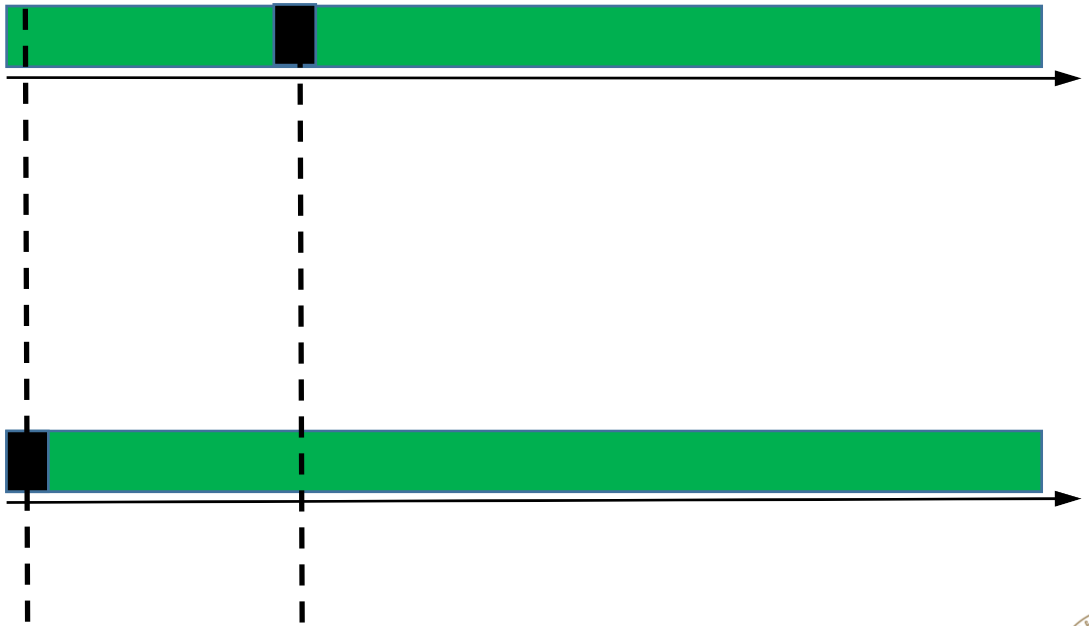
Operational





Failed

No Degradation Signal



two crew visits

Adaptive Opportunistic Maintenance - Concept

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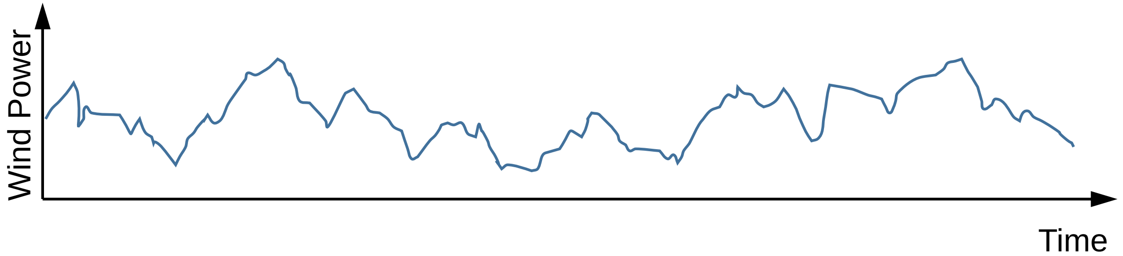

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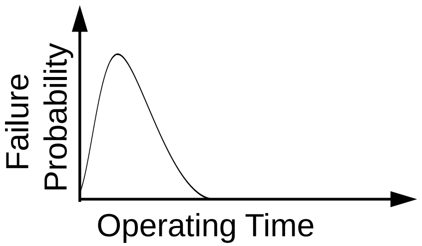

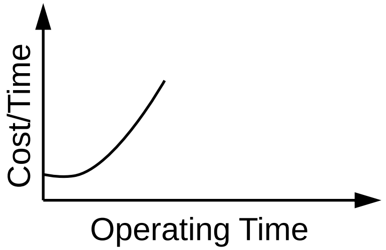

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No Degradation Signal

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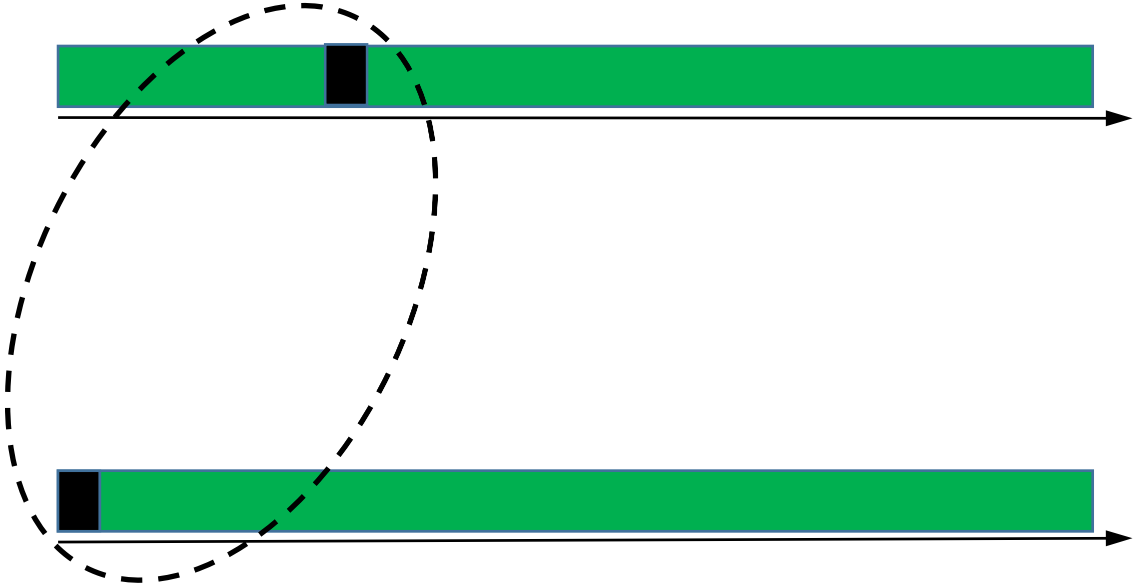
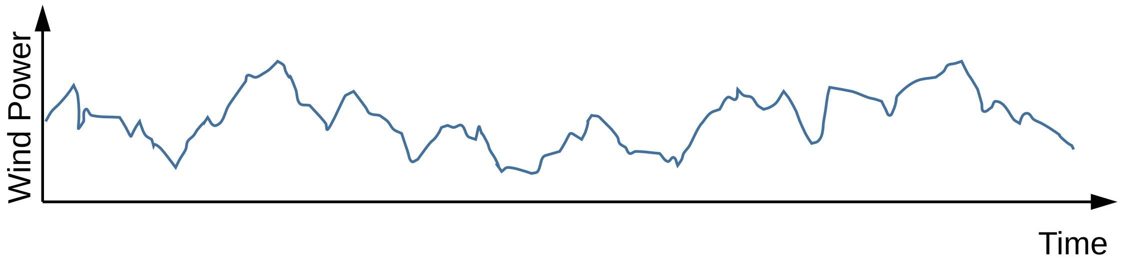


Adaptive Opportunistic Maintenance - Concept

Preventive maintenance for an operational turbines with short life expectancy, and a failed turbine.



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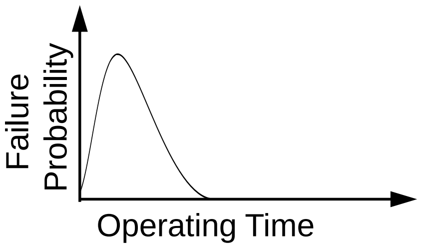

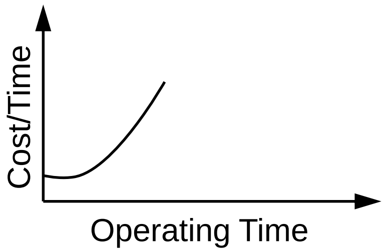

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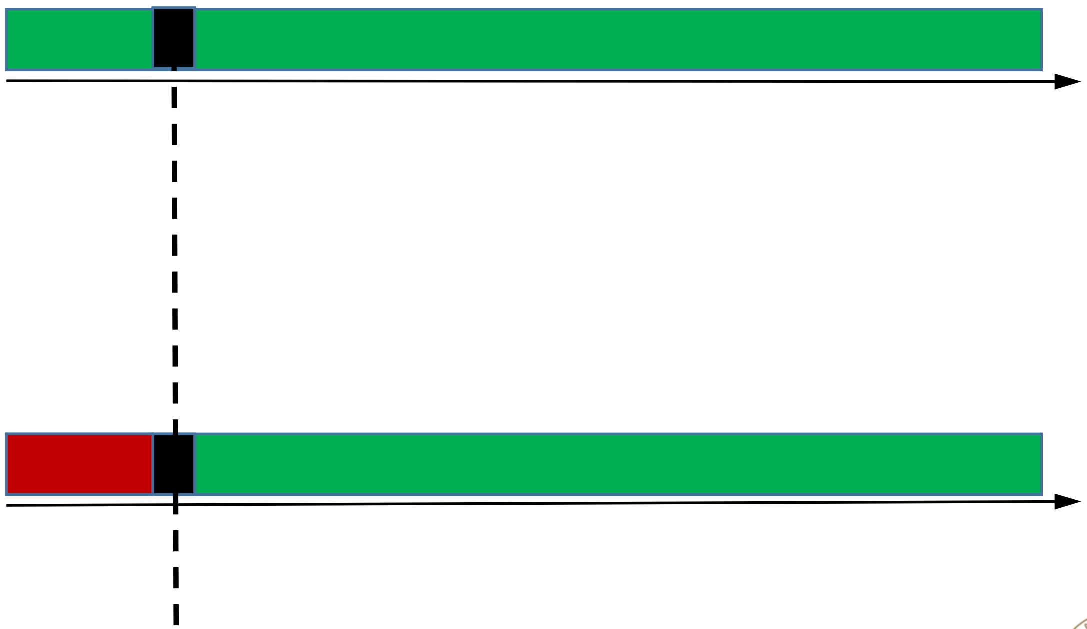

single crew visit

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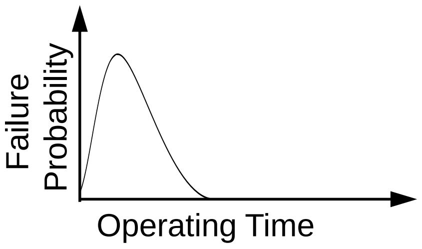
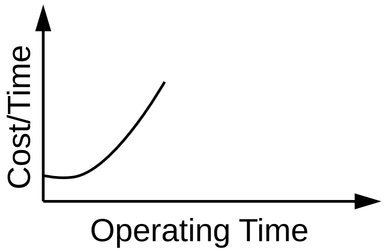
Preventive maintenance for an operational turbines with short life expectancy, and a failed turbine.

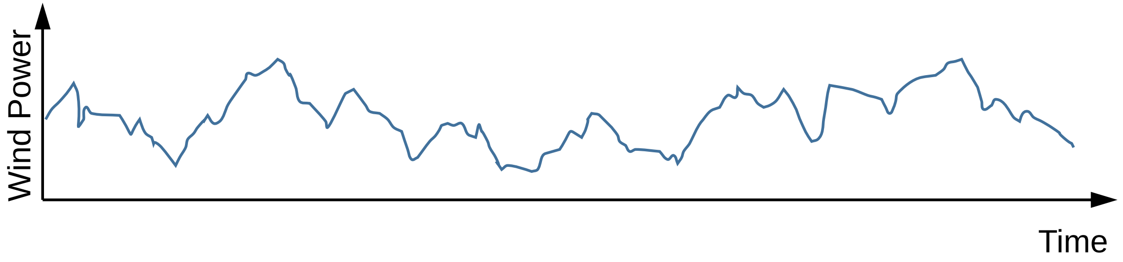
Operational

Failed

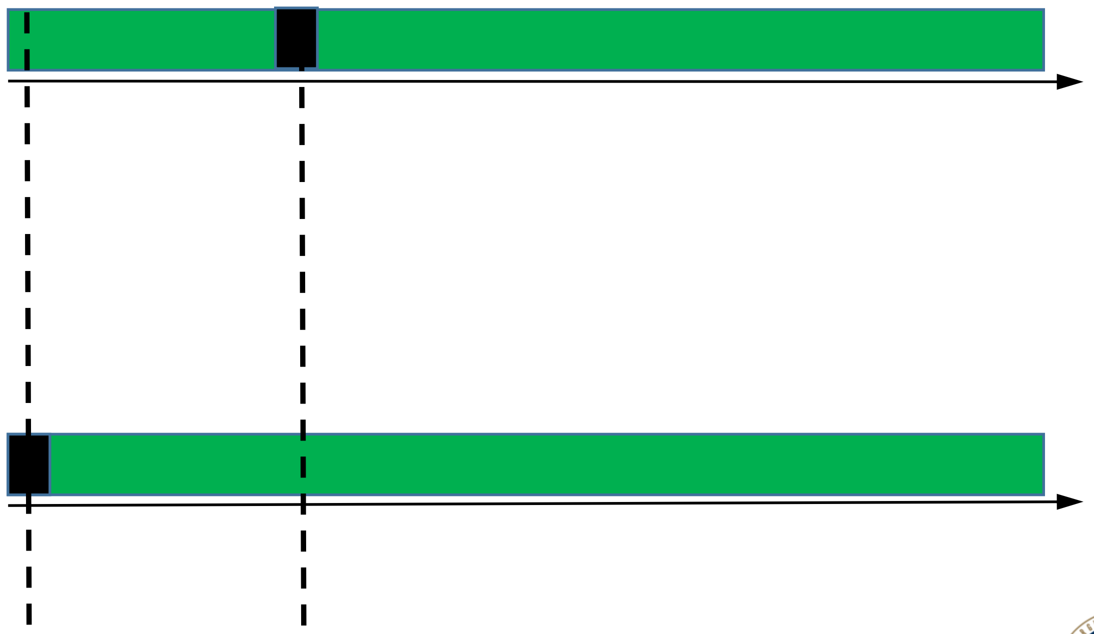




No Degradation Signal



as the site electricity price increases…



two crew visits

Adaptive Opportunistic Maintenance

- **Decision Variables:**
  - Fleet Maintenance Schedule
    - Optimal preventive and corrective actions
  - Generation Schedule
    - Optimal dispatch profile

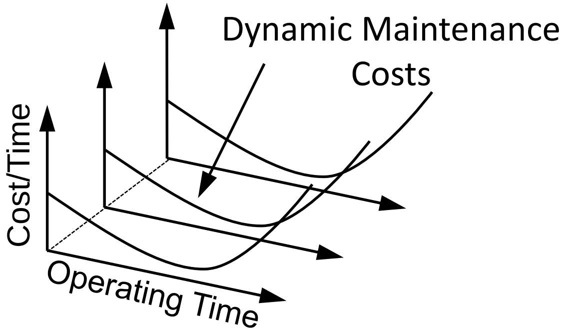
- **Objective:**
  - Maximize Revenue and Maintenance Costs

- **Subject to:**
  - Maintenance Constraints
  - Operations Constraints

- **Challenge:**
  - Incorporate the new sensor-driven dynamic cost function to the maintenance problem
  - Consider the maintenance scheduling of multiple windfarm locations

→ New Formulation

Adaptive Opportunistic Maintenance



Operational revenue

Crew deployment cost

$$
\begin{aligned}
\max_{z,\kappa,y} \quad & \boldsymbol{b}^\top \boldsymbol{y} - \boldsymbol{c}^\top \boldsymbol{z} - \boldsymbol{\upsilon}^\top \boldsymbol{\kappa} \\
\text{s.t.} \quad & \boldsymbol{A}\boldsymbol{z} \leq \boldsymbol{h} \\
& \boldsymbol{R}\boldsymbol{z} + \boldsymbol{E}\boldsymbol{\kappa} \leq \boldsymbol{r} \\
& \boldsymbol{P}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{y} \leq \boldsymbol{p} \\
& \{\boldsymbol{z}, \boldsymbol{\kappa}, \boldsymbol{y}\} \in \mathcal{F}^m.
\end{aligned}
$$

Maintenance constraints:

- Labor and material capacity
- Weather restrictions
- others…

Site visit coupling constraints:

- Crew should visit the site if any of the turbines are to be maintained

Dispatch coupling constraints:

- Turbine cannot produce while under preventive maintenance
- Failed turbine cannot produce before reactive maintenance

Maintenance and Operations Constraints

1. ***Coupling over generators:***
   - Maintenance capacity: number of turbines under maintenance is limited
   - Accessibility: maintenance crew can access only if the weather conditions permit
   - Maintenance site constraint: maintenance crew can visit only one location at a time
   - …
2. ***Coupling over different time periods:***
   - Travel time: maintenance crew needs a certain time to move between locations
   - Operations coupling: turbine production is determined by the time of maintenance
3. ***For every generators, and every time period***

Experiment

- Single Location: 100 Turbine Single Wind Farm
- Multiple Locations: 200 Turbines within 3 Wind Farms

- 120 day maintenance planning horizon, with 2-day maintenance decisions

- 96 day maintenance plan in a rolling horizon fashion

- Degradation database from a real rotating machinery application used to mimic turbine degradation, used NREL database for wind power input

- As our benchmarks, we use periodic, reactive and non-opportunistic sensor-driven maintenance policies.

http://www04.abb.com/global/seitp/seitp202.nsf/0/e13cc818bd46db88c1257be900470b8e/$file/Thornton_Bank_wind_turbines.jpg

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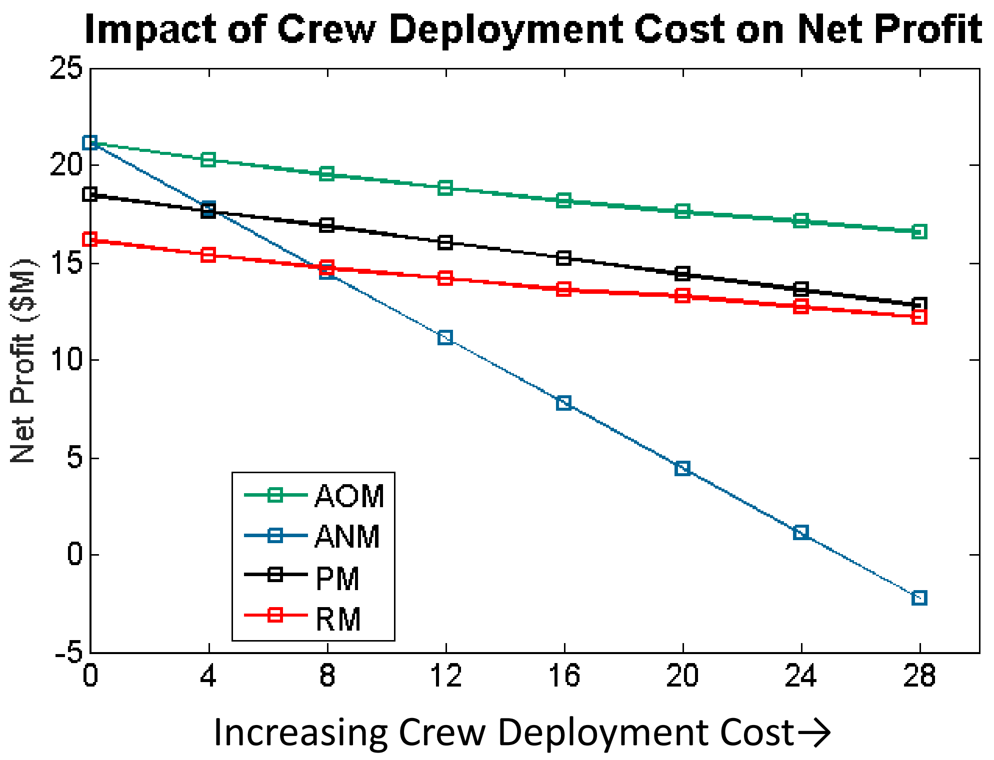
Experimental Results: Benchmarking



Observations:

- AOM policy always provides **significant improvements in profit**.
- Sensor-driven policies that do not consider turbine dependencies (typical of degradation modeling literature) are not effective, even worse than traditional policies at higher crew site visit costs.

Experimental Results: Crew Deployment Cost

c^v / c^p:=	0	4	8	12	16	20	24	28
Net Profit	$21.14 M	$20.28 M	$19.50 M	$18.82 M	$18.15 M	$17.59 M	$17.08 M	$16.56 M
Operational Revenue	$23.63 M	$23.60 M	$23.53 M	$23.42 M	$23.30 M	$23.14 M	$23.15 M	$23.05 M
Expenditures	$2.49 M	$3.32 M	$4.03 M	$4.60 M	$5.15 M	$5.55 M	$4.07 M	$6.50 M
· **Turbine Maintenance**	$2.49 M	$2.59 M	$2.80 M	$3.02 M	$3.29 M	$3.47 M	$3.50 M	$3.53 M
· **Crew Deployment**	$0 M	$0.73 M	$1.22 M	$1.58 M	$1.86 M	$2.08 M	$2.57 M	$2.97 M
# Preventive Actions	185.5	177.8	171.7	158.4	145.6	134.6	136.6	134.1
# Turbine Failures	15.9	20.3	27.1	35.8	45.9	53.2	53.4	54.8
# Crew Visits	83.5	18.2	15.3	13.2	11.6	10.4	10.7	10.6
# Idle Days	107.6	163.4	244.4	391	564.8	778.0	762.8	886.4

Observations:

- Increasing the crew deployment cost, dynamically leads to **more aggressive grouping**, thus:
  - increases expenditures, and decreases operational revenue
  - increases failure instances, and idle days
  - decreases preventive actions

Experimental Results: Electricity Price

IMPACT OF ELECTRICITY PRICE ON MAINTENANCE SCHEDULE

Electiricty Price (kWh)	**\$0.0625**	**\$0.1250**	**\$0.1875**	**\$0.2500**	**\$0.3125**	**\$0.3125**	**\$0.4375**	**\$0.5000**
Net Profit	\$7.09 M	\$18.81 M	\$30.47 M	\$42.18 M	\$53.91 M	\$65.68 M	\$77.46 M	\$89.15 M
Expenditures	\$4.60 M	\$4.60 M	\$4.69 M	\$4.72 M	\$4.74 M	\$4.77 M	\$4.77 M	\$4.82 M
# Turbine Failures	37.4	36.2	35.3	36.4	34.7	34.5	33.1	34.2
# Idle Days	433.2	407.2	368.8	358.4	346.8	315.0	300.8	284.3

Observations:

- Increasing the electricity price, leads to **more emphasis on availability**, thus increases crew visits in order to minimize idle days.

Experimental Results: Multiple Locations

MULTIPLE LOCATIONS PERFORMANCE OF AOM

$c^{v,1}$ / c^p:=	**0**	**4**	**8**	**12**	**16**
Location 1: 100 Turbines, Nominal Crew Deployment Cost					
# Preventive Actions	180.0	170.8	167.9	137.8	131.9
# Turbine Failures	19.9	27.6	32.5	51.9	56.4
# Crew Visits	47.2	15.6	13.0	10.4	9.8
# Idle Days	161.2	290.6	389.4	790.6	844.4
Location 2: 50 Turbines, Nominal Crew Deployment Cost					
# Preventive Actions	87.0	80.2	60.7	51.1	45.4
# Turbine Failures	10.0	18.1	31.8	36.7	39.4
# Crew Visits	32.0	11.6	7.6	6.5	5.8
# Idle Days	111.2	262.0	582.0	847.4	1002.6
Location 3: 50 Turbines, Expensive (10×) Crew Deployment Cost					
# Preventive Actions	88.4	39.2	33.1	21.7	21.2
# Turbine Failures	12.2	45.5	49.7	56.4	58.9
# Crew Visits	27.7	4.8	4.1	2.0	1.9
# Idle Days	149.4	1546.4	1906.0	2749.2	3045.2

Observations:

- Location 3 has higher crew deployment cost, thus experiences less number preventive maintenances, incurs more failures, and longer idle times.

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Agenda

- Part I. Introduction
  - Current Practice
  - Motivation and Objectives
- Part II. Predictive Analytics
  - Proposed Framework
  - Predictive Analytics
  - Dynamic Maintenance Cost
- Part III. Opportunistic Adaptive Maintenance– Wind Farms
- Part IV. Adaptive Predictive Maintenance – Conventional Fleets
- Part V. Conclusion

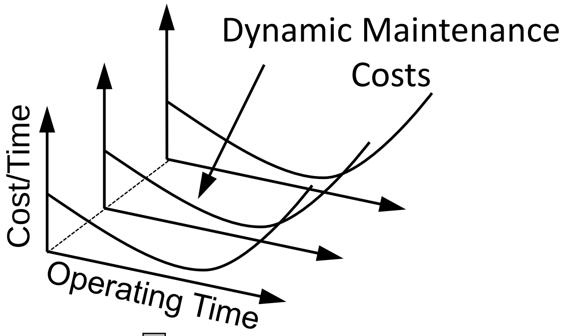
Adaptive Predictive Maintenance

- **Decision Variables:**
  - Fleet Maintenance Schedule
    - Number of maintenances for each generator
    - Time of each maintenance
  - Generation Schedule
    - Unit commitment
    - Generation dispatch

- **Objective:**
  - Minimize Total Operation and Maintenance Costs

- **Subject to:**
  - Maintenance Constraints
  - Operations Constraints

Adaptive Predictive Maintenance



$$
\begin{aligned}
\underset{\boldsymbol{z},\boldsymbol{\nu},\boldsymbol{x},\boldsymbol{y}}{\text{minimize}} \quad & \boldsymbol{c}^\top \boldsymbol{z} \qquad\qquad + \boxed{\boldsymbol{s}^\top \boldsymbol{x} \quad + \boldsymbol{b}^\top \boldsymbol{y}} \\
\text{subject to} \quad & \boldsymbol{A}\boldsymbol{z} \quad + \boldsymbol{K}\boldsymbol{\nu} \qquad\qquad\qquad\qquad \leq \boldsymbol{g} \\
& \qquad\qquad \boldsymbol{B}\boldsymbol{\nu} \quad + \boldsymbol{E}\boldsymbol{x} \qquad\qquad \leq \boldsymbol{h} \\
& \qquad\qquad\qquad\qquad + \boldsymbol{F}\boldsymbol{x} \quad + \boldsymbol{G}\boldsymbol{y} \quad \leq \boldsymbol{\ell}
\end{aligned}
$$

$$\{\boldsymbol{z},\boldsymbol{\nu}\} \in \mathcal{F}^m,\ \boldsymbol{x} \in \{0,1\}^{NG*NT},\ \boldsymbol{y} \in \mathbb{R}^{(NG+NS)*NT}$$

$$\mathcal{F}^m = \{\boldsymbol{z},\boldsymbol{\nu}|\ z_{t,i,k} \in \{0,1\}, \nu_{t,i,k}, \in \{0,1\} \quad \forall t \in \mathcal{T}, \forall i \in \mathcal{G}, \forall k \in \mathcal{M}_t, \quad z^o_{t,k} \quad \forall i \in \mathcal{G}, \forall k \in \{2,\ldots,NM_i\}\}.$$

Operational costs

Maintenance constraints:

- Labor and material capacity
- Maintenance inclusion/exclusion
- others…

Coupling constraints:

- Generator cannot produce while under maintenance

Operational constraints:
Unit Commitment

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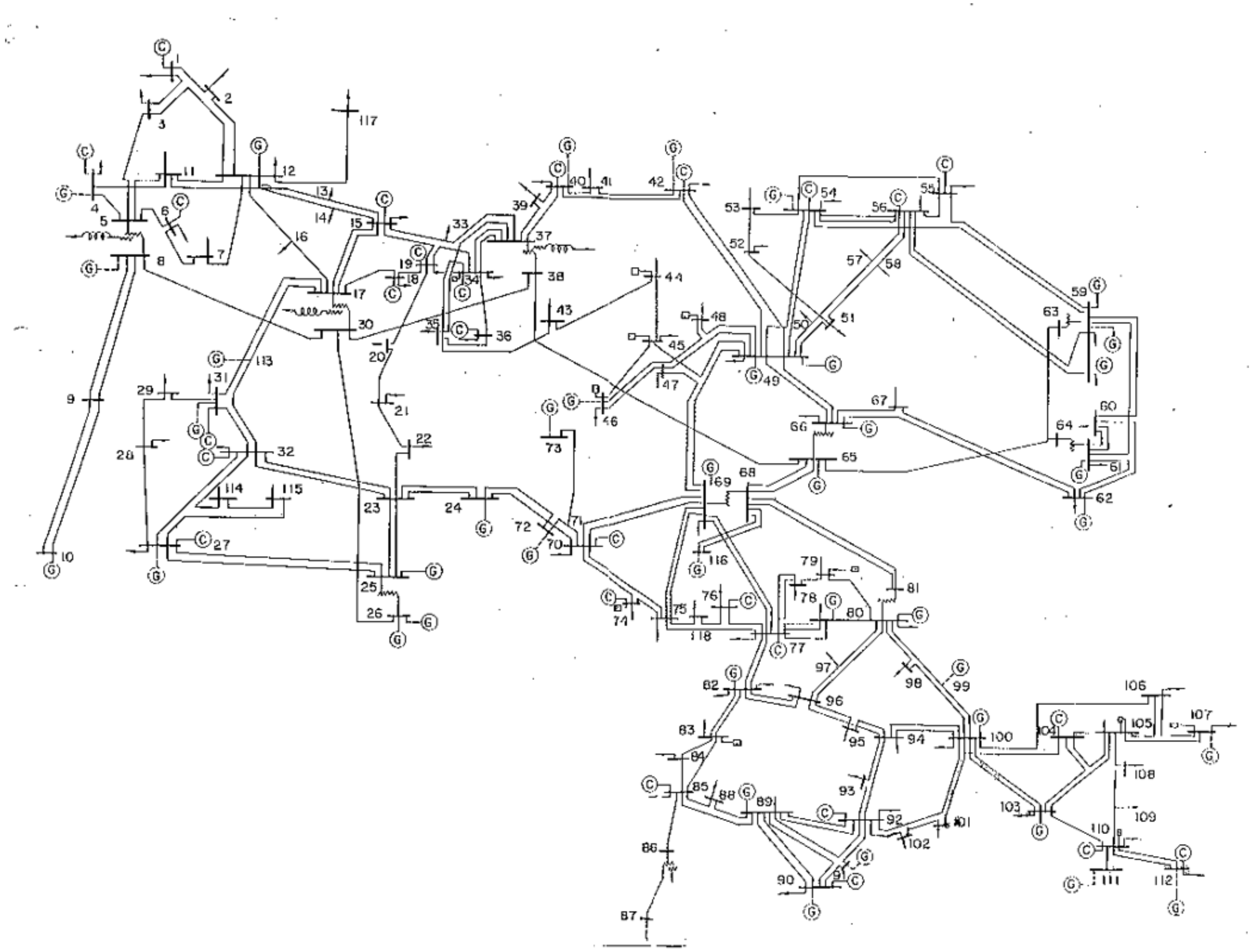
Unit Commitment Constraints

Operational Planning Problem of Large Power Systems:

1. ***Coupling over generators:***
    - Energy balance equation
    - Transmission flow constraint
    - …
2. ***Coupling over different time periods:***
    - Ramping constraints
    - Minimum up-down
    - …
3. ***For every generators, and every time period:***
    - Logical constraints on commitment
    - …

Experiment

- IEEE-118 bus problem, maintenance of 54 generators
- 110 week maintenance planning horizon, with weekly maintenance and hourly unit commitment decisions
- 48 week maintenance plan is simulated in a rolling horizon fashion
- Degradation database from a real rotating machinery application used to mimic generator degradation
- As our benchmarks, we use periodic maintenance and reliability based maintenance policies.



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Experimental Results: Benchmarking

Benchmark for APM

	Periodic	RBM	APM
# Preventive	24.0	25.3	25.7
# Failures	13.7	12.2	1.9
# Total Outages	37.7	37.5	27.6
Unused Life (wks)	950.1	1012.9	295.6
Maintenance Cost	\$15.76 M	\$14.82 M	\$6.66 M
Operations Cost	\$191.24 M	\$186.54 M	\$185.08 M
Total Cost	\$207.00 M	\$201.36 M	\$191,74 M

Observations:

- APM policy **improves the reliability** (decreases failures by >84%) of the generator fleet and causes a **small number of interruptions** (decreases outages by >26%).
- APM policy **extends the equipment lifetime** (decreases unused life by >68%).
- APM policy **decreases the maintenance and operations cost**.

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Experimental Results: Updating Frequency

IMPACT OF THE FREEZE TIME ON APMI

	$\tau_R = 8$	$\tau_R = 6$	$\tau_R = 4$	$\tau_R = 2$
# Preventive	26.6	27.2	26.9	26.8
# Failures	1.5	1.1	0.7	0
# Total Outages	28.1	28.3	27.6	26.8
Unused Life (wks)	309.5	306.9	255.2	187.7
Maintenance Cost	\$6.52 M	\$6.32 M	\$5.94 M	\$5.36 M

Observations:

- As the maintenance updates become more frequent, APM **learns more about the underlying degradation processes**, and hence improves every aspect of the maintenance policy.

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Conclusions

- We proposed a sensor-driven framework consisting of the following modules:
  1. Predictive analytics
  2. Dynamic maintenance cost analysis
  3. Novel optimization models for maintenance and operations
- We significantly improved the maintenance objectives suggested by the IEEE taskforce.

Questions?