# On Modeling and Diagnosis of Friction and Wear in Industrial Robots

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Automatic Control, Linköping University, Sweden

Background

Understanding Friction

Wear Identification

Diagnosis of Repetitive Systems

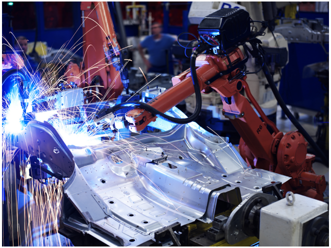
Conclusions

Industrial robots' applications may be

- harsh
- dull
- safety / quality / cost critical

Reliability/availability are keys for success!

- Robots are reliable by design



# Industrial Robots - The need for service



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Service actions may avoid faults, increasing the availability

# Service of IRB's - Two sides of the coin



The robot user seeks for

- $\Uparrow$ availability
- $\Uparrow$ productivity
- $\Downarrow$ downtimes

The service provider

- $\Downarrow$ service/maintenance costs
- $\Uparrow$ accuracy
- $\Uparrow$ automated/remote

Achieving all compromises is difficult!

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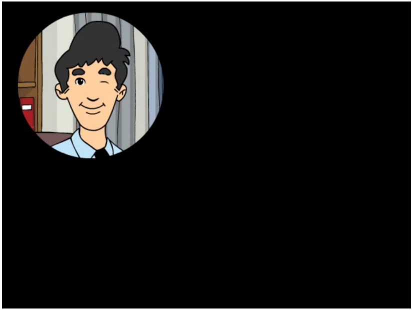

Q: What is super service man's secret?

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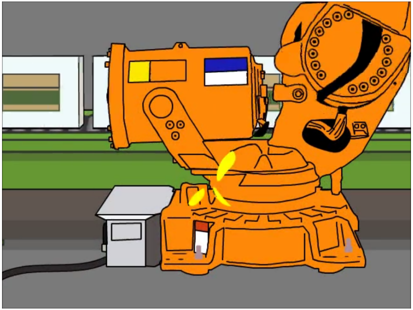

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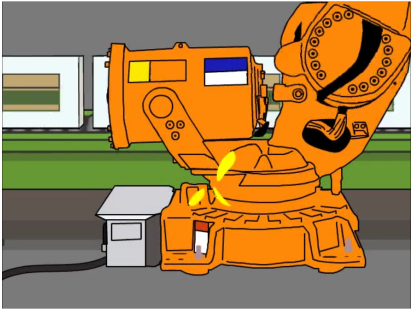

Ans: Condition monitoring/diagnosis methods!

## Why?

- Certain
- Gradual
- Allows for early diagnosis

## Where does it happens?

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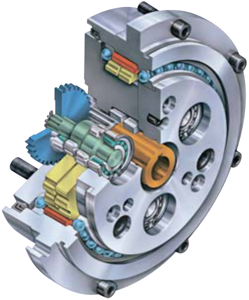

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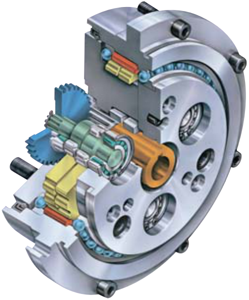

## How we can diagnose wear?


Inspection allows for CBM (not suitable)

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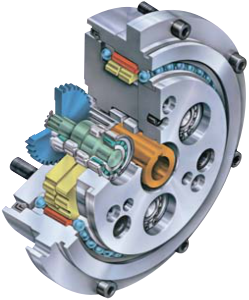

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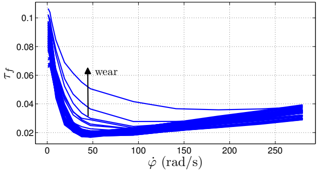


Friction changes affect measured signals!


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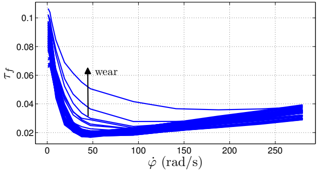


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**Main idea:**

Monitor friction to infer about wear

Possible to automate!



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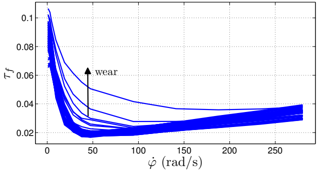


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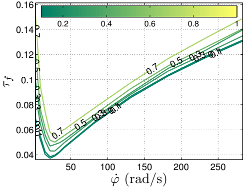


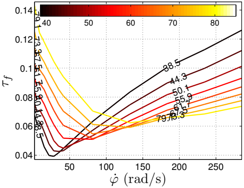


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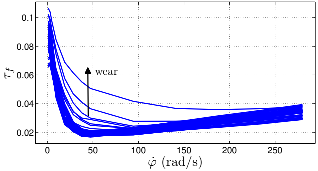


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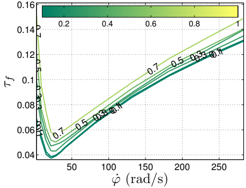


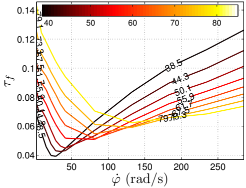


Friction changes affect measured signals!

**Main idea:**

Monitor friction to infer about wear

(with careful!)

Possible to automate!

**Objective**: design wear diagnosis methods to allow for CBM of IRB's

**Approach**:

1. Understand friction - Paper A (and B)
2. Design of diagnosis methods
   - Wear identification - Paper B
   - Diagnosis of repetitive systems - Paper C

Background

Understanding Friction

- Estimating Friction
- Friction Modeling
- Summary

Wear Identification

Diagnosis of Repetitive Systems

Conclusions


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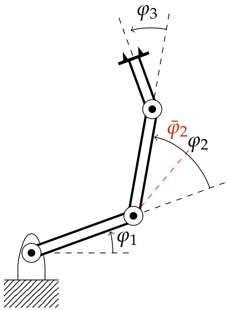
Here is our robot. We want $\tau_f$.

$$M(\varphi)\ddot{\varphi} + C(\varphi, \dot{\varphi}) + \tau_g(\varphi) + \tau_f(\dot{\varphi}) = u$$



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Here is our robot. We want $\tau_f$.

Move at a cte speed $\bar{\dot{\varphi}}$

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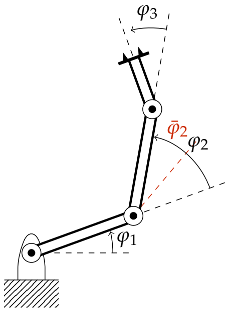

Here is our robot. We want $\tau_f$.
Move at a cte speed $\bar{\dot{\varphi}}$ one axis at a time

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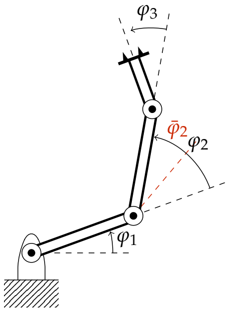

# Estimating Friction

Here is our robot. We want $\tau_f$.

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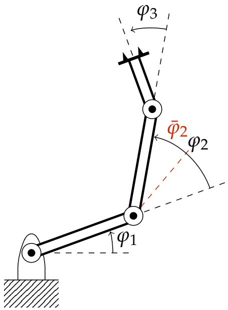
Move back and forth around $\bar{\varphi}$

$$\tau_f(\bar{\dot{\varphi}}) + \tau_g(\bar{\varphi}) = u^+,$$
$$\tau_f(-\bar{\dot{\varphi}}) + \tau_g(\bar{\varphi}) = u^-$$

if $\tau_f(-\bar{\dot{\varphi}}) = -\tau_f(\bar{\dot{\varphi}})$

$$\boxed{\tau_f(\bar{\dot{\varphi}}) = 1/2(u^+ - u^-)}$$



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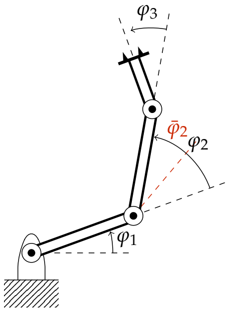

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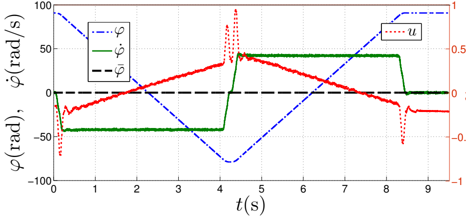


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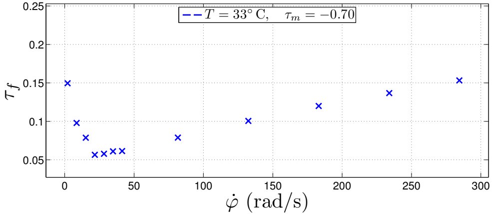
Repeat for several speeds to get a *static friction curve*





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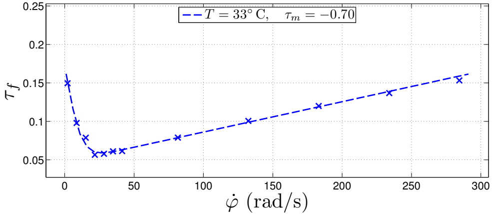
Can we model these effects?




Here is a model to describe it

$$\tau_f(\dot{\varphi}) = F_c + F_s e^{-\left|\frac{\dot{\varphi}}{\dot{\varphi}_s}\right|^{\alpha}} + F_v \dot{\varphi} \qquad (\mathcal{M}_0)$$

Works well!

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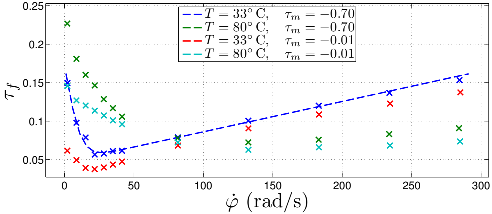


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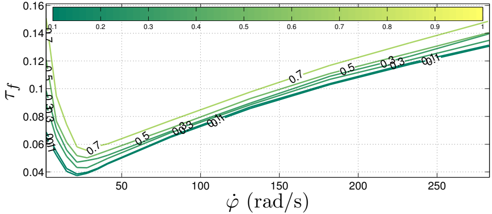
## Load, can we model these effects?




Here is a model to describe it

$$\tau_f(\tau_l) = \{F_{c,0} + F_{c,\tau_l}|\tau_l|\} + F_{s,\tau_l}|\tau_l| e^{-\left|\frac{\dot{\varphi}}{\dot{\varphi}_{s,\tau_l}}\right|^{\alpha}}$$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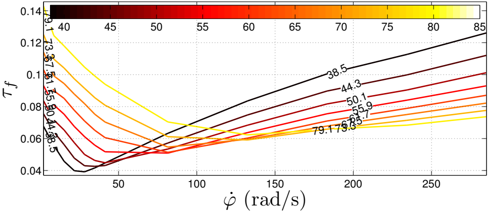
## Temperature, can we model these effects?




Here is a model to describe it

$$\tau_f(T) = \{F_{s,0} + F_{s,T}\}\, e^{-\left|\frac{\dot{\varphi}}{\dot{\varphi}_{s,0}+\dot{\varphi}_{s,T}T}\right|^{\alpha}} + \{F_{v,0} + F_{v,T}\}\, e^{-\frac{T}{T_{\text{Vo}}}}$$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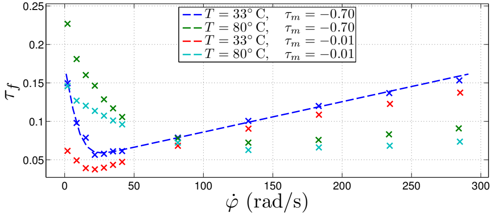
## Validation




$$\tau_f(\dot{\varphi}, \tau_l, T) \qquad (\mathcal{M}^*)$$

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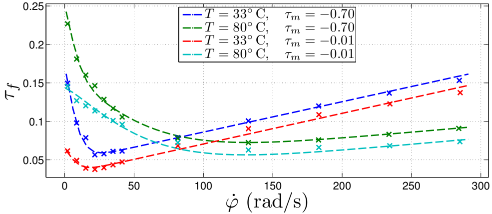


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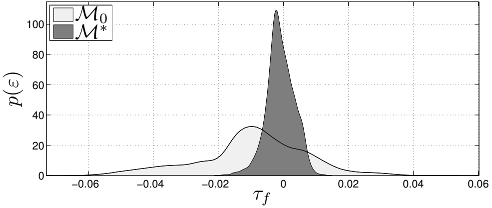


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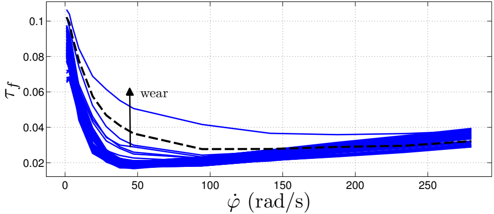
## Wear, can we model these effects?




Consider effects of wear only! (wear profile)



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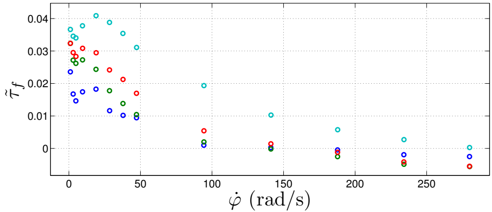


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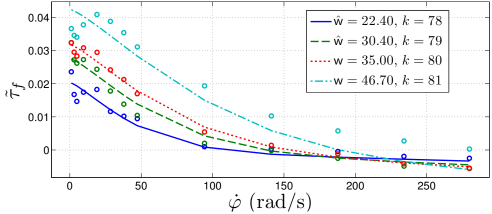
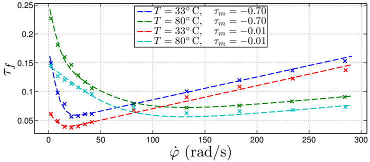
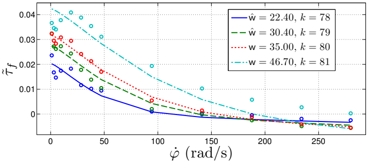



Here is a model to describe it

$$\tilde{\tau}_f(\mathrm{w}) = F_{s,\mathrm{w}} e^{-\left|\frac{\dot{\varphi}}{\dot{\varphi}_{s,\mathrm{w}}\mathrm{w}}\right|^{\alpha}} + F_{v,\mathrm{w}}\mathrm{w}\dot{\varphi}$$

Models for speed, load, temperature and wear!




$$\tau_f(\dot{\varphi}, \tau_l, T, \mathrm{w}) = \tau_f(\dot{\varphi}, \tau_l, T) + \tilde{\tau}_f(\mathrm{w})$$

# Some Remarks

## Relevant Aspects

- Useful for design and evaluation
- Effects of load and temperature should be considered
- Load torques might be estimated
- Temperature is not measured
- Several parameters needed (hard to identify)

## Future Work

- Verify models in other devices
- Include dynamic friction models
- Define a sound identification procedure

Background

Understanding Friction

Wear Identification

- Problem Formulation
- Simulation Studies
- Case Study
- Summary

Diagnosis of Repetitive Systems

Conclusions

# Wear Identification

Can wear be robustly identified?

- Temperature is not measured
- Complex and uncertain robot dynamics
- On-line identification might be difficult



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A setup used for analysis (a proof of concept)

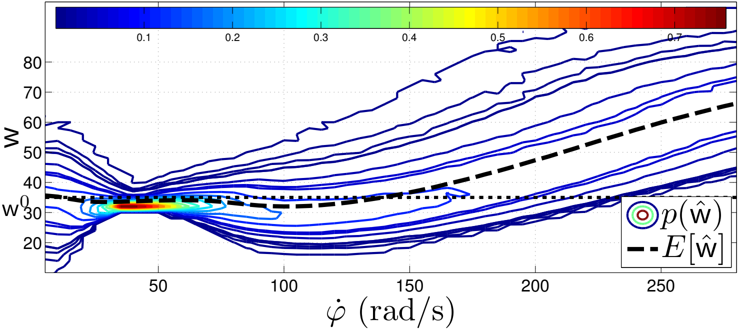
- Friction levels estimated with a test-cycle at 1 speed
- Known friction model (wear and temperature)
- Temperature treated as random with known bounds

Identification of a static nonlinearity with uncertainties

$$\hat{\mathsf{w}}_i(\dot{\varphi}) = \arg\min_{\mathsf{w}} V\left(\tau_f(\dot{\varphi}) - \hat{\tau}_f(\dot{\varphi}, \tau_l, T_i, \mathsf{w})\right), \quad T_i \sim \mathcal{U}(\underline{T}, \overline{T})$$
$$\hat{\mathsf{w}}(\dot{\varphi}) = E\left[\hat{\mathsf{w}}_i(\dot{\varphi})\right], \quad i = 1, \ldots, N$$

Choice of $\dot{\varphi}$ is a design criteria. What region is best?

Estimated distribution for a critical wear level ($w = 35$)




- Large bias at high $\dot{\varphi}$
- Large variance at low/high $\dot{\varphi}$
- Selective $\dot{\varphi}$ region where $\hat{w}$ estimates are useful

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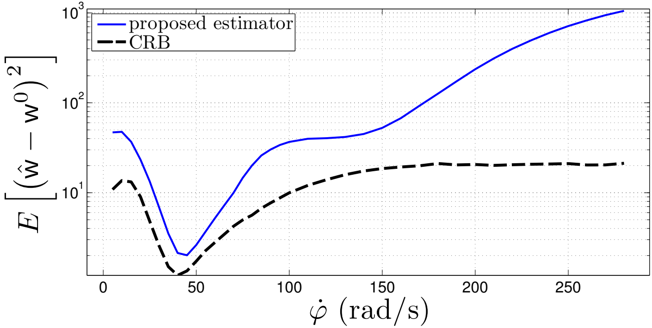


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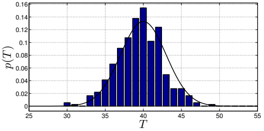
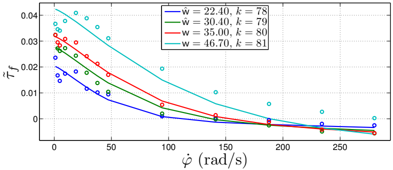
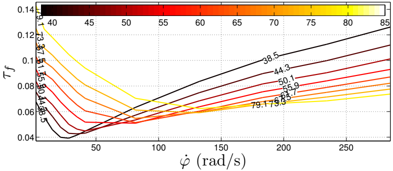
Real failure data combined with fault free data (temperature)

$$\tau_f^*(k) = \tilde{\tau}_f(k) + \tau_f^0(T)$$



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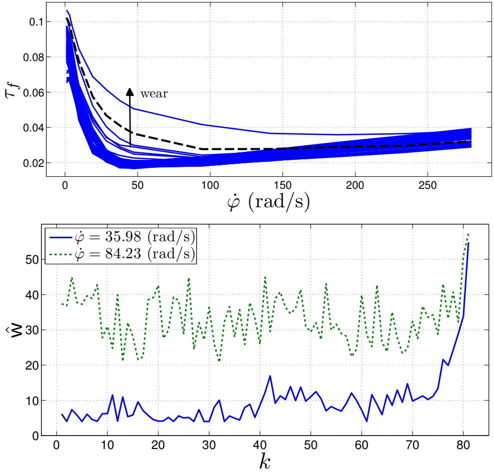
## Results


0.1
0.08
0.06
0.04
0.02
$\tau_f$
wear
0 50 100 150 200 250
$\dot{\varphi}$ (rad/s)
$\dot{\varphi} = 35.98$ (rad/s)
$\dot{\varphi} = 84.23$ (rad/s)
50
40
30
20
10
0
$\hat{w}$
0 10 20 30 40 50 60 70 80
$k$

# Some Remarks



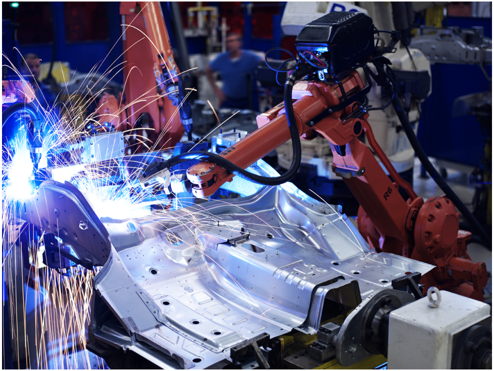
## Relevant Aspects

- Based on a test-cycle (reduced availability)
- Requires knowledge of a model with several parameters
- Narrow optimal speed range (not easy)
- Allows for robust wear diagnosis

## Future Work

- Include analysis of variations of lubricant and load
- Robust wear identification with no test-cycle (no interruptions)

Systems that perform a task in a fixed pattern repetitively



Typical in automation

Systems that perform a task in a fixed pattern repetitively


Can be forced with a test-cycle

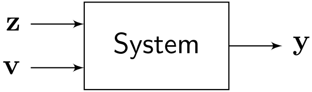
Systems that perform a task in a fixed pattern repetitively

Basic idea for diagnosis

> Compare how the task is executed now
>
> to how it is executed when healthy

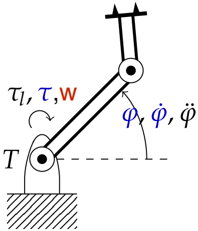
# Problem Formulation

Consider a general system




$\mathbf{v}$ are random unknown

$$\mathbf{z}: \begin{cases} \mathbf{u}, & \text{known} \\ \mathbf{d}, & \text{unknown} \\ \mathbf{f}, & \text{unknown of interest} \end{cases}$$




$$\mathbf{y} = \tau, \ \mathbf{f} = \mathrm{w}, \ \mathbf{d} = \underbrace{\varphi, \dot{\varphi}, \ddot{\varphi}, \tau_l}_{\mho}, T$$

A task $\mho$ is executed $M$ times

$$\mathbf{Y}^M = [\mathbf{y}^0, \cdots, \mathbf{y}^j, \cdots, \mathbf{y}^{M-1}]$$
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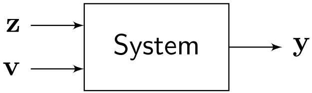


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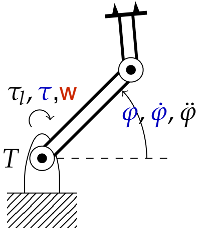


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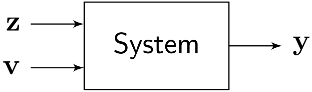


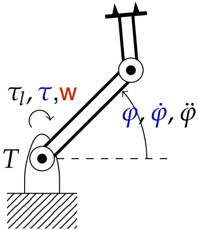


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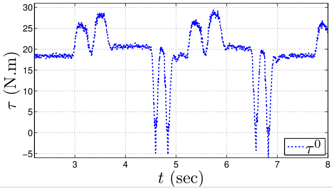


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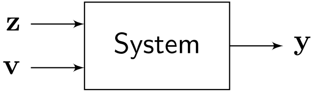


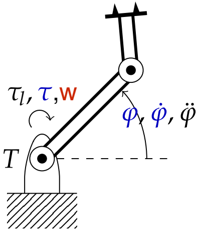


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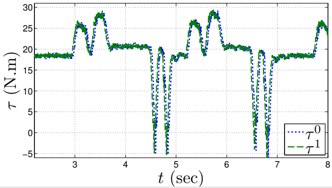


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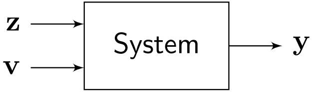


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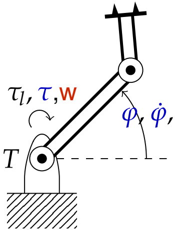


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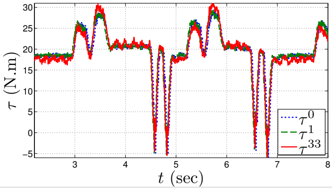

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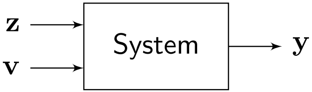


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Conditions & Assumptions:

1. Faults are observable
2. Reg. of $\mathbf{y}^j$ over $\mho$ if $\mathbf{f} = 0$
3. Reg. of $\mathbf{d}^j$ over $\mho$
4. Nominal data $\mathbf{y}^0$ available

Basic idea:

**Compare $\mathbf{y}^0$ with $\mathbf{y}^j$**

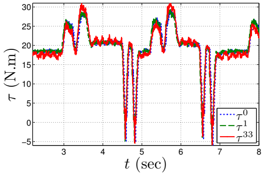
1. How to characterize $\mathbf{y}^j$?
2. How to compare $\mathbf{y}^0$ with $\mathbf{y}^j$?
3. How to relax the Assumps.?

Characterizing the data $\mathbf{y}^j$

smooth density estimate

$$\hat{p}^j(y) \triangleq \frac{1}{N}\sum_{i=1}^{N} k_h(y - y_i^j)$$

An experimental wear fault (acc. wear tests)



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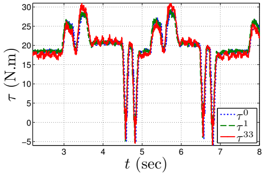


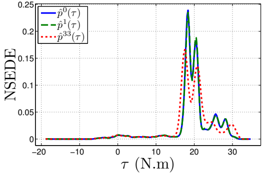

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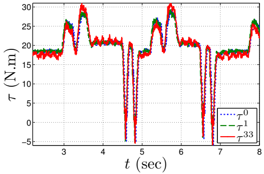
## Comparing $\mathbf{y}^0$ with $\mathbf{y}^j$

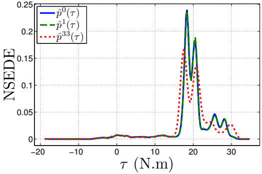
Kullback-Leibler distance

$$\mathsf{KL}\left(\hat{p}^0||\hat{p}^j\right) \triangleq D_{\mathsf{KL}}\left(\hat{p}^0||\hat{p}^j\right) + D_{\mathsf{KL}}\left(\hat{p}^j||\hat{p}^0\right)$$

$$D_{\mathsf{KL}}\left(\hat{p}^0||\hat{p}^j\right) \triangleq -\int_{-\infty}^{\infty} \hat{p}^0(y) \log \frac{\hat{p}^j(y)}{\hat{p}^0(y)} \, \mathrm{d}y$$

An experimental wear fault (acc. wear tests)



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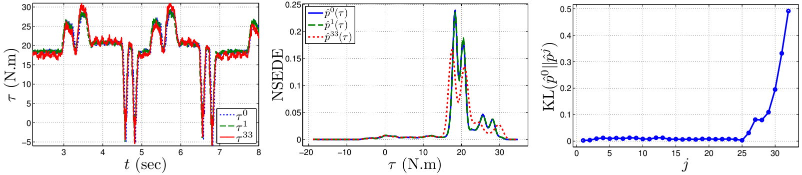


Characterizing the data $\mathbf{y}^j$

smooth density estimate

$$\hat{p}^j(y) \triangleq \frac{1}{N} \sum_{i=1}^{N} k_h(y - y_i^j)$$

+ no synchronization
+ no ordering
+ little tuning
+ simple (no model)

Comparing $\mathbf{y}^0$ with $\mathbf{y}^j$

Kullback-Leibler distance

$$\mathrm{KL}\left(\hat{p}^0 || \hat{p}^j\right) \triangleq D_{\mathrm{KL}}\left(\hat{p}^0 || \hat{p}^j\right) + D_{\mathrm{KL}}\left(\hat{p}^j || \hat{p}^0\right)$$

$$D_{\mathrm{KL}}\left(\hat{p}^0 || \hat{p}^j\right) \triangleq - \int_{-\infty}^{\infty} \hat{p}^0(y) \log \frac{\hat{p}^j(y)}{\hat{p}^0(y)} \, \mathrm{d}y$$

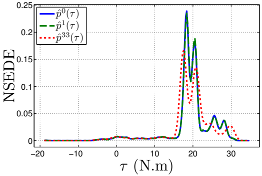
– requires $\mathbf{y}^0$
– data should be from same $\mho$
– “nice” disturbances
– no physical meaning

No assignment of $\mathbf{y}^0$

the KL $(\cdot||\cdot)$ is a metric

$$\text{KL}\left(\hat{p}^0||\hat{p}^j\right) \leq \sum_{k=1}^{j} \text{KL}\left(\hat{p}^{k-1}||\hat{p}^k\right)$$

An experimental wear fault (acc. wear tests)



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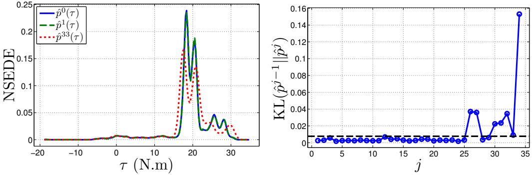

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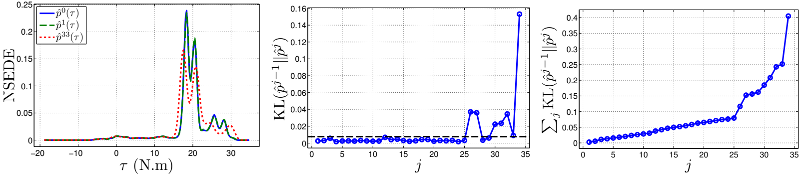

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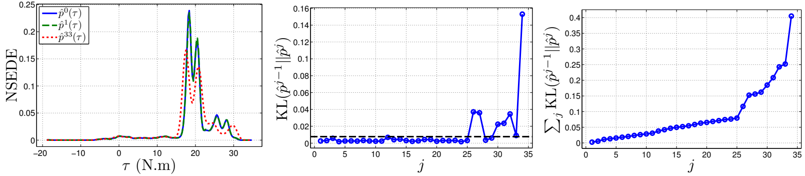
CUSUM filter

$$\begin{cases} g^j &= g^{j-1} + \mathrm{KL}\left(\hat{p}^{j-1}||\hat{p}^j\right) - \nu \\ g^j &= 0 \text{ if } g^j < 0 \end{cases}$$

with $\nu = \kappa\sigma + \mu$

An experimental wear fault (acc. wear tests)



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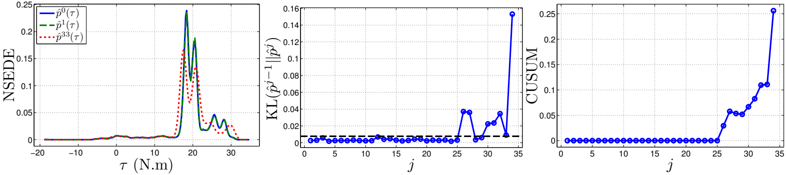

# Extending the Framework

No assignment of $\mathbf{y}^0$

the KL $(\cdot||\cdot)$ is a metric

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How to handle several ℧?

CUSUM filter

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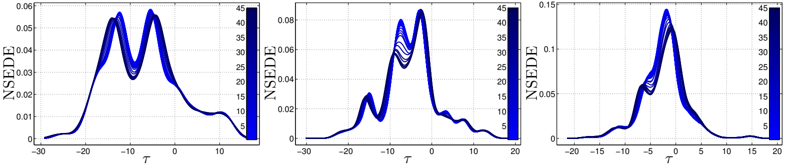
with $\nu = \kappa\sigma + \mu$

Behavior of the data differs with ℧ (simulation)



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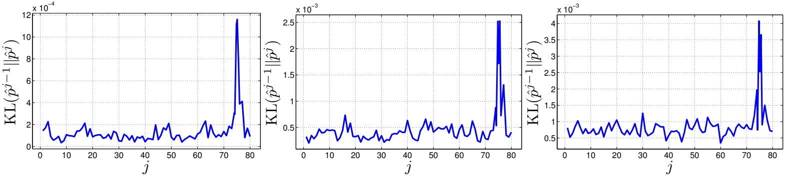
How to handle several $\mho$?

CUSUM filter

$$\begin{cases} g^j &= g^{j-1} + \text{KL}\left(\hat{p}^{j-1}||\hat{p}^j\right) - \nu \\ g^j &= 0 \text{ if } g^j < 0 \end{cases}$$

with $\nu^j = \kappa\sigma(\mho^j) + \mu(\mho^j)$

Idea: mix the increments in the CUSUM



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How to handle several $\mho$?

when $\mho^{k-1} = \mho^k$, same!

CUSUM filter

$$\begin{cases} g^j &= g^{j-1} + \mathsf{KL}\left(\hat{p}^{j-1}||\hat{p}^j\right) - \nu \\ g^j &= 0 \text{ if } g^j < 0 \end{cases}$$

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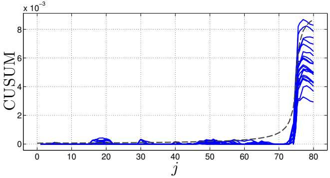
Simulations with several $\mho$'s



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Handling disturbances $\mathbf{d}$

apply weights to the data

$$\bar{\mathbf{y}} \triangleq \mathbf{w} \circ \mathbf{y}$$

Idea: choose $\mathbf{w}$ to $\max$ sens. to $\mathbf{f}$ and $\min$ sens. to $\mathbf{d}$



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Let the data decide!

$$\mathbf{Y}^M \triangleq \Big[\underbrace{\mathbf{y}^0, \dots, \mathbf{y}^{M_0}}_{\mathcal{C}_0}, \underbrace{\mathbf{y}^{M_0+1}, \dots, \mathbf{y}^{M_1+M_0}}_{\mathcal{C}_1}\Big]$$

Handling disturbances $\mathbf{d}$

apply weights to the data $\bar{\mathbf{y}} \triangleq \mathbf{w} \circ \mathbf{y}$

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Optimal criteria would be

$$\mathbf{w}^* = \arg\max_{\mathbf{w}} \mathsf{KL}\left(\hat{p}(\bar{\mathbf{y}}^{\mathcal{C}_0}) || \hat{p}(\bar{\mathbf{y}}^{\mathcal{C}_1})\right)$$

which is not so easy to solve



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Handling disturbances $\mathbf{d}$

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Idea: choose $\mathbf{w}$ to $\max$ sens. to $\mathbf{f}$ and $\min$ sens. to $\mathbf{d}$

Let the data decide!

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Alt., $\max$ average distance while $\min$ variability within class

$$\frac{(\bar{m}^1 - \bar{m}^0)^2}{\bar{s}_1 + \bar{s}_0} \propto \frac{\mathbf{w}^T(\mathbf{m}^1 - \mathbf{m}^0)(\mathbf{m}^1 - \mathbf{m}^0)^T\mathbf{w}}{\mathbf{w}^T(\mathbf{S}^1 + \mathbf{S}^0)\mathbf{w}},$$ which has optimum

$$\mathbf{w}^* \propto (\mathbf{S}^1 + \mathbf{S}^0)^{-1}(\mathbf{m}^1 - \mathbf{m}^0)$$

Optimal weights

$$\mathbf{w}^* \propto (\mathbf{S}^1 + \mathbf{S}^0)^{-1}(\mathbf{m}^1 - \mathbf{m}^0)$$

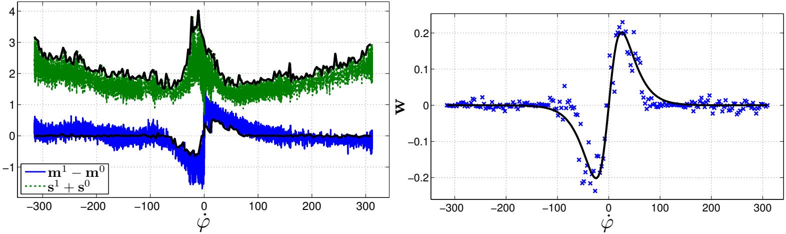
for an industrial robot under temperature disturbances (simulation)

# Reducing Sensitivity to Disturbances

Optimal weights

$$\mathbf{w}^* \propto (\mathbf{S}^1 + \mathbf{S}^0)^{-1}(\mathbf{m}^1 - \mathbf{m}^0)$$

for an industrial robot under temperature disturbances (simulation)

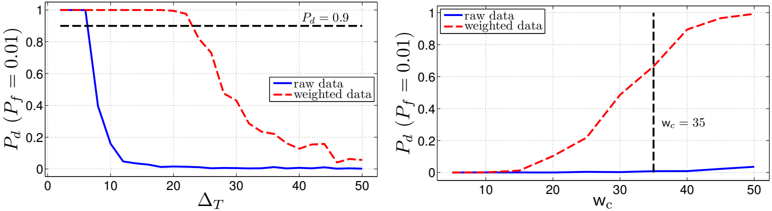



Optimal weights correlate with speed!

Optimal weights

$$\mathbf{w}^* \propto (\mathbf{S}^1 + \mathbf{S}^0)^{-1}(\mathbf{m}^1 - \mathbf{m}^0)$$

for an industrial robot under temperature disturbances (simulation)




The use of weights considerable improves the detection performance

# Some Remarks

## Relevant Aspects

- Overlooked problem, commonly found in automation
- No interruption of the system (batch)
- Can handle the use of several tasks and disturbances
- Simple (no model) and easy to implement, with little tuning

## Future Work

- Multivariate case
- Study the choice of kernel and distances
- Fault isolation and alarm generation
- Conditions on the data and disturbances



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Background

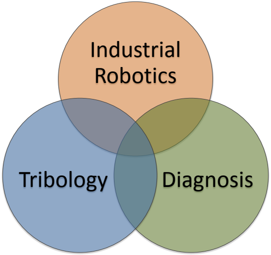
Understanding Friction

Wear Identification

Diagnosis of Repetitive Systems

Conclusions

Design methods for wear diagnosis in industrial robots




Intersection of 3 fields
Different solutions/limitations
You can find more on the thesis!

Main contributions

- Studies of friction and wear
- Friction and wear models
- Wear identification
- Monitoring of repetitive systems
- Practical perspective (robustness)

3(1) conference papers
1 journal paper

# Future Work

Friction and wear

- Other gear types
- Different wear failures
- Relations to lifetime (prognosis)

Design of diagnosis methods

- Limitations by disturbances
- When do they work or not (scope)

Evaluation

- Simulations (benchmark)
- Accelerated tests
- Field tests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Thank you!

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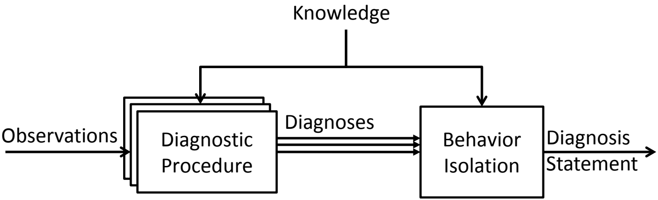
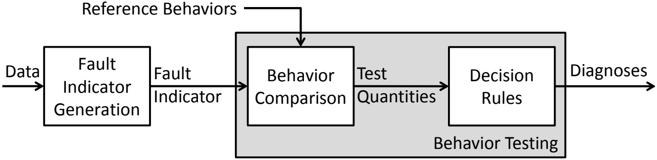
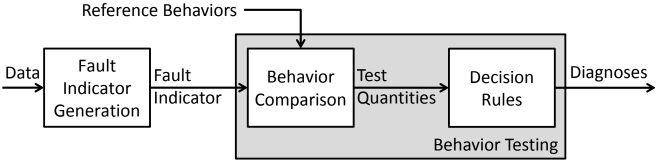
Overview of diagnosis




A diagnostic test






Fault indicator — a quantity that can be affected to a fault ($\varepsilon$, $\hat{\theta}$, densities, spectra)

Fault Indicator Generation — given data, generates a fault indicator (observer, kernel density estimator, FFT)

Behavior Comparison — compares the behavior of the FI with reference behaviors, generates test quantities (whiteness, chi-square, distances, Kullback-Leibler)

Decision Rule — decides the behavioral mode present (thresholding, CUSUM, delay-timer)

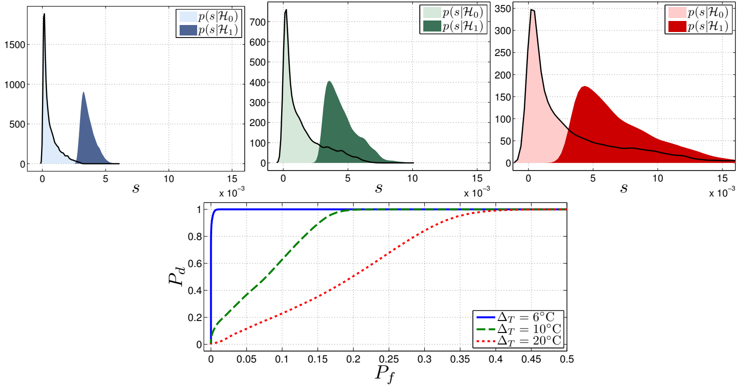
(Binary) Hypothesis testing

Given $s(k)$ decide behavioral mode presence, $\mathcal{H}_0$ or $\mathcal{H}_1$

$$s(k) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \hbar$$

$$P_f = \int_{\hbar}^{\infty} p(s|\mathcal{H}_0)\,\mathrm{d}s, \text{ assigns } \mathcal{H}_1 \text{ when } \mathcal{H}_0 \text{ is present.}$$
$$P_d = \int_{\hbar}^{\infty} p(s|\mathcal{H}_1)\,\mathrm{d}s, \text{ assigns } \mathcal{H}_1 \text{ when } \mathcal{H}_1 \text{ is present.}$$

# Evaluation of test quantities



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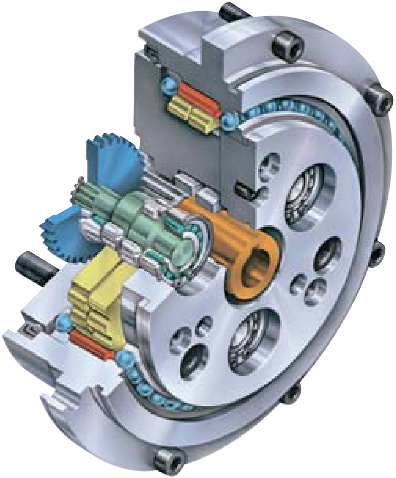
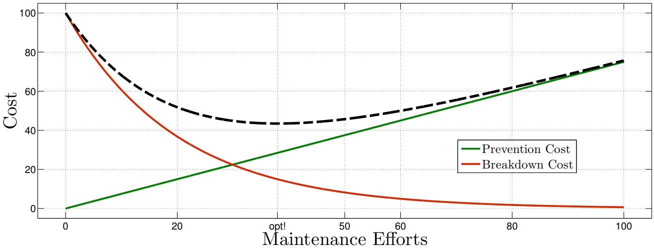
# Why isolation is simple?

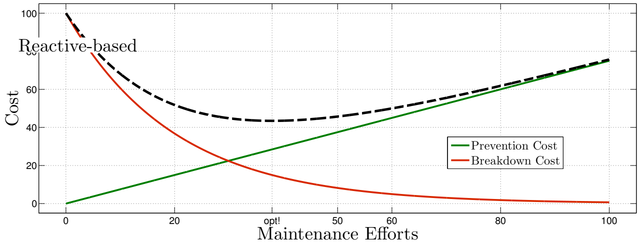


Which joint?
Not which bearing!

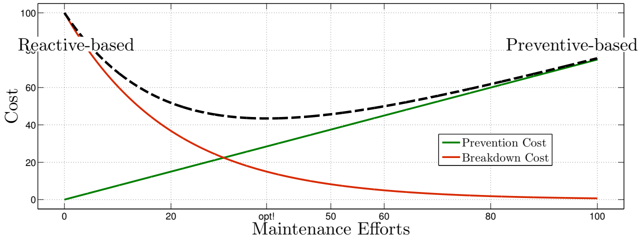
Example: Changing your truck's lubricant



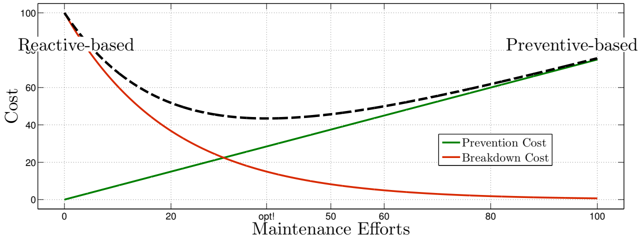
## Example: Changing your truck's lubricant




Example: Changing your truck's lubricant

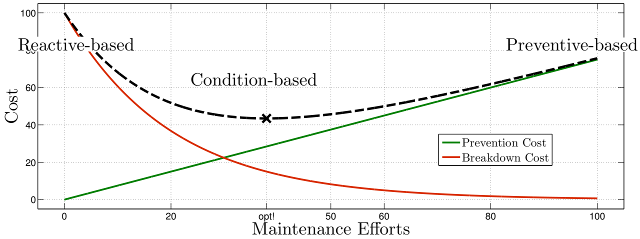



Example: Changing your truck's lubricant





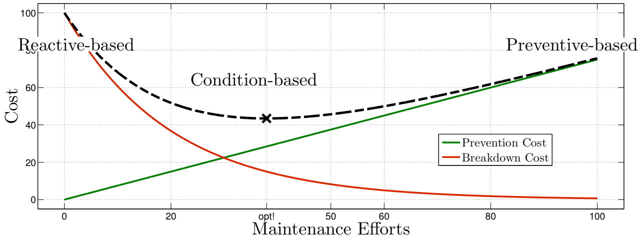
## Example: Changing your truck's lubricant





# The three Maintenance Strategies

Example: Changing your truck's lubricant









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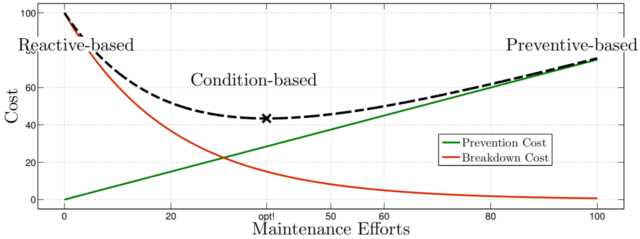
# The three Maintenance Strategies



## Example: Changing your truck's lubricant

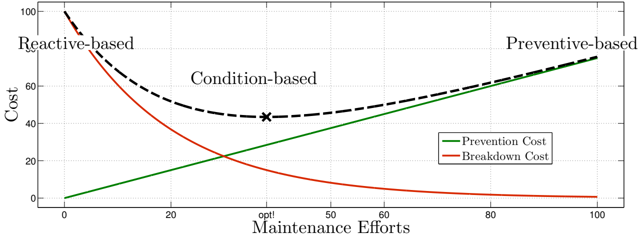





# The three Maintenance Strategies



Example: Changing your truck's lubricant



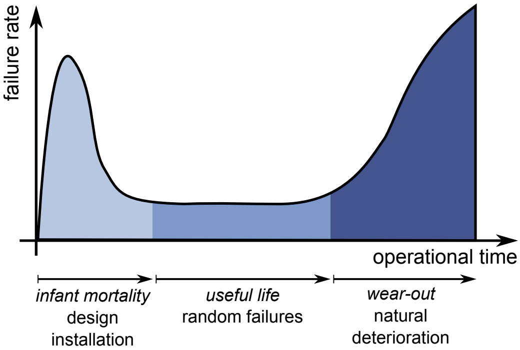




Ans: Condition monitoring/diagnosis methods!

# Which faults to begin with?

Failure of equipments. The bathtub curve




For increased availability

- do service before failure
- $\rightarrow$ diagnose before failure

Failures due to wear are

- certain
- gradual

Wear diagnosis is a good candidate to allow for CBM!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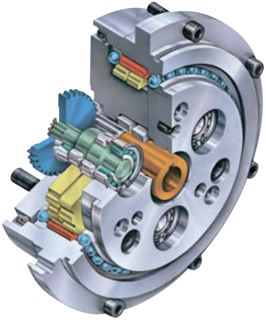
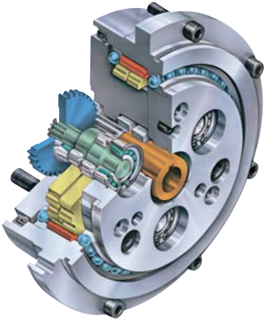
Where does it happens?

Where does it happens?



Where does it happens?



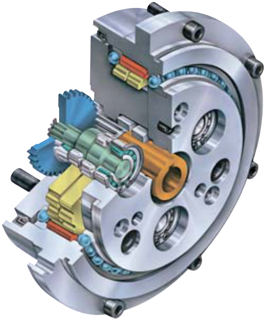
How we can diagnose wear?

Inspection allows for CBM (not suitable)

# Wear Diagnosis - Where and How



Where does it happens?



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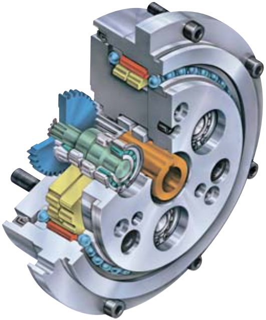
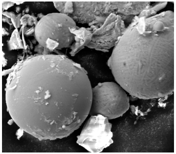
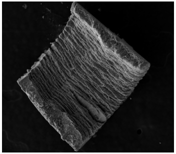
Where does it happens?



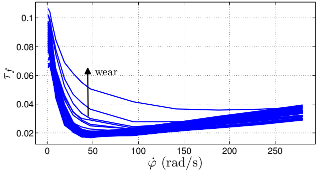
Wear debris particles accumulate in the lubricant



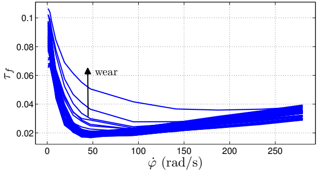


Ferrography allows for CBM (not suitable)

## Wear effects



Wear effects

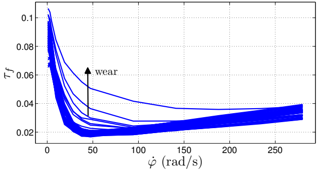



**Main idea:**

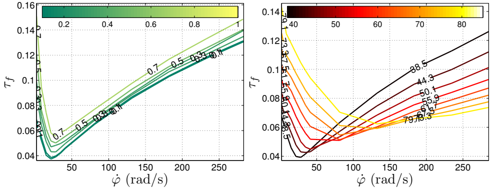
Monitor friction to infer about wear

Possible to automate!

## Wear effects




## … however!

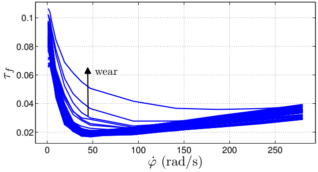



**Main idea:**

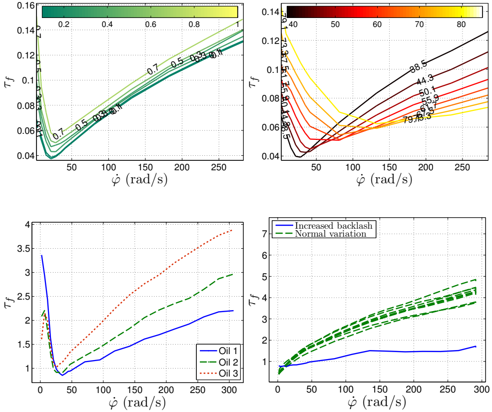
Monitor friction to infer about wear

Possible to automate!

## Wear effects




## ... however!




## Main idea:

**Monitor friction to infer about wear**

Possible to automate!



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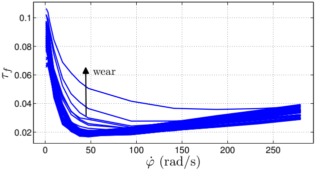
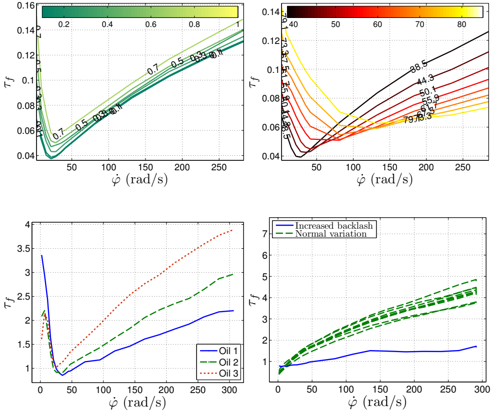
## Wear effects




## ... however!




**Main idea:**

> Monitor friction to infer about wear

Possible to automate!
(with careful!)