Strengthening the Rail Mode of Transport by Condition Based Preventive Maintenance

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Research Programs of DLR

- Aeronautics
- Space
- Energy
- Security
- Transport

Figure: Next Generation Train®️, DLR
Institute of Transportation Systems

Residence: Braunschweig, Berlin
Since: 2001
Director: Prof. Dr.-Ing. Karsten Lemmer
Employees: About 150 employees from various scientific disciplines
Fields of Research: Automotive
Railway Systems
Traffic Management
Range of Tasks: Basic research
Creating concepts and strategies
Prototype development
Quality: DIN EN ISO 9001
VDA 6.2
ISO 17025 (RailSiTe®)
Institute of Transportation Systems
1 Condition Based Preventive Maintenance

2 Localization

3 Prognostics
Motivation

- **conflicting demands:** profitability, availability, safety, and punctuality
- **potential solution:** optimized scheduling of maintenance actions taking account of the actual infrastructure condition and its expected degradation
- **critical railroad infrastructure:** railway track (misaligned track sections + railsurface failures)

(a) Misalignment  
(b) Squat  
(c) Corrugation
Preventive Maintenance Framework

Data Acquisition
- Switch Point Diagnostics
- Environmental Conditions

Data Linkage
- Digital Map / Infrastructure

Data Analysis

Train Operation
- kg

Measurement Trains

Sensor Systems on In-Line Trains

Maintenance Actions
In-Line trains equipped with low-cost sensor systems are a key element for a continuous condition monitoring.
In-Line Trains == Moving Sensor Systems

- rail irregularities $\Rightarrow$ vehicle response/vibration
- autonomous train-born measurement systems including...
- inertial measurement unit (IMU), acceleration sensors, microphone ... and other low-cost sensors

(d) RailDriVE®
(e) Data Logger
(f) Acceleration Sensor
LOCALIZATION

Track Selective: Location/Position of the train on the correct track
State-of-the-Art (Measurement Trains)

- localization based on the train’s odometer
- uncertainty up to dozens of meters
- ⇒ NO automated and precise (below 10m) georeferencing

(railway network == large area with insufficient GNSS reception)
State-of-the-Art (Measurement Trains)

- localization based on the train’s odometer
- uncertainty up to dozens of meters
- ⇒ NO automated and precise (below 10m) georeferencing

Multi-Sensor Concept (In-Line Trains)

- GNSS (Global Navigation Satellite System) receiver
- odometer + speed sensor (Doppler radar)
- balise-antenna
- digital map of the railroad network
- ⇒ track selective accuracy
### $\sigma$-Accuracies of Different Sensors

<table>
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<tr>
<th>Sensor</th>
<th>Accuracy Description</th>
</tr>
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<tbody>
<tr>
<td>GNSS RTK</td>
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![Diagram of sensors and data collection equipment]
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⇒ Data Fusion via **Extended Kalman Filter** for Localization
GNSS (red dots) vs. Multi-Sensor concept (orange dots)
GNSS (red dots) vs. Multi-Sensor concept (orange dots)
Failure (Corrugation)

Localization

Failure (Squat)

Localization
Railway Network

(a) Misalignment  (b) Squat  (c) Corrugation

⇓

In-Line Trains + Low-Cost Sensors + Localization

⇓

Key Performance Indicators (KPIs) of Monitored Track Segments
Railway Network

(a) Misalignment  (b) Squat  (c) Corrugation

⇒

In-Line Trains + Low-Cost Sensors + Localization

⇒

Key Performance Indicators (KPIs) of Monitored Track Segments

⇒

Expected Future Degradation? ⇒ Prognostics
PROGNOSTICS

- In-Line Trains
- Measurement Trains

Degradation vs. Operating Time
Local Degradation Models

- various approaches
- common: number of influencing parameters
- e.g. soil/rail quality, operating conditions, weather...
- ⇒ $\theta \equiv$ parameter vector
- in general, $\theta$ is uncertain (random variable)

Monte Carlo simulation of railway track geometry deterioration and restoration

L.M. Quiroga and E. Schneider
Institute for Traffic Safety and Automation Technologies, TU Braunschweig, Braunschweig, Germany

The manuscript was received on 23 December 2010 and was accepted after revision for publication on 8 July 2011.

DOI: 10.1177/1748006X1148422
More than degradation

A stochastic model for railway track asset management

John Andrews, Darren Prescott, Florian De Rzières

*Network Rail, Engineering Division, University of Nottingham, UK

**Granada Institute of Technology, France

Fig. 1. Petri net of the degradation process.
Holistic Approach

- incorporation of several track segments
- difficult to parameterize
- complex and cpu-intensive analyzes
- Polynomial Chaos Expansion (PCE) might help to decrease computational burden
Start

Input

Default Processing

1. Segment Model($\theta_1$)

2. Segment Model($\theta_2$)

\ldots

n. Segment Model($\theta_n$)

Output

Stop
Input

Default Processing

1. Segment Model($\theta_1$)

2. Segment Model($\theta_2$)

... 

n. Segment Model($\theta_n$)

$PCE(\theta_1, \theta_2, \ldots, \theta_n)$

Output

Stop

Bypass Processing
Polynomial Chaos Expansion

- handy surrogate model, \( \hat{g}(\theta) \)
- needs to be parameterized

\[
y = g(\theta) \approx \hat{g}(\theta) = \sum_{i=0}^{l_{pce}} a_i \Psi_i(\theta)
\]

\( \Psi_i(\theta) \) - proper orthogonal functions (Hermite Polynomials)
Polynomial Chaos Expansion

- handy surrogate model, $\hat{g}(\theta)$
- needs to be parameterized

$$y = g(\theta) \approx \hat{g}(\theta) = \sum_{i=0}^{l_{pce}} a_i \Psi_i(\theta)$$

$$a_i = \frac{\int_{\Omega} g(\theta) \Psi_i(\theta) \, pdf_\theta \, d\theta}{\int_{\Omega} \Psi_i(\theta)^2 \, pdf_\theta \, d\theta} = \frac{\int_{\Omega} g'(\theta) \, pdf_\theta \, d\theta}{\int_{\Omega} \Psi_i(\theta)^2 \, pdf_\theta \, d\theta}$$
Polynomial Chaos Expansion

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\]

\[
\int_{\Omega} g'(\theta) \, pdf(\theta) \, d\theta = E[g'(\theta)] \approx \sum_{i=1}^{L} w_i g'(\Theta_i)
\]
An ideal approximation method should provide:

- good approximation power
- workable computational load

$$E [g'(\theta)] \approx \sum_{i=1}^{L} w_i g'(\Theta_i)$$ by Numerical Integration Methods

**Point Estimate Method (PEM)**

- Generator Function, $GF[\cdot]$, makes the difference
- describes how sample points are directly determined in $\mathbb{R}^n$ by:
  - permutation
  - change of sign-combinations
\[ E \left[ g'(\theta) \right] \approx \sum_{i=1}^{L} w_i g'(\Theta_i) \] by Numerical Integration Methods

**Point Estimate Method (PEM)**

- Generator Function, \( GF[\cdot] \), makes the difference
- describes how sample points are directly determined in \( \mathbb{R}^n \) by:
  - permutation
  - change of sign-combinations

\[ \int_{\Omega} g'(\theta) p df_\theta d\theta \approx w_0 g'(GF_0) + w_1 \sum g'(GF_1) + w_2 \sum g'(GF_2) \]

Any statement about the ...

- approximation power ?
- computational load ?
\[
E [g'(\theta)] \approx w_0 g'(GF_0) + w_1 \sum g'(GF_1) + w_2 \sum g'(GF_2)
\]

- correct approximation for **monomials of order 5**
- PEM implies \(2n^2 + 1\) sample points (\(\theta \in \mathbb{R}^n\))

- PEM provides a workable compromise on accuracy and computational load
Illustration: In-silico example

• many degradation models include exponential terms

\[ y = g(\theta, t) = \theta_1 e^{-\theta_2(e^{-\theta_3 t})} \]

\[ \theta_1 \sim \mathcal{N}(5, 1) \]
\[ \theta_2 \sim \mathcal{N}(2, 1) \]
\[ \theta_3 \sim \mathcal{N}(3, 1) \]
\[ y = g(\theta, t) = \theta_1 e^{-\theta_2(e^{-\theta_3 t})} \]
Importance Measure

\[ s(\theta_i) = \int_\Omega |pdf(y) - pdf(y|\theta_i)| \, dy \]

- global sensitivity analysis
- impact on the entire pdf
Importance Measure

- $\theta_1$ dominates the long-term progression
Summary

- In-line trains as moving sensors
- Continuous track monitoring via low-cost sensor systems
- Precise localization is mandatory
- ⇒ Multi-sensor concept for localization
- Efficient algorithm to take account of uncertain parameters
- ⇒ Combination of PCE and PEM