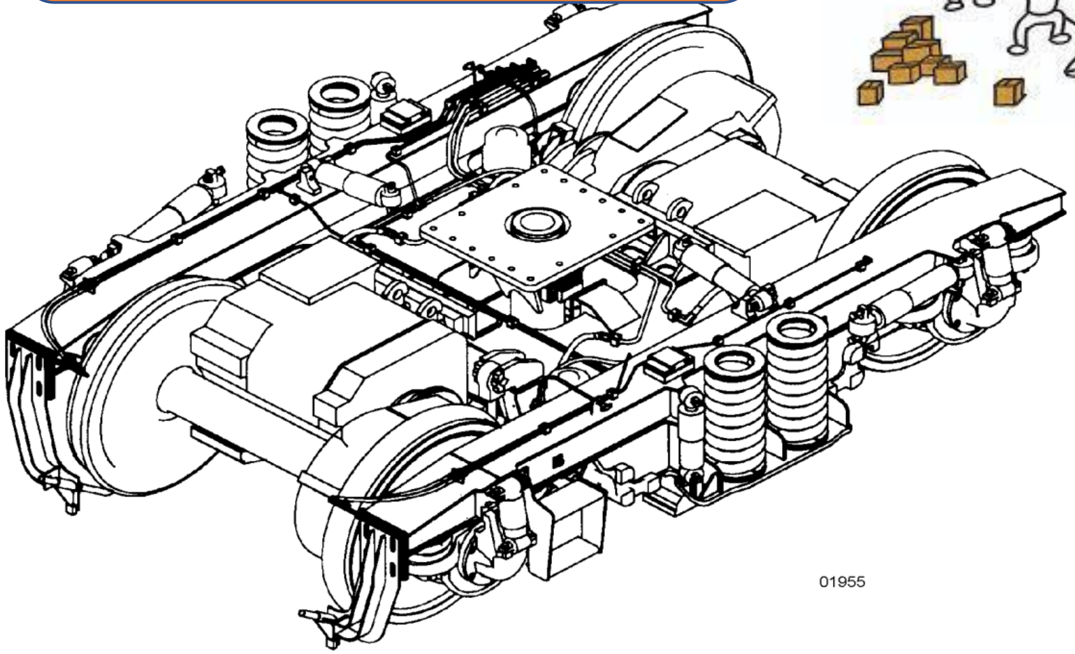
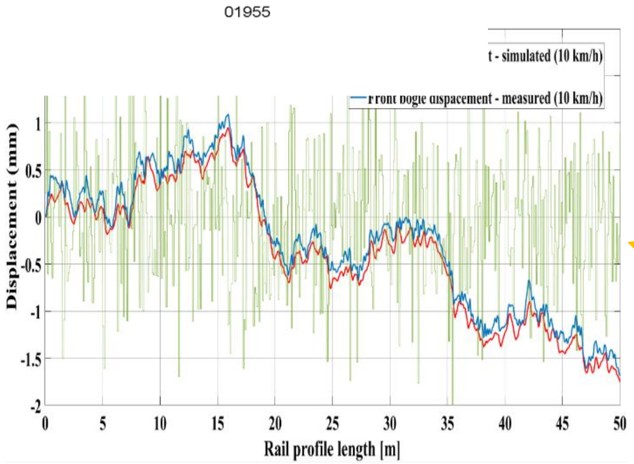
Digital Twins and Engineering for Performance

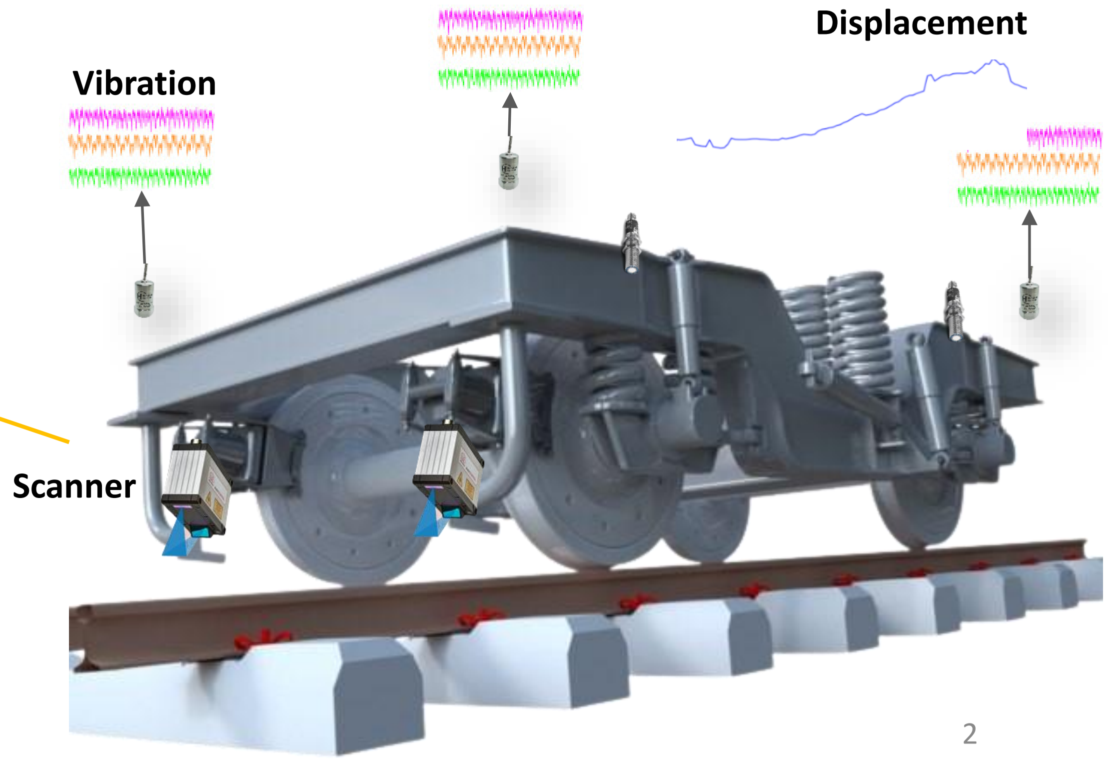
Prof Ron Kenett

Engineering the design



Engineering the performance





From

Nominal engineering

Contractual requirements

Architectural design

System design

Testing to requirements

Expected performance

Scheduled maintenance

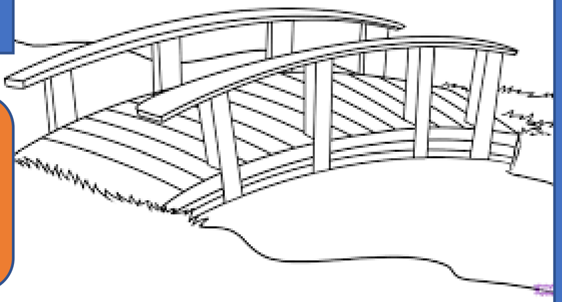
MBSE

Engineering the design

Engineering the performance

To

Performance engineering



Life cycle view

Digital twins

System and IoT integrated design

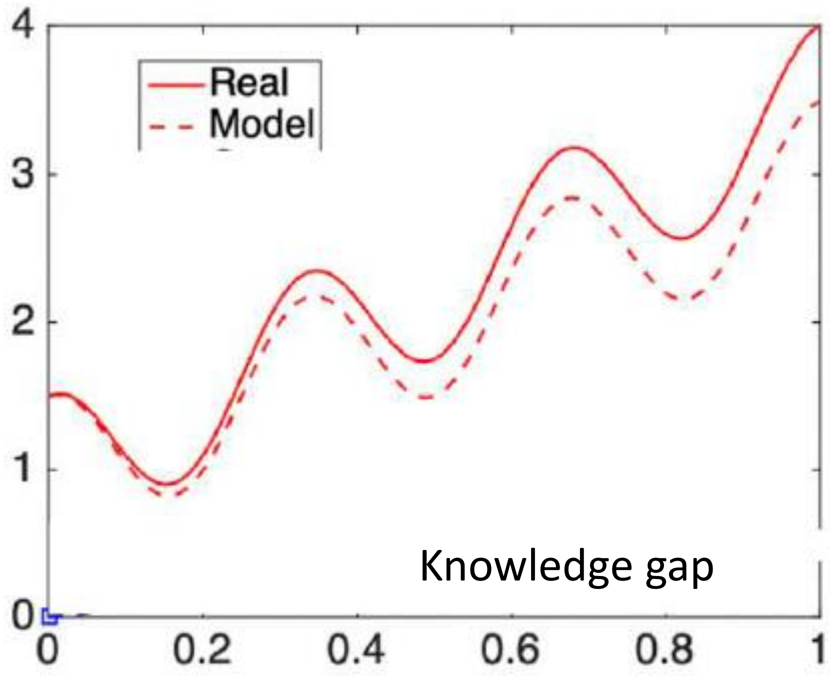
Models for fault detection, diagnostics, prediction and optimization

Variability in performance

Condition based maintenance (PHM)

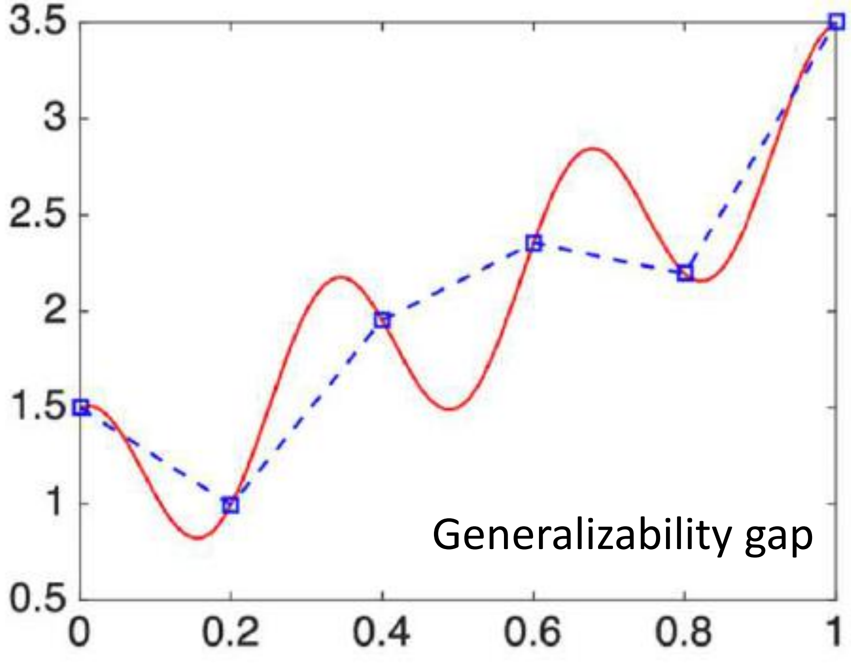
Background

Physics based model



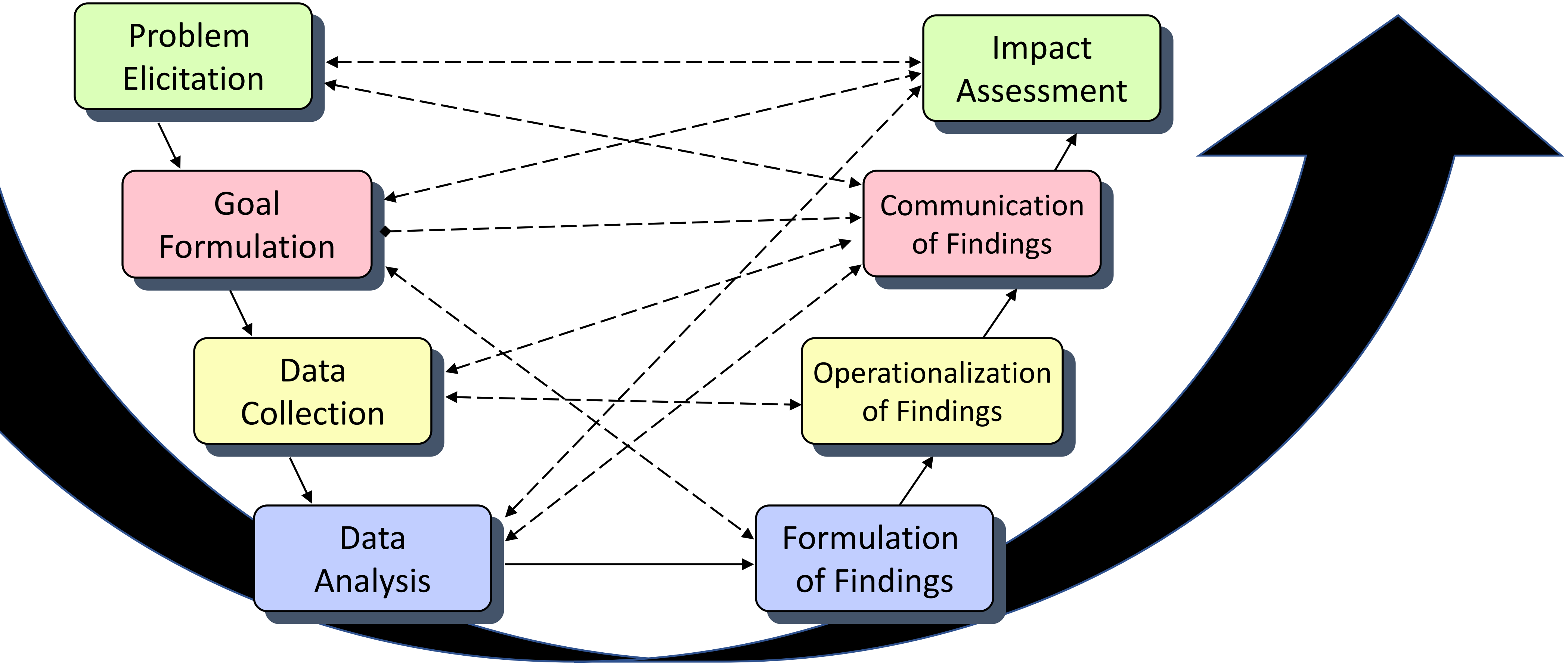
Poor precision

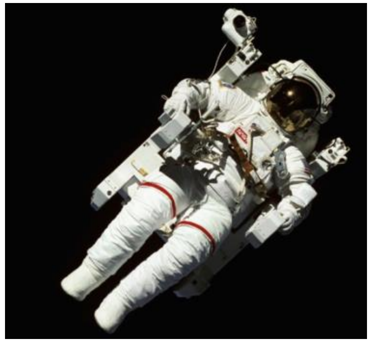
Data based model



Poor generalizability

A Life Cycle View





Kenett, R.S. (2015) Statistics: A Life Cycle View, *Quality Engineering*, 27(1):111-129


The delivery
The theory
The need

What is information quality?

Insight, knowldge

information

findings

statistical analysis

data

numbers

Information Quality:

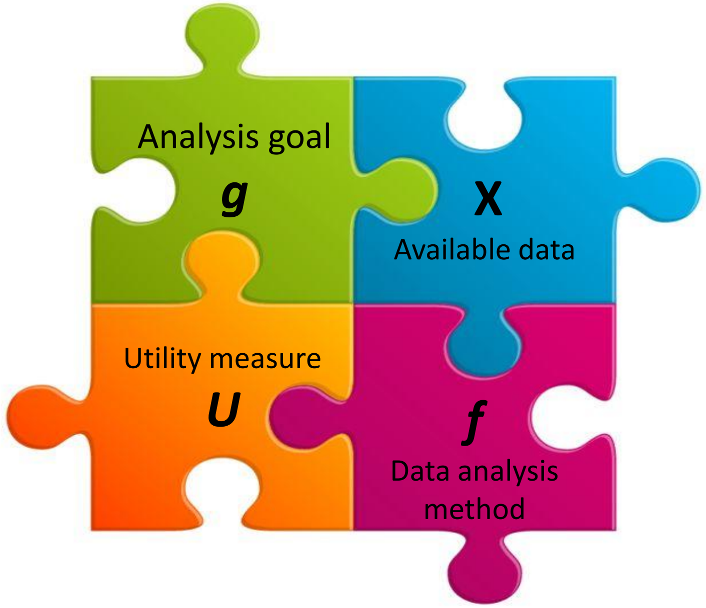
"The potential of a particular dataset to achieve a particular goal using a given empirical analysis method"

InfoQ dimensions

1. Data resolution
2. Data structure
3. Data integration
4. Temporal relevance
5. Chronology of data and goal
6. **Generalizability**
7. **7.** Operationalization
8. Communication

InfoQ(U,f,X,g) = U(f(X|g))

InfoQ components



Generalizability

F is the net force applied, *m* is the mass of the body, and **a** is the body's acceleration. The net force applied to a body produces a proportional acceleration.

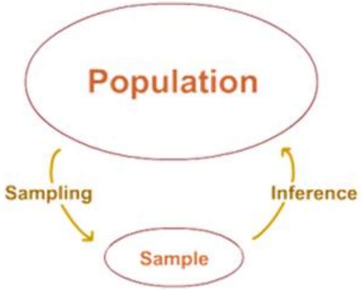
$$\mathbf{F} = \frac{\mathrm{d}(m\mathbf{v})}{\mathrm{d}t} = m\frac{\mathrm{d}\mathbf{v}}{\mathrm{d}t} = m\mathbf{a},$$

Data

Modes of Generalization

Decisions about

Hard Data



Soft Data

Laws of nature

Statistical generalization

Domain generalization

Mechanistic models

Predictive analytics

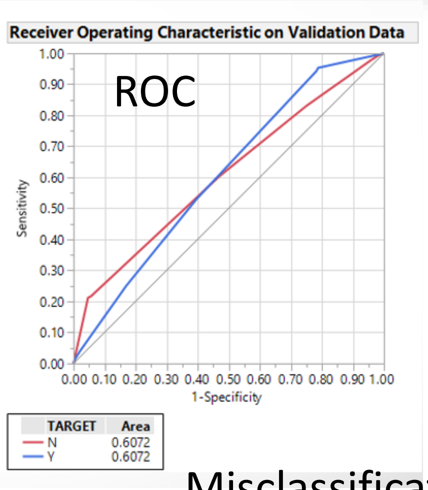
Transportability

Population from where the data was drawn

The Future

A Related Population

Intuition



Misclassifications

Confusion Matrix

Training

Actual TARGET	Predicted Count N	Predicted Count Y
N	1253	16
Y	453	37

Validation

Actual TARGET	Predicted Count N	Predicted Count Y
N	540	12
Y	185	8

[Befitting Cross Validation]

Generalizability

TECHNICAL REPORT
R-452
July 2015

DE GRUYTER J. Causal Infer. 2015; 3(2): 259–266

Causal, Casual and Curious

Judea Pearl*

Generalizing Experimental Findings

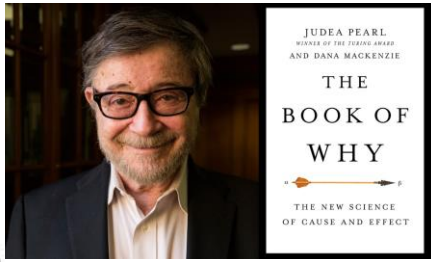
DOI 10.1515/jci-2015-0025

Abstract: This note examines one of the most crucial questions in causal inference: "How generalizable are randomized clinical trials?" The question has received a formal treatment recently, using a non-parametric setting, and has led to a simple and general solution. I will describe this solution and several of its ramifications, and compare it to the way researchers have attempted to tackle the problem using the language of ignorability. We will see that ignorability-type assumptions need to be enriched with structural assumptions in order to capture the full spectrum of conditions that permit generalizations, and in order to judge their plausibility in specific applications.

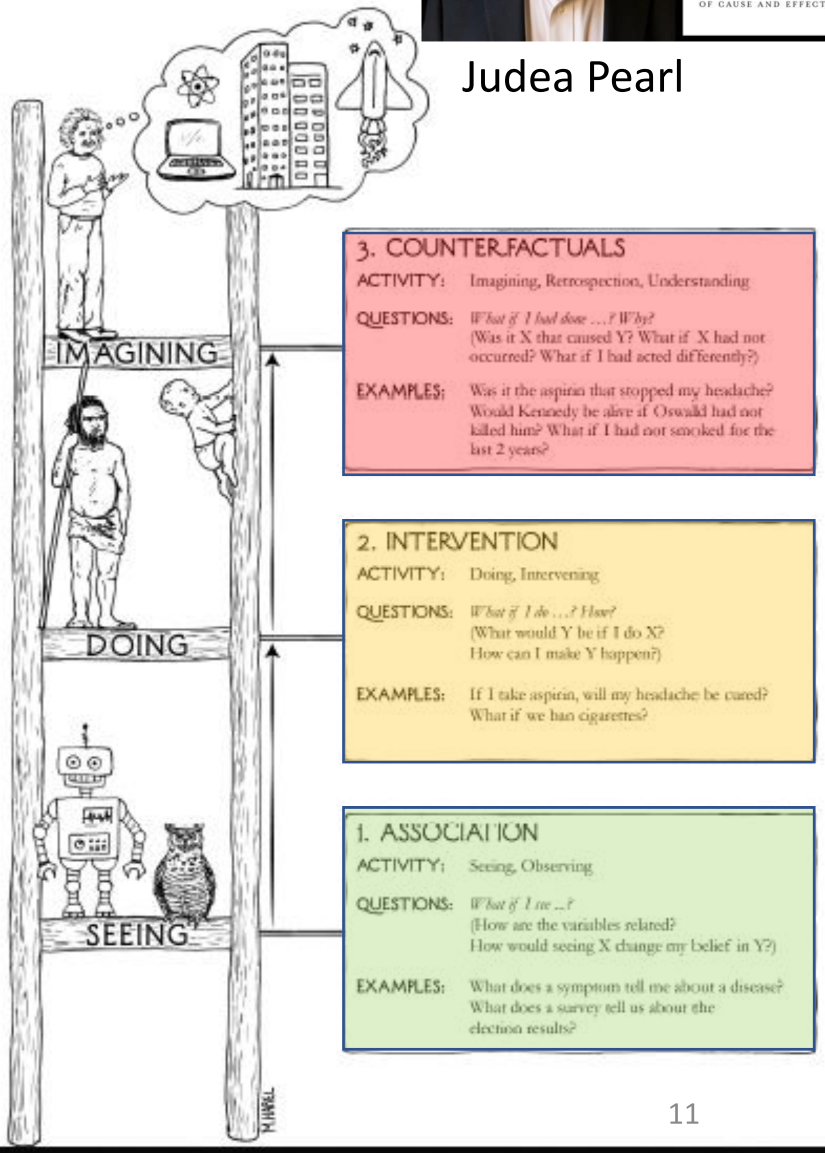
Keywords: generalizability, transportability, selection bias, admissibility, ignorability

1 Transportability and selection bias

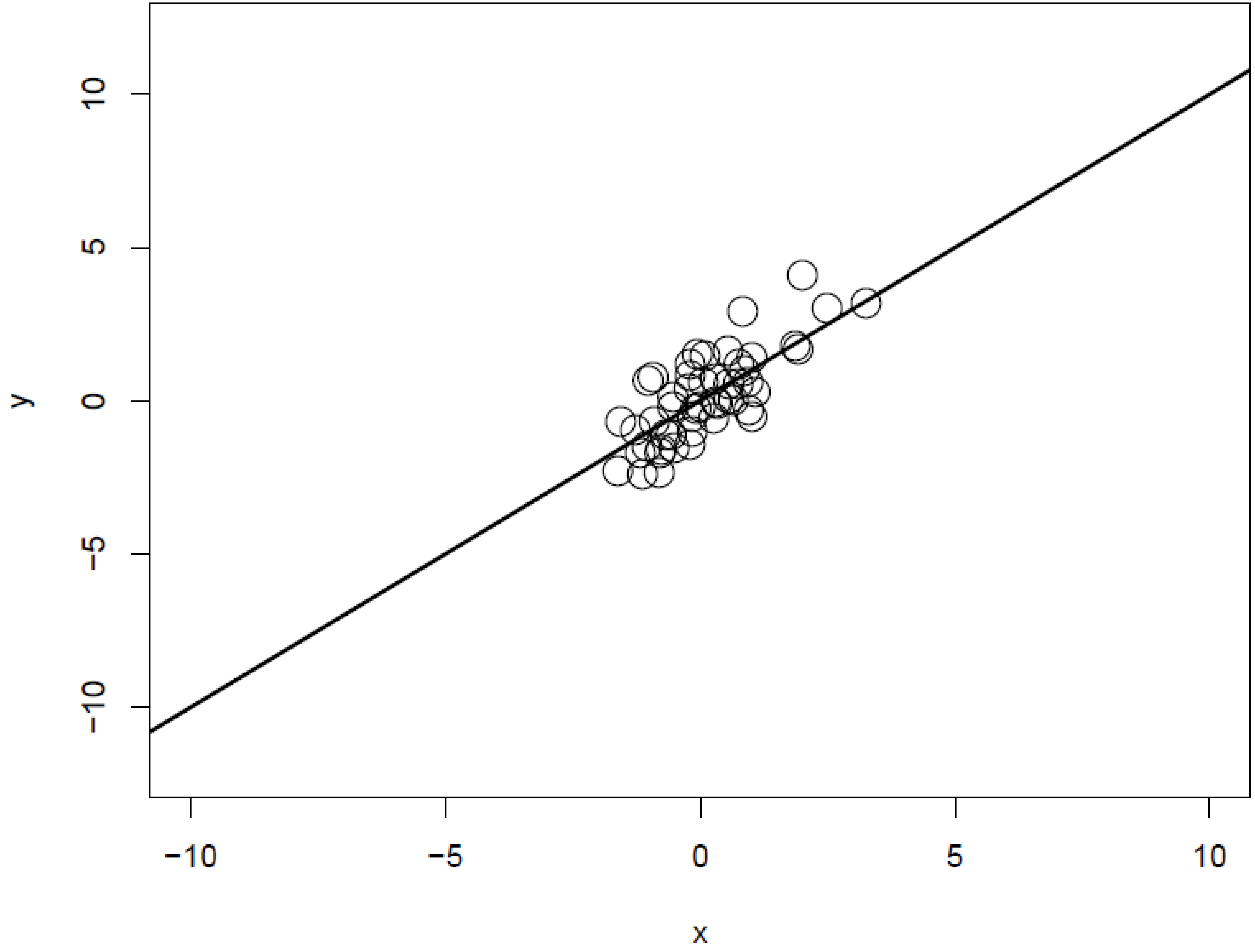
The long-standing problem of generalizing experimental findings from the trial sample to the population as a whole, also known as the problem of "sample selection-bias" [1, 2], has received renewed attention in the past decade, as more researchers come to recognize this bias as a major threat to the validity of experimental findings in both the health sciences [3] and social policy making [4]. Since participation in a randomized trial cannot be mandated, we cannot guarantee that the study population would be the same as the population of interest. For example, the study population may consist of volunteers, who respond to financial and medical incentives offered by pharmaceutical firms or experimental teams, so, the distribution of outcomes in the study may differ substantially from the distribution of outcomes under the policy of interest.



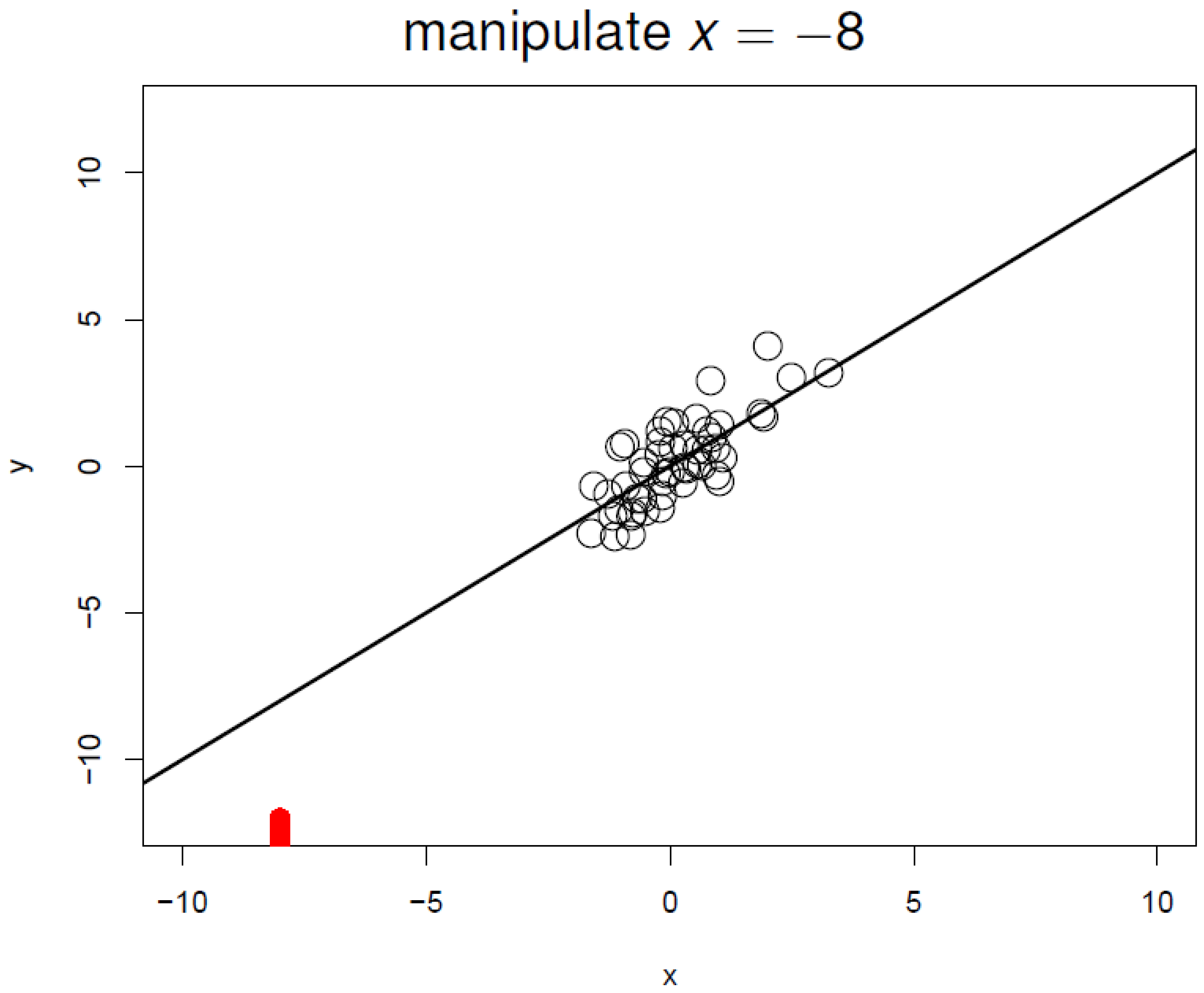
Judea Pearl



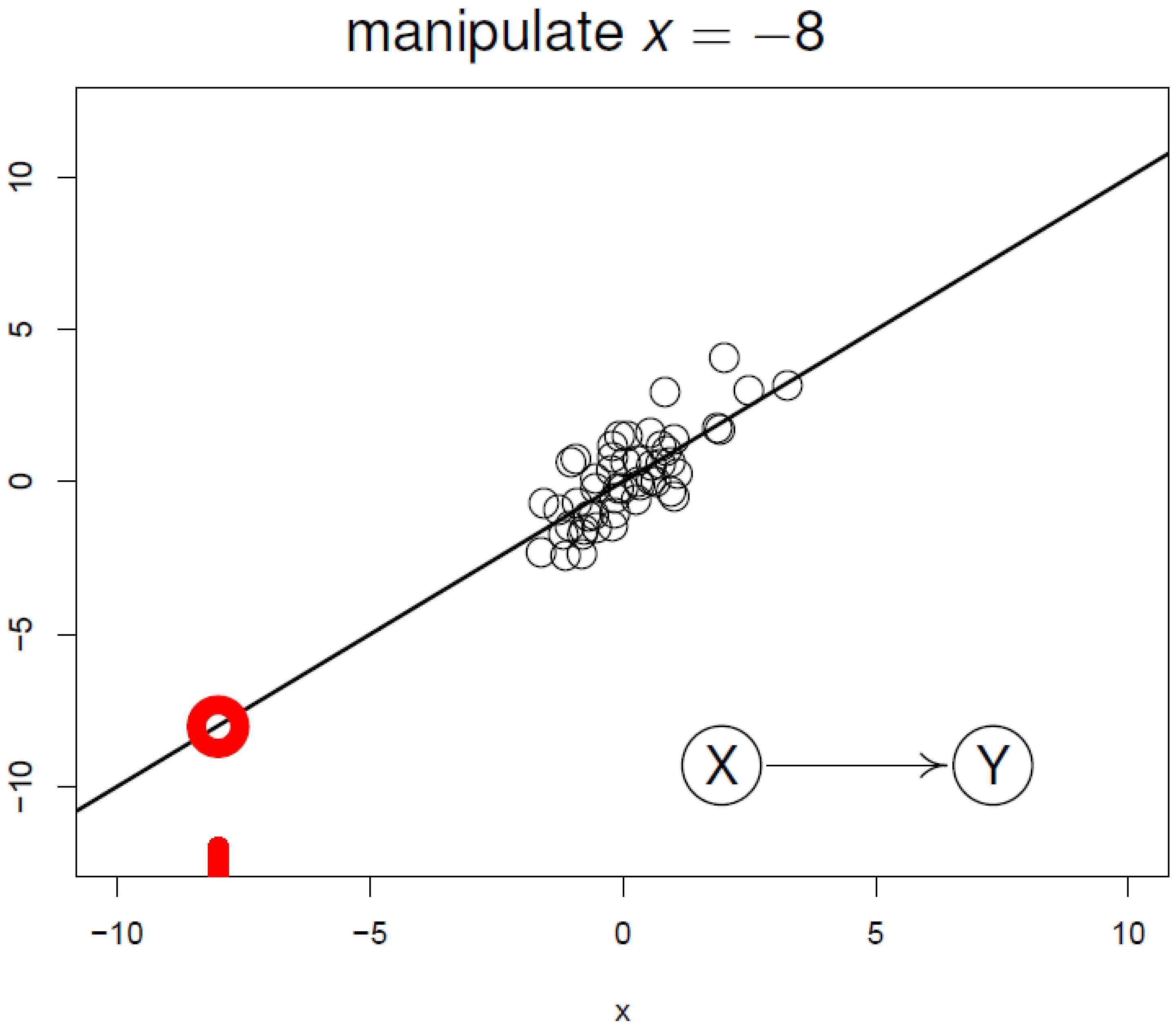
Causal Models



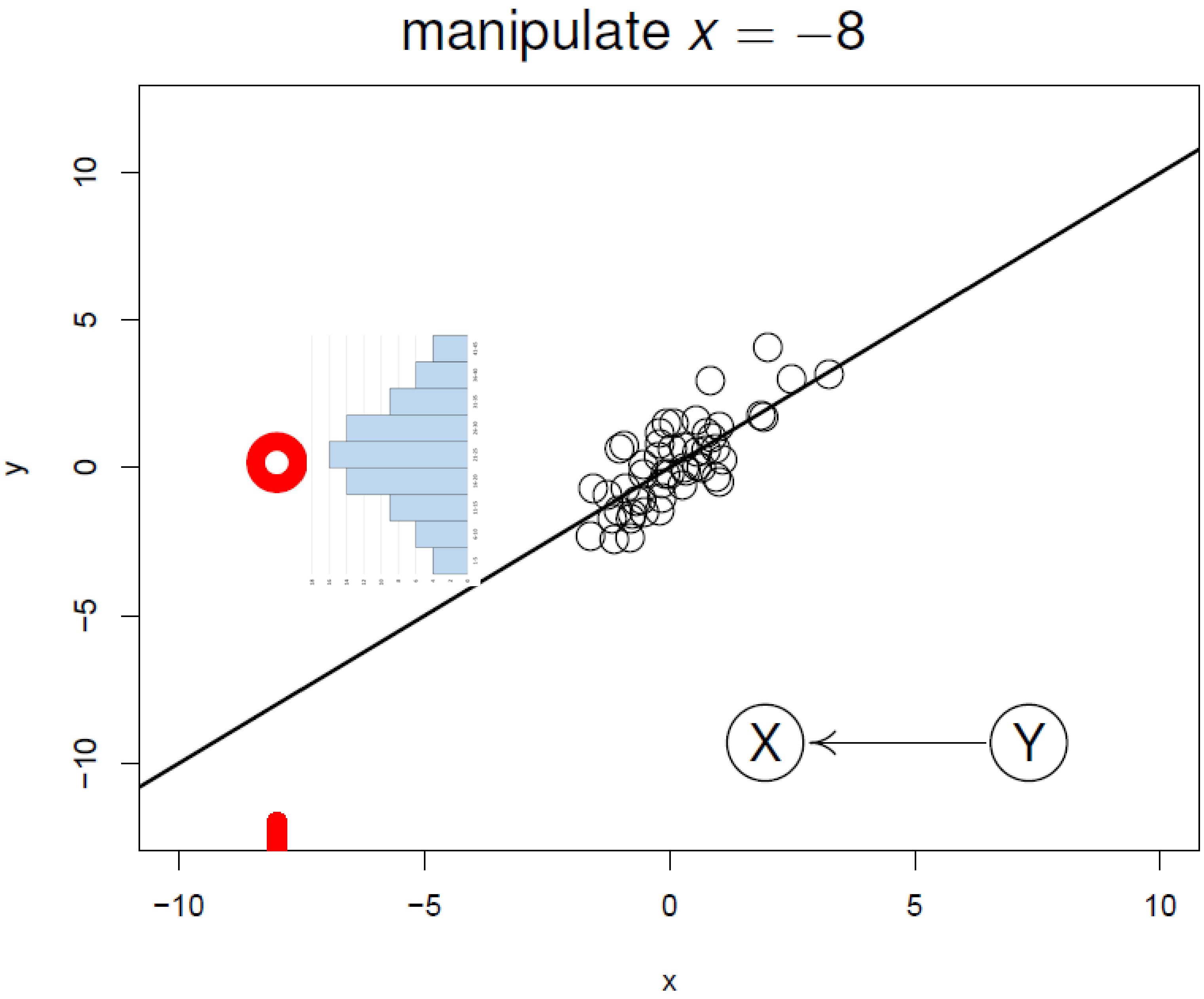
Causal Models



Causal Models

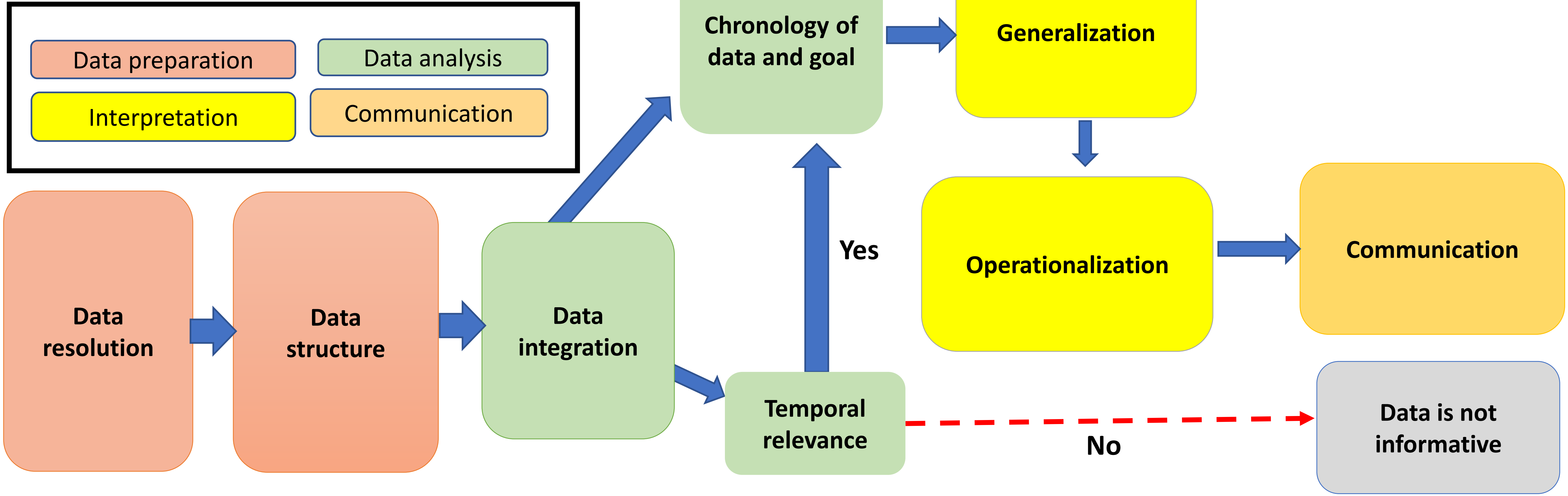


Causal Models



https://sites.google.com/site/datainfoq

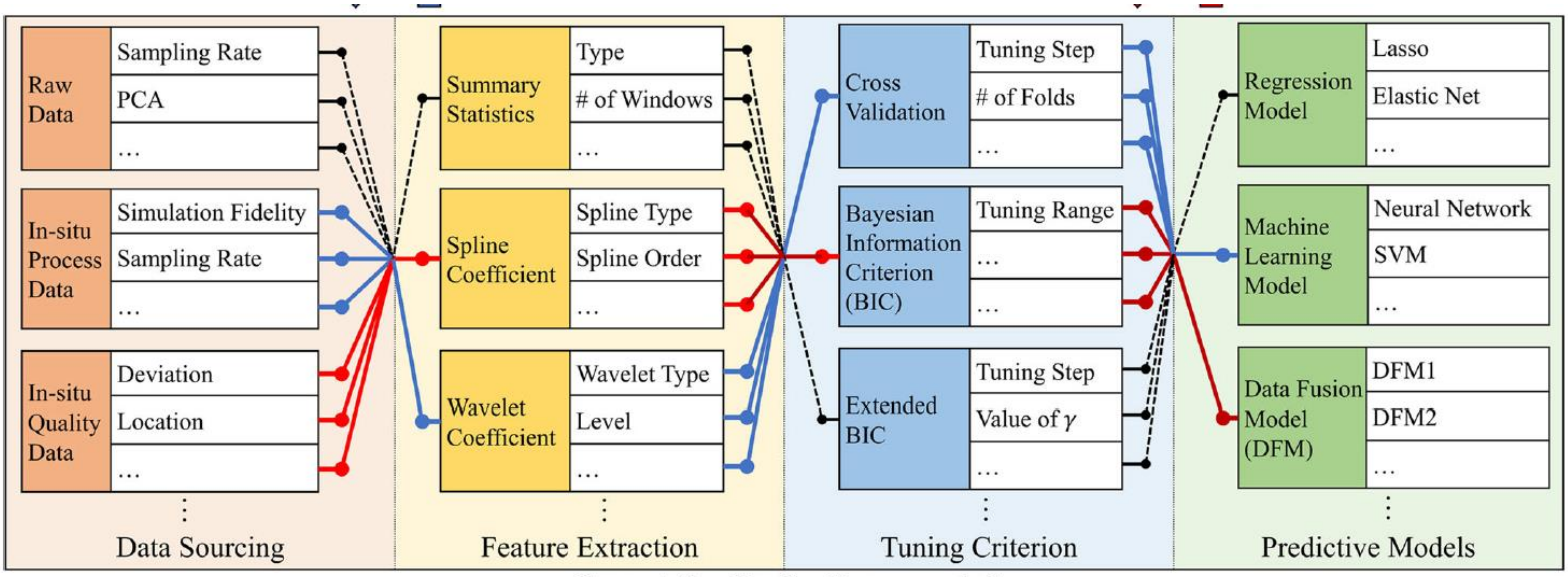
Information quality



The Information Quality Workflow

Journal of Intelligent Manufacturing
https://doi.org/10.1007/s10845-021-01817-9

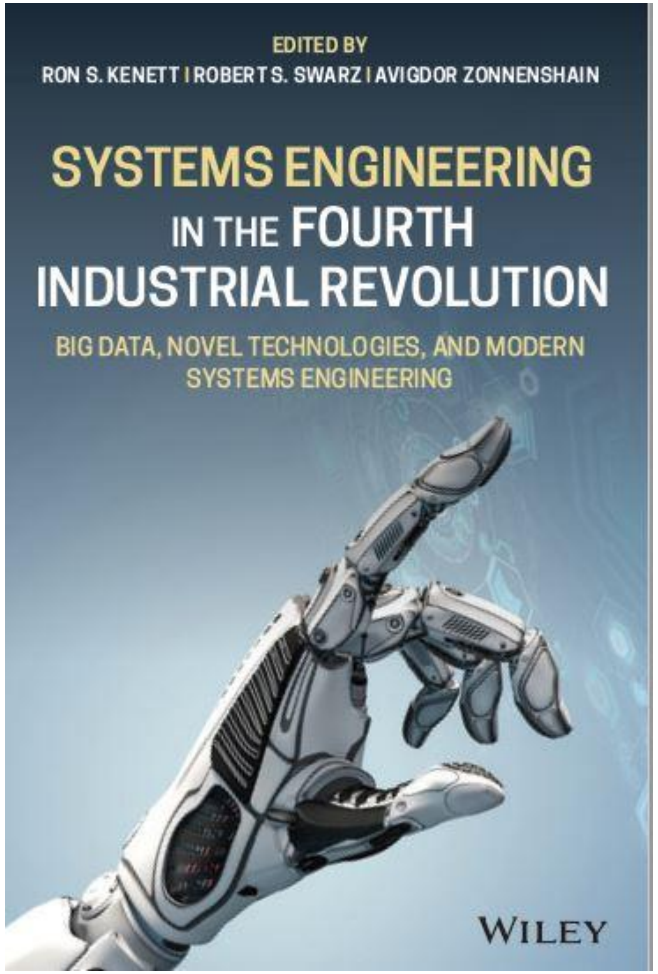
Challenges of modeling and analysis in cybermanufacturing: a review from a machine learning and computation perspective



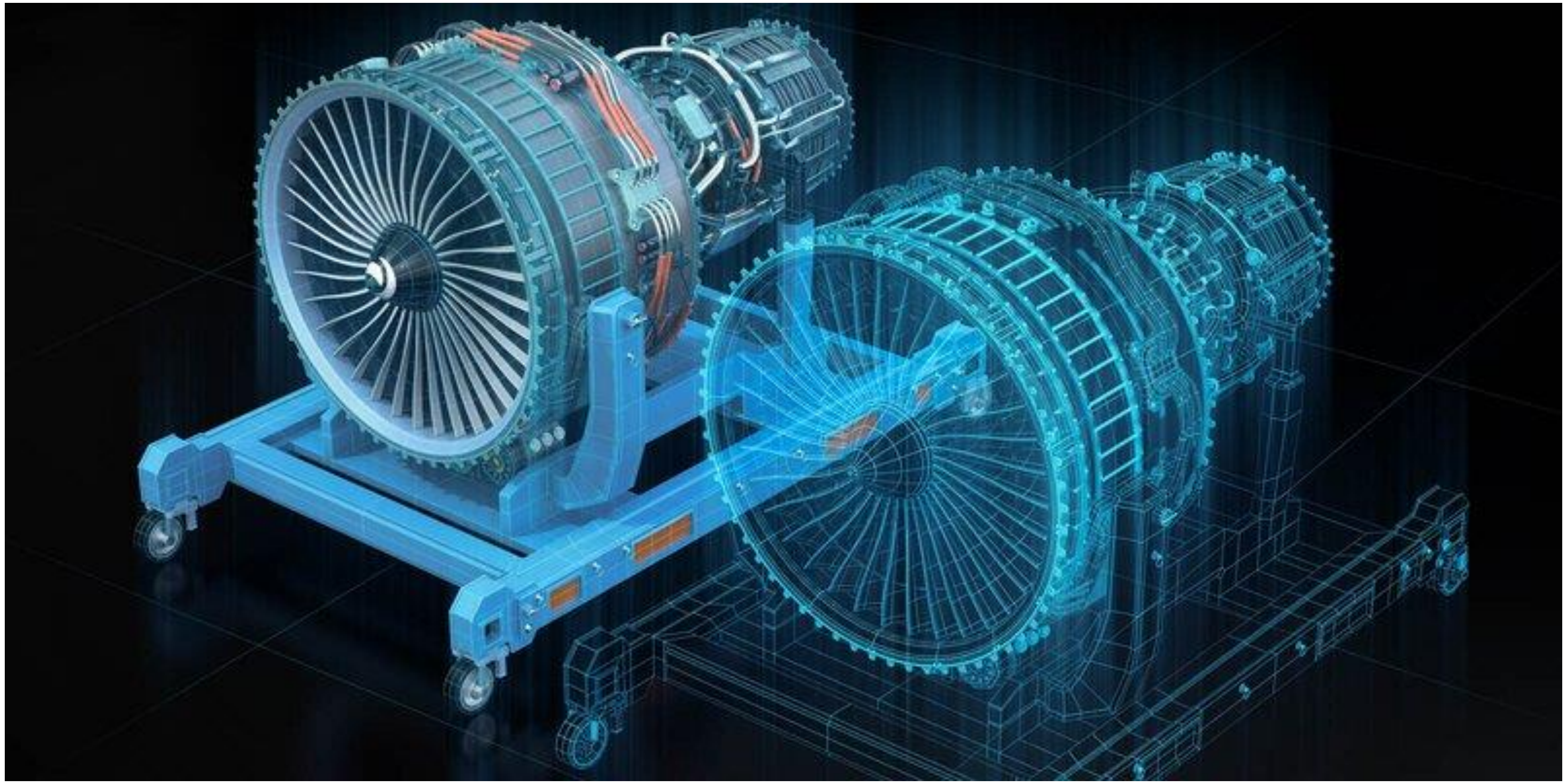
https://link.springer.com/content/pdf/10.1007/s10845-021-01817-9.pdf

Digital Twins

Digital Twins



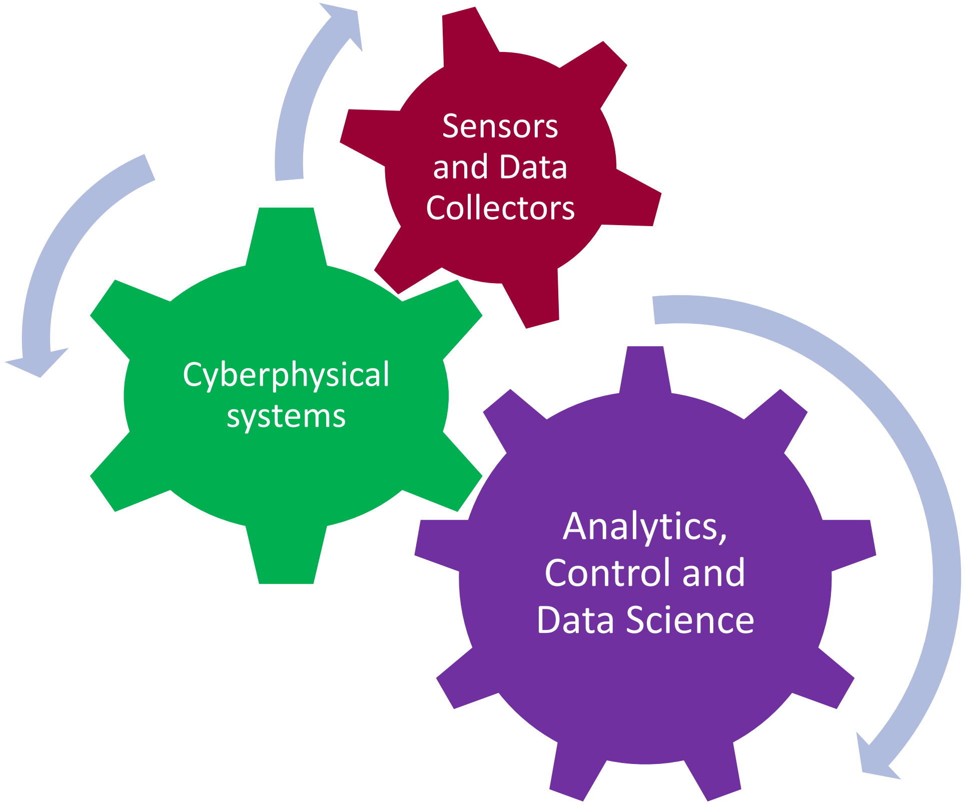
Monitoring, diagnostic, prognostic and prescriptive capabilities



Sensor technologies
Flexible systems
Monitoring algorithms

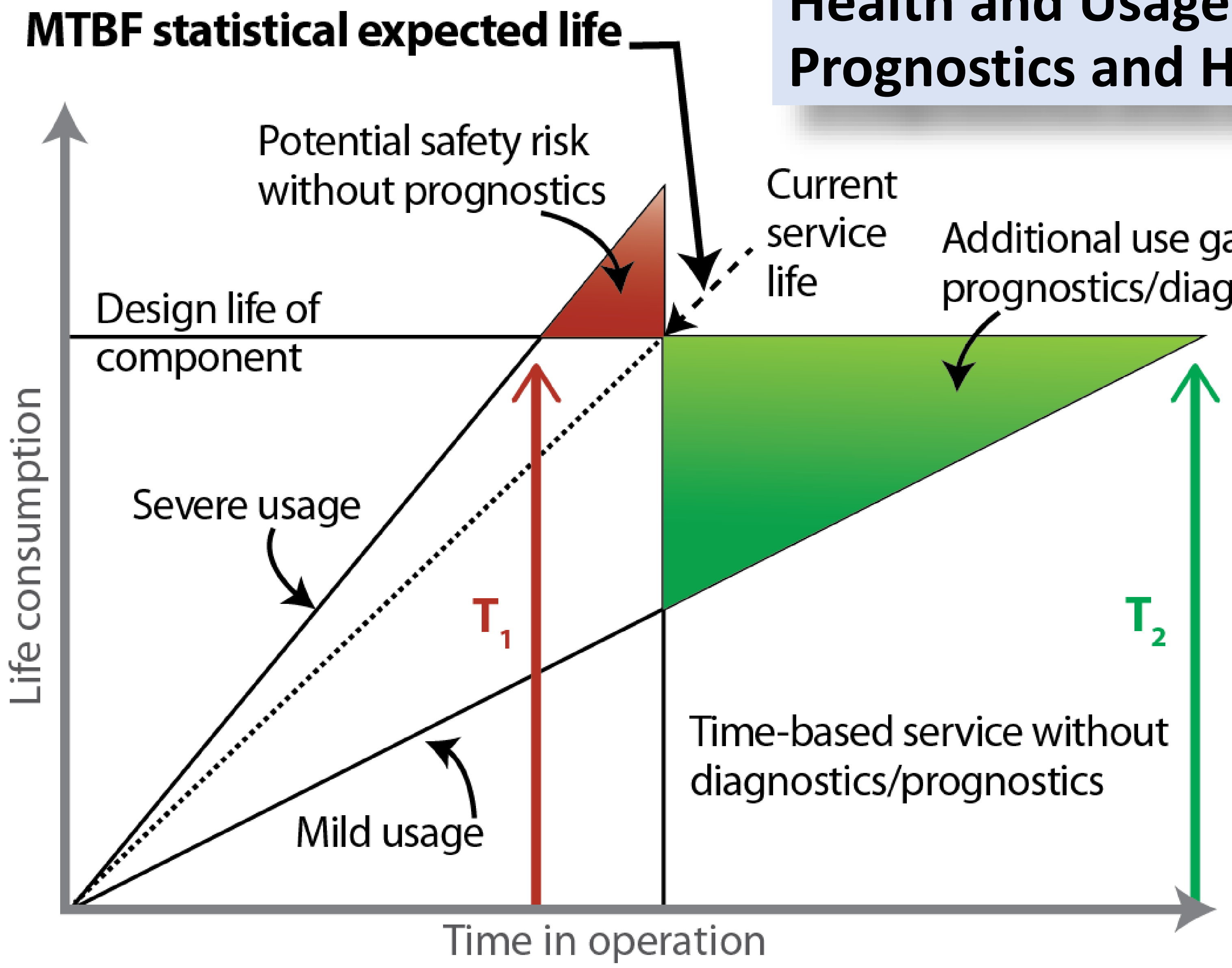
Diagnostic methods
Prognostic predictions
Prescriptive optimization

Analytics in Performance Engineering



- Monitoring
- Diagnostics
- Prognostics
- Prescriptive

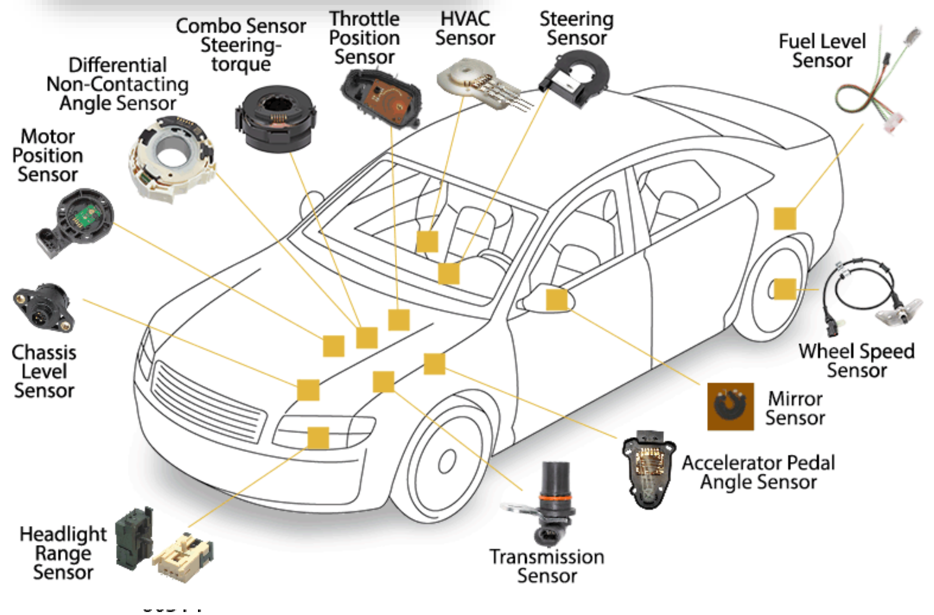
Condition Based Maintenance (CBM)
Health and Usage Monitoring Systems (HUMS)
Prognostics and Health Management (PHM)



Source: Economic and Safety Benefits of Diagnostics & Prognostics (Romero et al. 1996)

Sensor technology

Analytics



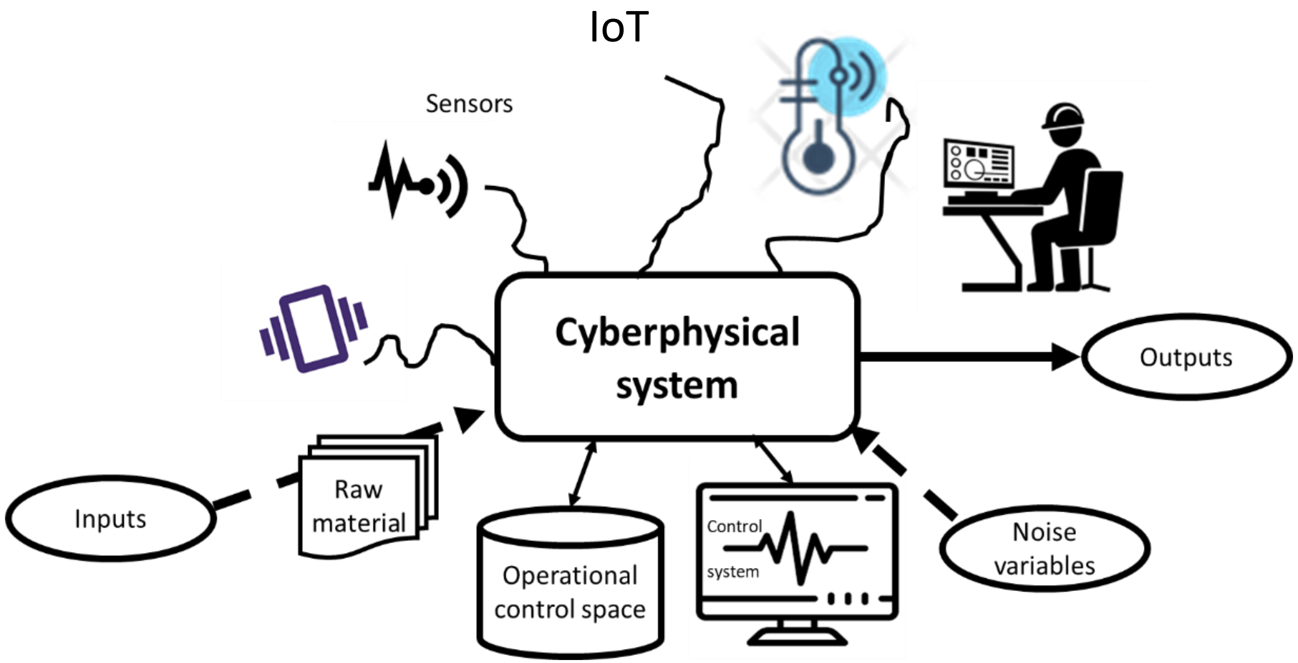
Received: 17 October 2020 | Revised: 15 May 2021 | Accepted: 4 June 2021
DOI: 10.1002/qre.2948

SPECIAL ISSUE ARTICLE

WILEY

The digital twin in Industry 4.0: A wide-angle perspective

Ron S. Kenett[1] | Jacob Bortman[2]



Physical assets

Received: 17 October 2020 | Revised: 15 May 2021 | Accepted: 4 June 2021
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SPECIAL ISSUE ARTICLE

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The digital twin in Industry 4.0: A wide-angle perspective

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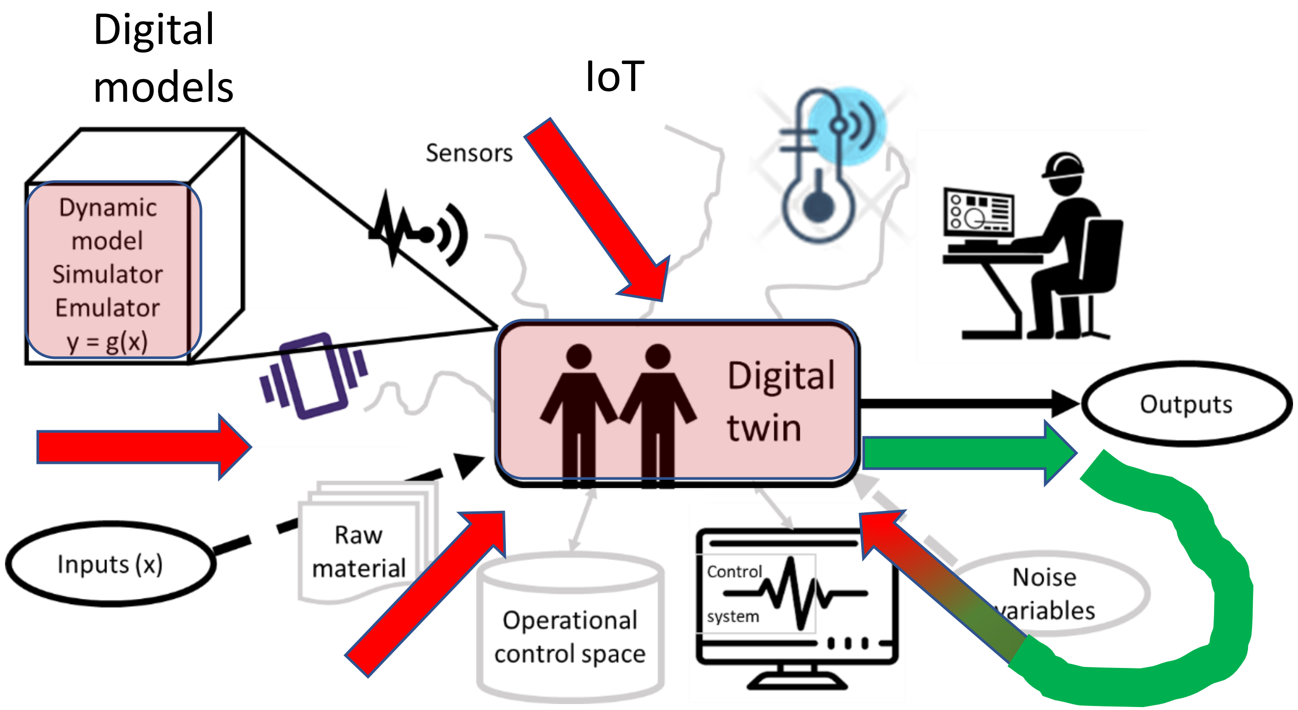


Digital assets

Why mathematical models ?

1. Understanding of a dynamical system
2. Examination of the effect of interventions on a dynamic process
3. Measurement and prediction of the state of the process in time and space
4. Enabling the development of monitoring, diagnostic and prognostic capabilities for optimal control, condition based maintenance and process performance certification

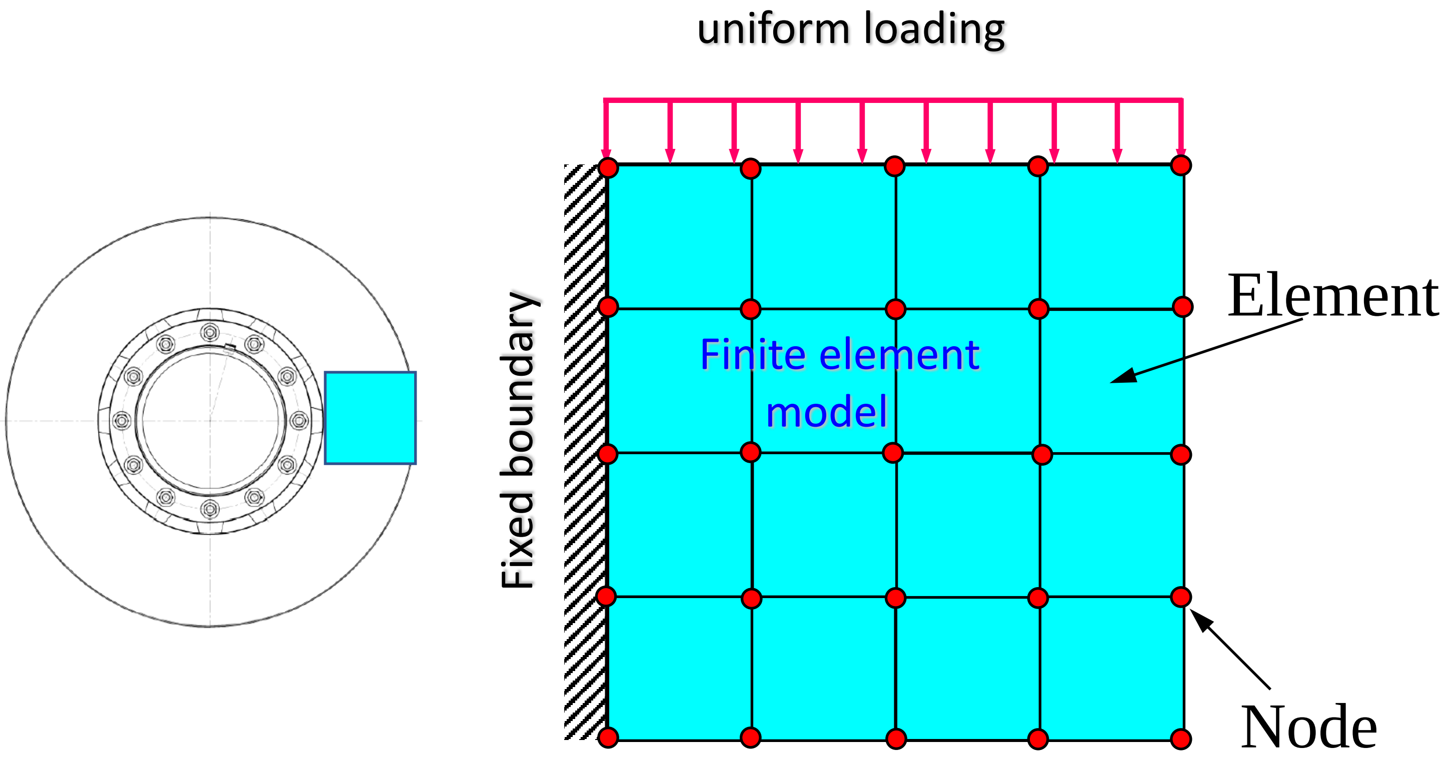
Uncertainty Quantification

*"A further **complication** is that the existence of **uncertainty** means that validation (comparison with reality) needs to be treated as a **statistical process**…. This requirement means that there must also be **trust in the data**, **trust in the model**, and **trust in the updating procedure**."*

*"**Uncertainty evaluation** also gives a better understanding of **how much trust** can be placed in the **model results**"*

Wright & Davidson (2020). How to tell the difference between a model and a digital twin. *Advanced Modeling and Simulation in Engineering Sciences*. 7, 13.

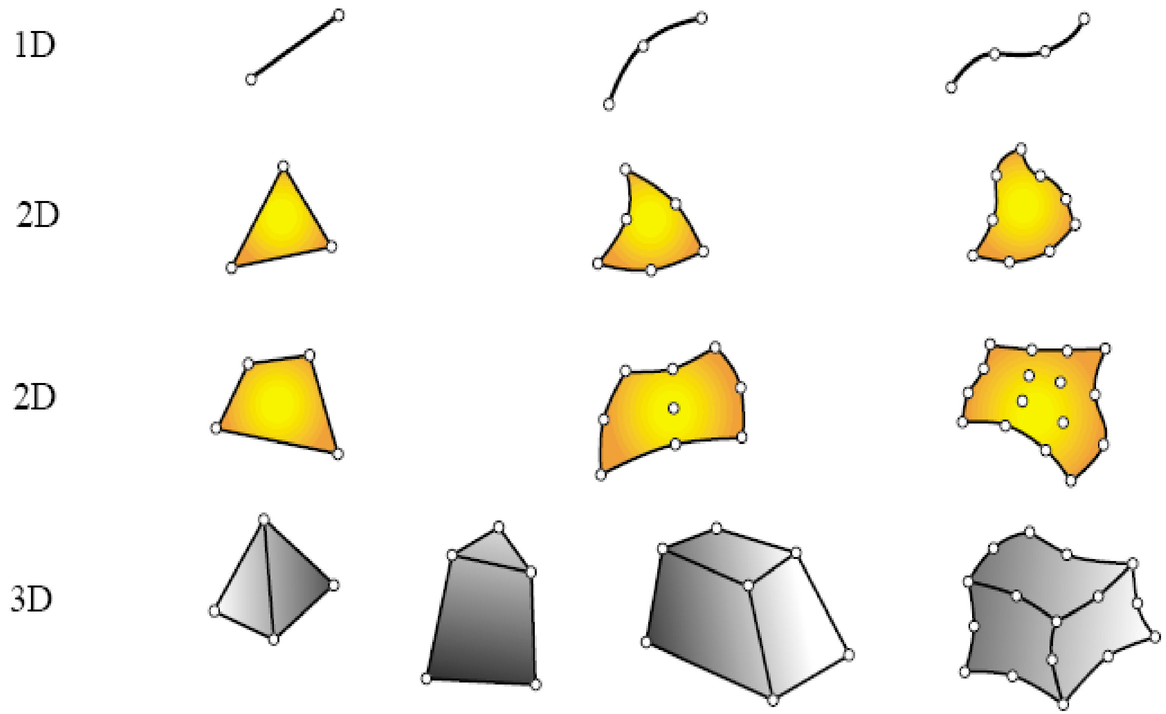
Finite element analysis (FEM)



- Approximate method
- Geometric model
- Node
- Element
- Mesh
- Discretization

Obtain stresses/strains in the plate

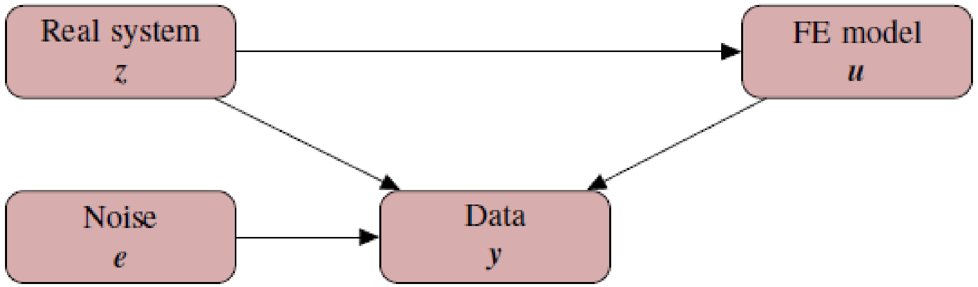
Finite element analysis (FEM)



$$p(\boldsymbol{u}|\boldsymbol{y},\, \rho,\, \sigma_d,\, \ell_d) = \frac{p(\boldsymbol{y}|\boldsymbol{u},\, \rho,\, \sigma_d,\, \ell_d)p(\boldsymbol{u})}{p(\boldsymbol{y}|\rho,\, \sigma_d,\, \ell_d)}$$

Bayes theorem

- Updated FE density $p(\boldsymbol{u}|\boldsymbol{y},\, \rho,\, \sigma_d,\, \ell_d)$
- Data likelihood $p(\boldsymbol{y}|\boldsymbol{u},\, \rho,\, \sigma_d,\, \ell_d) = \mathcal{N}\left(\rho \boldsymbol{P}\overline{\boldsymbol{u}},\, \boldsymbol{C}_d(\sigma_d,\, \ell_d) + \boldsymbol{C}_e\right)$
  - Probability that the data $\boldsymbol{y}$ was generated by a specific generating model
- Marginal likelihood $p(\boldsymbol{y}|\rho,\, \sigma_d,\, \ell_d) = \int p(\boldsymbol{y}|\boldsymbol{u},\, \rho,\, \sigma_d,\, \ell_d)p(\boldsymbol{u})\, \mathrm{d}\boldsymbol{u}$
  - Probability of observing the data $\boldsymbol{y}$ averaged over all possible FE solutions $\boldsymbol{u}$



https://www.youtube.com/watch?v=xAkWboORuyA

- Finite element solution $\boldsymbol{u} \sim p(\boldsymbol{u}) = \mathcal{N}(\overline{\boldsymbol{u}},\, \boldsymbol{C}_u)$
- Model misspecification $\boldsymbol{d} \sim p(\boldsymbol{d}|\sigma_d,\, \ell_d) = \mathcal{N}(\boldsymbol{0},\, \boldsymbol{C}_d(\sigma_d,\, \ell_d))$
- Measurement noise $\boldsymbol{e} \sim p(\boldsymbol{e}) = \mathcal{N}(\boldsymbol{0},\, \boldsymbol{C}_e)$

Received: 12 April 2022 | Revised: 25 October 2022 | Accepted: 6 February 2023
DOI: 10.1002/asmb.2752

Applied Stochastic Models in Business and Industry

WILEY

DISCUSSION PAPER

Specifying prior distributions in reliability applications

Qinglong Tian[1] | Colin Lewis-Beck[2] | Jarad B. Niemi[3] | William Q. Meeker[3]

Received: 12 February 2023 | Revised: 20 February 2023 | Accepted: 21 February 2023
DOI: 10.1002/asmb.2755

WILEY

COMMENTARY

Discussion of 'Specifying prior distributions in reliability applications'

Ron S. Kenett[1,2]

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[2]The KPA Group, Raanana, Israel

Correspondence
Ron S. Kenett, Samuel Neaman Institute, Technion, Haifa, Israel.
Email: ron@kpa-group.com

Bayes theorem

Reliability modeling is an essential element in modern prognostic health management of systems and processes.[1] It is part of advances in industry 4.0 and digital twins.[2,3] This is a discussion of the paper by Tian, Lewis-Beck, Niemi and Meeker that provides an important contribution to Bayesian reliability applications. Specifically, the paper provides a systematic approach to reliability analysis with a small number of failures. It consists of a comprehensive review, excellent case studies, and covers a wide angle perspective of Bayesian analysis including applications with the `rstan` software, prior distributions, sensitivity analysis, combining informative with noninformative or weakly informative prior distributions and simulation studies. This discussion lists some peripheral add-on material that can be considered as complementary. Specifically, the discussion covers (i) prior elicitation methods, (ii) few shot learning, and (iii) additional references to Bayesian analysis not mentioned by the authors. The general challenge discussed by the paper of Tian et al is to model reliability when data on failures is scarce. Bayesian analysis, that relies on prior distributions, is a working option covered by the paper. In that context, elicitation of priors is a key necessary step. The next section discusses it.

Statistical finite elements for misspecified models

Connor Duffin[a,1], Edward Cripps[a], Thomas Stemler[a,b], and Mark Girolami[c,d]

[a]Department of Mathematics and Statistics, The University of Western Australia, Perth, WA 6009, Australia; [b]Complex Systems Group, The University of Western Australia, Perth, WA 6009, Australia; [c]Department of Engineering, University of Cambridge, Cambridge CB2 1PZ, United Kingdom; and [d]Lloyd's Register Foundation Programme for Data-Centric Engineering, The Alan Turing Institute, London NW1 2DB, United Kingdom

Edited by Nancy M. Reid, University of Toronto, Toronto, ON, Canada, and approved November 18, 2020 (received for review July 23, 2020)

We present a statistical finite element method for nonlinear, time-dependent phenomena, illustrated in the context of nonlinear internal waves (solitons). We take a Bayesian approach and leverage the finite element method to cast the statistical problem as a nonlinear Gaussian state–space model, updating the solution, in receipt of data, in a filtering framework. The method is applica-le to problems across science and engineering for which finite lement methods are appropriate. The Korteweg–de Vries equa-ion for solitons is presented because it reflects the necessary omplexity while being suitably familiar and succinct for peda-ogical purposes. We present two algorithms to implement this nethod, based on the extended and ensemble Kalman filters, nd demonstrate effectiveness with a simulation study and a case tudy with experimental data. The generality of our approach ; demonstrated in *SI Appendix*, where we present examples rom additional nonlinear, time-dependent partial differential quations (Burgers equation, Kuramoto–Sivashinsky equation).

FEM model, which represents all assumed knowledge before observing data. The mean is the standard Galerkin solution, and the covariance results from the action of the discretized PDE operator on the covariance $\mathbf{G}(\theta)$; further details are contained in *SI Appendix*, section 1. This was first developed in ref. 4, and we demonstrate the generality of such an approach by extending it to nonlinear, time-dependent PDEs.

An area in which nonlinear and time-dependent problems are ubiquitous is ocean dynamic processes, where essentially all problems stem from a governing system of nonlinear, time-dependent equations (e.g., the Navier–Stokes equations). The ocean dynamics community has grown increasingly cognizant of the importance of accurate uncertainty quantification (5, 6), with many possible applications [e.g., rogue waves (7), turbulent flow (8)] for our proposed methodology.

An example process is nonlinear internal waves (solitons), which are observed as waves of depression or elevation along a

https://www.pnas.org/doi/10.1073/pnas.2015006118

ADVANCED THEORY AND SIMULATIONS

emulators

Review | Full Access

Challenges and Opportunities in Simulations and Computer Experiments in Industrial Statistics: An Industry 4.0 Perspective

Ron S. Kenett, Grazia Vicario

First published: 12 January 2021 | https://doi.org/10.1002/adts.202000254 | Citations: 2

SECTIONS PDF TOOLS SHARE

Abstract

This paper is a review of the growing role of simulations and computer experiments in industrial statistics, with an emphasis on Industry 4.0 applications. It maps the background, the current state, and the future directions of computer simulations in a wide range of process engineering, product design, and analytic disciplines.

Applied Stochastic Models in Business and Industry
The official journal of the International Society for Business and Industrial Statistics

Deep learning (DL) has been revived over the last two decades in what is considered as the third DL wave.[12] This wave began after the publication by Hinton et al.[13] DL algorithms learn meaningful pattern from training data by determining how to represent the data via hierarchically meaningful features. DL algorithms successfully resolved several challenging artificial intelligence tasks like photos and speech recognition, that until then had not been resolved successfully by other types of algorithms.

Domain adaptation techniques are categorized by two properties: (i) what the learner tries to learn and (ii) how the learner does it. What the algorithm tries to learn can be divided in three categories: (1) Learning invariant functions between the source and the target domain, where the functions use invariant features of the source and the target domain and are also successful in classifying data in the source domain. (2) Learning two different functions for the source and the target domains where some of their properties are similar or identical. For example they can use the same features extractor but different classifiers. (3) Learning a mapping function that maps examples from the target domain to the source domain and learning a function that successfully classifies data in the source domain or the target domain.

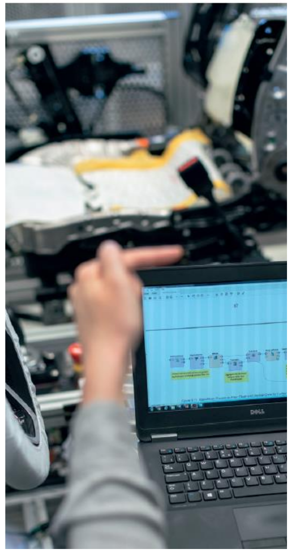
How the learner learns can be categorized into four categories: (a) Minimizing distribution metrics between the extracted features of the source and the target domain, like maximum mean discrepancy and central moment discrepancy (b) Using adversarial approaches. For example, a feature extractor E learns to extract features from the source and the target domains, and a discriminator D competes with E for learning, to find if the extracted features correspond to an example from the source or the target domains. In parallel to that, another network learns to classify the extracted features based on the labeled examples of the source domain. (c) Batch-normalization methods. (d) Parameter transfer methods, where the network is first pre-trained using the source domain and then tuned with examples from the target domain.[14]

Leturiondo et al.[15] refer to the case of zero-fault shot learning and suggest using simulated data as the source domain to classify unseen faults in the target. However, they did not apply their idea on measured data. Sobie et al.[16] refer to the case of zero-fault shot learning and suggest using simulated data as the source domain to classify unseen faults in the target. In contrast to Leturiondo et al.,[15] they apply their algorithms to real cases and get satisfactory results. In their study, the signals are preprocessed by regular signal processing techniques and normalized. They show and emphasize that simulated signals can help in fault diagnosis. When real examples are added, the diagnosis results become much more accurate. Their study demonstrates how simulations, with a preprocessing of signals, can achieve zero-fault learning. These methods predict faults using DL algorithms, even in the case of very few or no failures. In some sense they provide an alternative to the Bayesian reliability models presented in the paper under discussion.

SIGNIFICANCE

Data and the Fourth Industrial Revolution

Ron S. Kenett and **Shirley Y. Coleman** outline the roles played by data and statistics in "Industry 4.0", from monitoring manufacturing processes to the building of "digital twins"



The word "manufacturing" conjures images of galleries of machines running day and night, maybe with rows of workers adjusting or sifting and sorting. What is missing from these mental images, though, are the sensors embedded in each of those machines, collecting data continuously on different aspects of production, transmitting that data to analytics computer packages, and – at the end of it all – a statistician monitoring the outputs in an effort to understand what is going on and to make sure things are working at their very best.

There is a whole world of data

continuous measurements such as temperature, flow rate, colour and purity between different parts of the production process.

2. *Flexible manufacturing* capabilities – such as 3D printing – that can efficiently produce batches of products to order.
3. *Data analytics*, including statistical analysis, machine learning and artificial intelligence that powers industry with the capability to control and optimise processes.

QUALITY PROGRESS
THE OFFICIAL PUBLICATION OF ASQ

DESIGN OF EXPERIMENTS

New Frontiers In the Design Of Experiments

By Ron S. Kenett and David M. Steinberg

Product and process development is fundamental to long-term business survival. Fostering innovation and reducing time to market while achieving top product performance are crucial to survival and success.

Statistically designed experiments play an important role in achieving such objectives and are an important component of industrial statistics. The expanding use of computers to run experiments in a simulated environment has created new frontiers.

Forefathers of Experimentation

Statistically designed experiments have been used to accelerate learning since their introduction by R.A. Fisher in the first half of the 20th century.

From System to Systems (SoS)

"I like to think of clinical trials in terms of the **five questions** one might be interested in answering", Senn, S. J. (2004) Controversies concerning randomization and additivity in clinical trials. *Statistics in Medicine*, 23, 3729-3753.

Q1. Was there an effect of treatment in this trial?

Treatment = intervention

Q2. What was the average effect of treatment in this trial?

Patient = system

Q3. Was the treatment effect identical for all patients in the trial?

Population = SoS

Q4. What was the effect of treatment for different subgroups of patients?

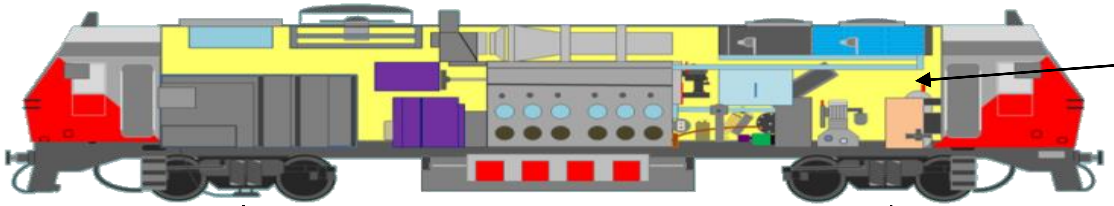
Q5. What will be the effect of treatment when used more generally?

Safety Valve

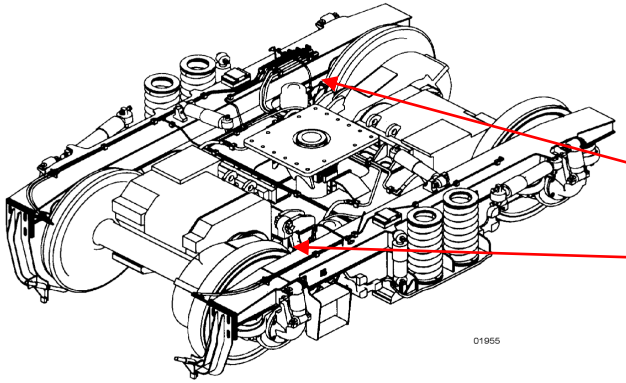
A Case Study

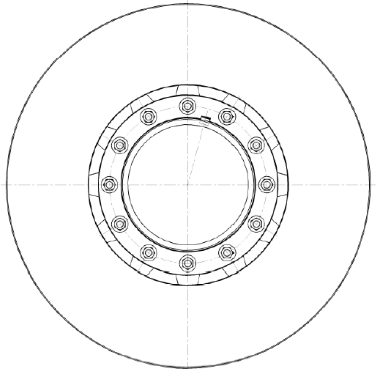
Railway Vehicle Digital Twin

Gabriel Davidyan, Prof. Jacob Bortman and Prof. Ron S. Kenett



Safety Valve



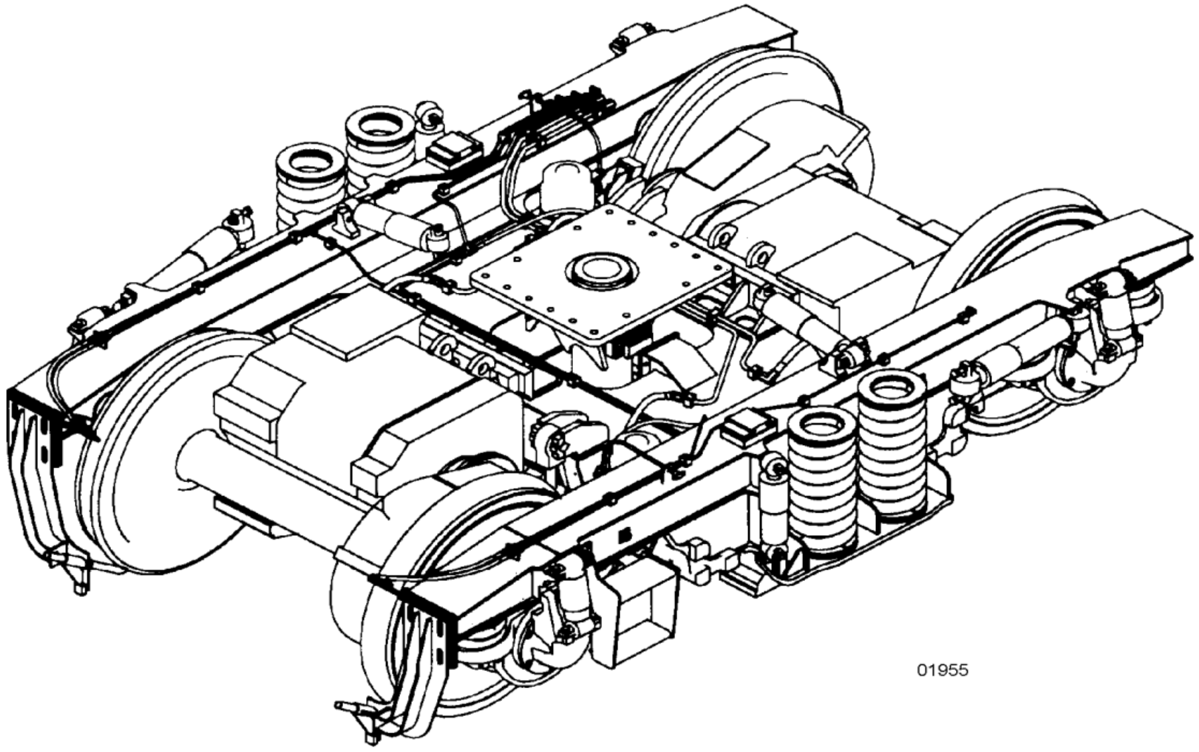


Suspension system

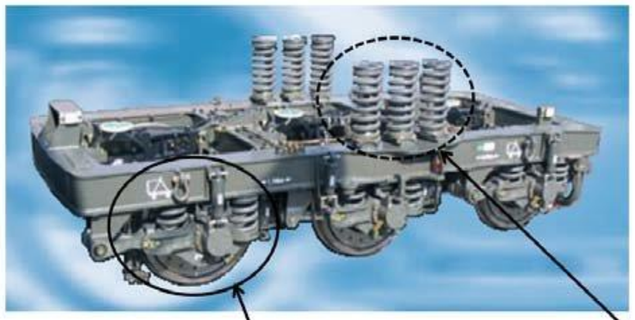
Parking Brake

Railway Vehicle Suspension – 4 failure states:

- Lateral damper
- Wheel flat
- Spring
- Spring & damper

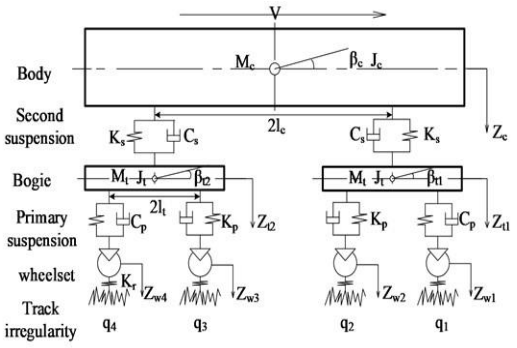


Railway Vehicle Suspension - Mathematical model



Primary Suspension between axle and bogie frame

Secondary Suspension between bogie and car-body

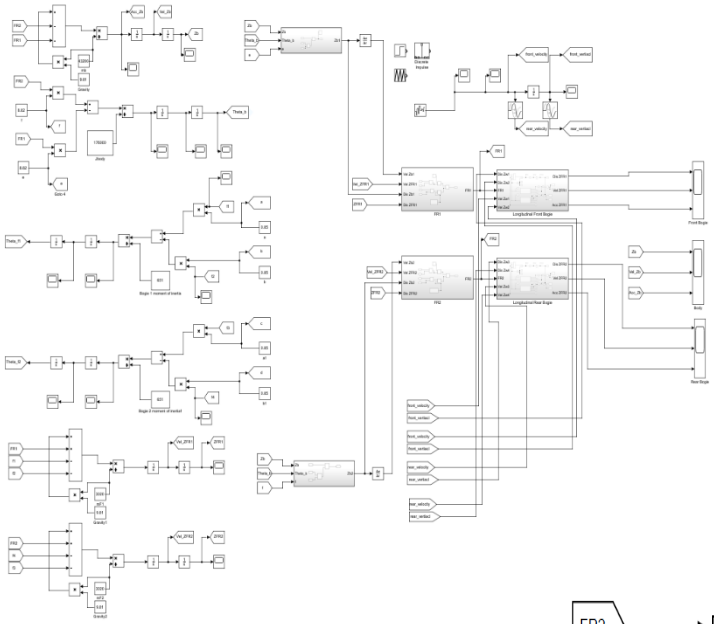


$$F = Ax$$

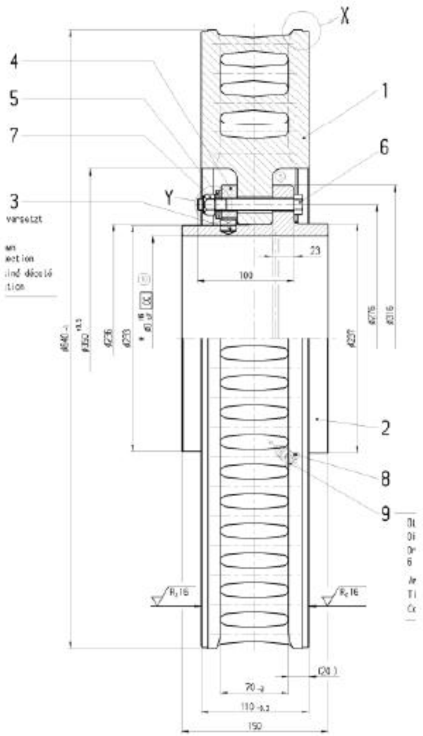
$$x = [Z_c \dot{Z}_c \beta_c \dot{\beta}_c Z_{t1} \dot{Z}_{t1} \beta_{t1} \dot{\beta}_{t1} Z_{t2} \dot{Z}_{t2} \beta_{t2} \dot{\beta}_{t2} Z_{\omega 1} \dot{Z}_{\omega 1} Z_{\omega 2} \dot{Z}_{\omega 2} Z_{\omega 3} \dot{Z}_{\omega 3} Z_{\omega 4} \dot{Z}_{\omega 4}]^T$$

$$A = \begin{pmatrix}
\frac{-2K_s}{M_c} & \frac{-2C_s}{M_c} & 0 & 0 & \frac{K_s}{M_c} & \frac{C_s}{M_c} & 0 & 0 & \frac{K_s}{M_c} & \frac{C_s}{M_c} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \frac{-2K_s l_c^2}{J_c} & \frac{-2C_s l_c^2}{J_c} & \frac{-K_s l_c}{J_c} & \frac{-C_s l_c}{J_c} & 0 & 0 & \frac{K_s l_c}{J_c} & \frac{C_s l_c}{J_c} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\frac{K_s}{M_t} & \frac{C_s}{M_t} & \frac{K_s l_c}{M_t} & \frac{C_s l_c}{M_t} & \frac{-(K_s+2K_p)}{M_t} & \frac{-(C_s+2C_p)}{M_t} & 0 & 0 & 0 & 0 & 0 & 0 & \frac{K_p}{M_t} & \frac{C_p}{M_t} & \frac{K_p}{M_t} & \frac{C_p}{M_t} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \frac{2K_p l_t^2}{J_t} & \frac{2C_p l_t^2}{J_t} & 0 & 0 & 0 & 0 & \frac{K_p l_t}{J_t} & \frac{C_p l_t^2}{J_t} & \frac{K_p l_t}{J_t} & \frac{C_p l_t^2}{J_t} & 0 & 0 & 0 & 0 & 0 & 0 \\
\frac{K_s}{M_t} & \frac{C_s}{M_t} & \frac{K_s l_c}{M_t} & \frac{C_s l_c}{M_t} & 0 & 0 & 0 & 0 & \frac{-(K_s+2K_p)}{M_t} & \frac{-(C_s+2C_p)}{M_t} & 0 & 0 & 0 & 0 & 0 & 0 & \frac{K_p}{M_t} & \frac{C_p}{M_t} & \frac{K_p}{M_t} & \frac{C_p}{M_t} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{2K_p l_t^2}{J_t} & \frac{2C_p l_t^2}{J_t} & 0 & 0 & 0 & 0 & \frac{K_p l_t}{J_t} & \frac{C_p l_t^2}{J_t} & \frac{K_p l_t}{J_t} & \frac{C_p l_t^2}{J_t}
\end{pmatrix}$$

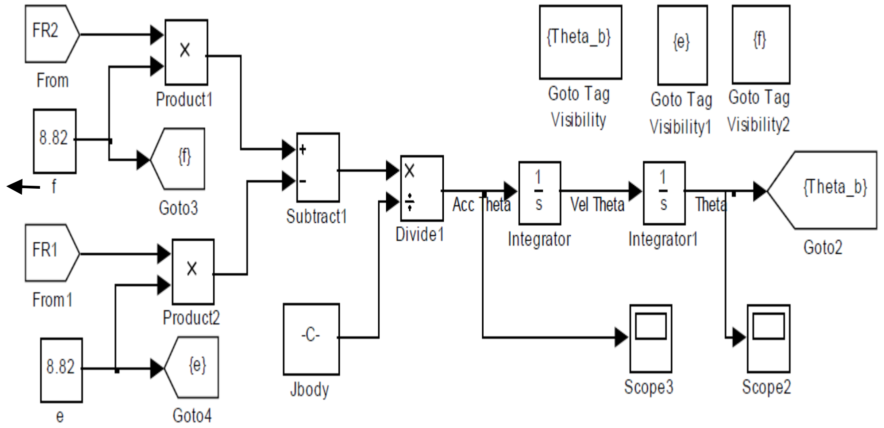
Railway Vehicle Suspension – FEM Model

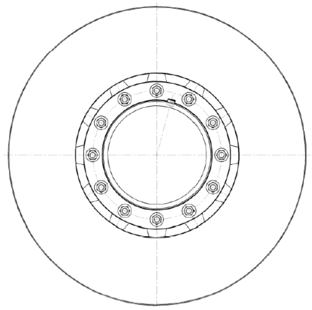


Parameter	Unit	Value
Mass of body M_c	kg	90000
Mass of bogie M_t	kg	2980
Mass of wheelset M_ω	kg	1350
Inertia body nod j_c	$kg\cdot m^2$	2.446×e6
Inertia bogie nod j_t	$kg\cdot m^2$	3605
Primary suspension stiffness K_s	N/m	2.14×e6
Second suspension stiffness K_p	N/m	2.535×e6
Primary suspension damping C_s	N·s/m	4.9×e4
Second suspension damping C_p	N·s/m	1.96×e5
Half length of the vehicle L_c	m	8.4
Half length of the bogie L_t	m	1.2
Wheel radius R	m	0.451
Acceleration of gravity g	m/s^{-2}	9.8

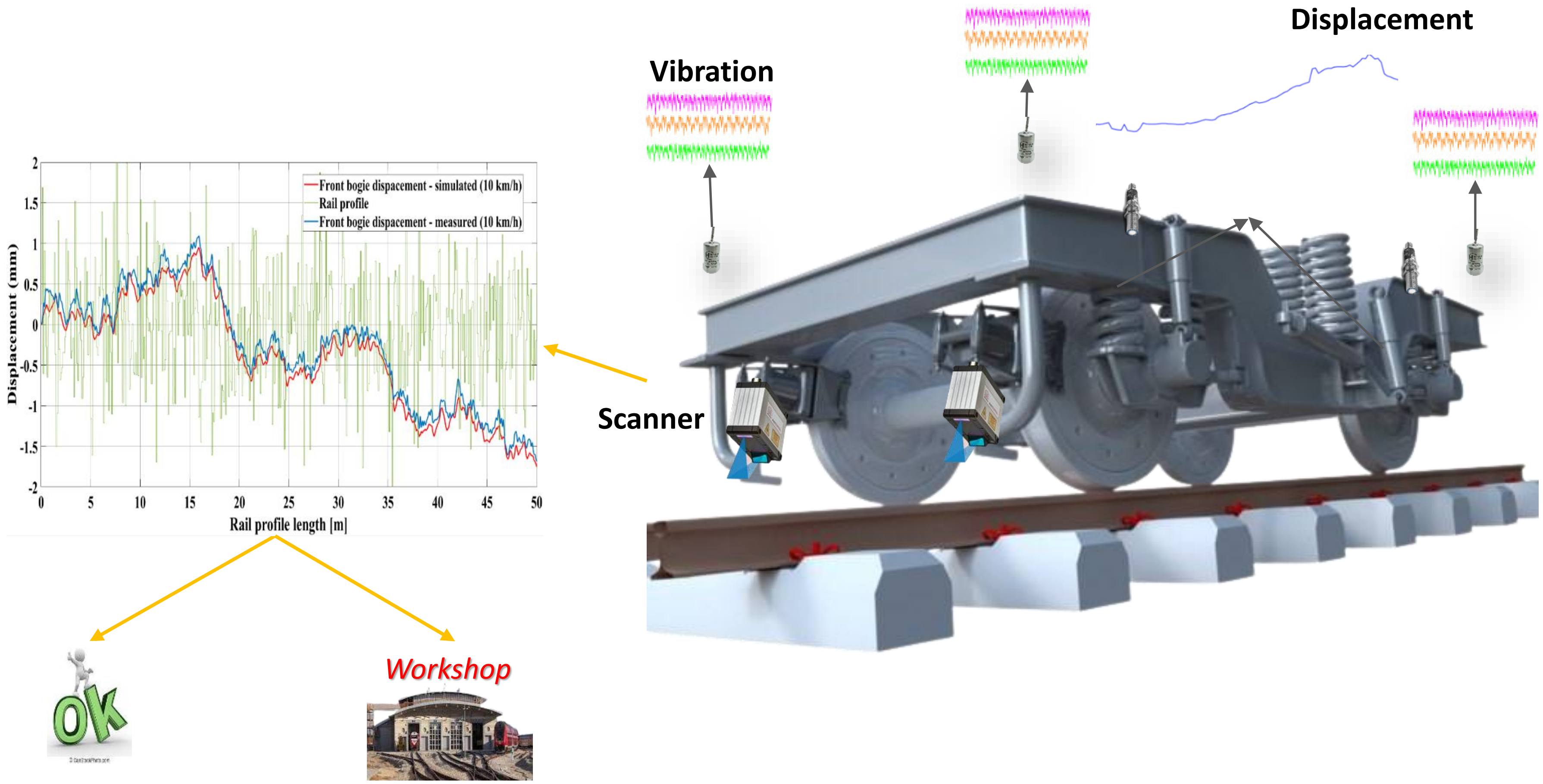


$$J_b\ddot{\theta}_b = T_{FR2} - T_{FR1}$$





Railway Vehicle Suspension - Monitoring System

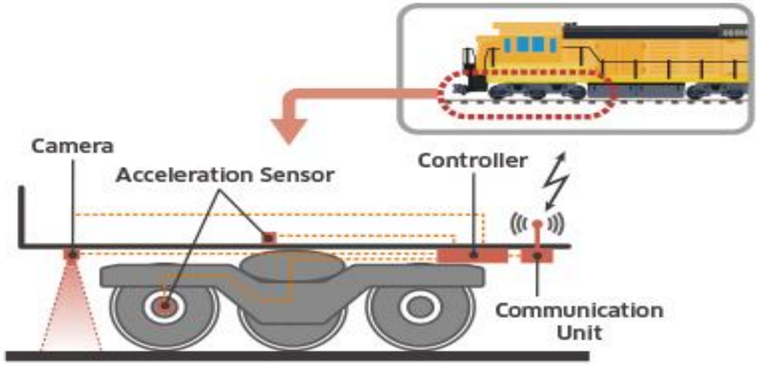


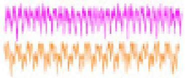
Railway Vehicle Suspension - Model Validation

The vibration signals of the bogie obtained under normal conditions
Sensors were mounted on the bogie of the locomotive which was running at the speed of 10 and 40 km/h

Sensors mounted on the bogie

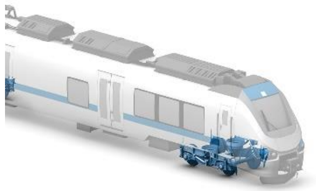
Track geometry and acceleration measurement System





$$Z_c\ \beta_c\ Z_{t1}\ \beta_{t1}\ Z_{t2}\ \beta_{t2}$$

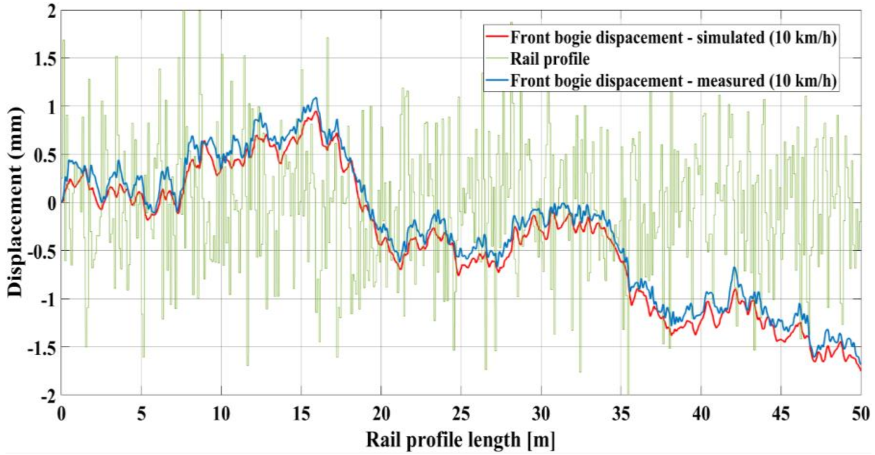
$$\dot{Z}_c\ \dot{\beta}_c\ \dot{Z}_{t1}\ \dot{\beta}_{t1}\ \dot{Z}_{t2}\ \dot{\beta}_{t2}$$



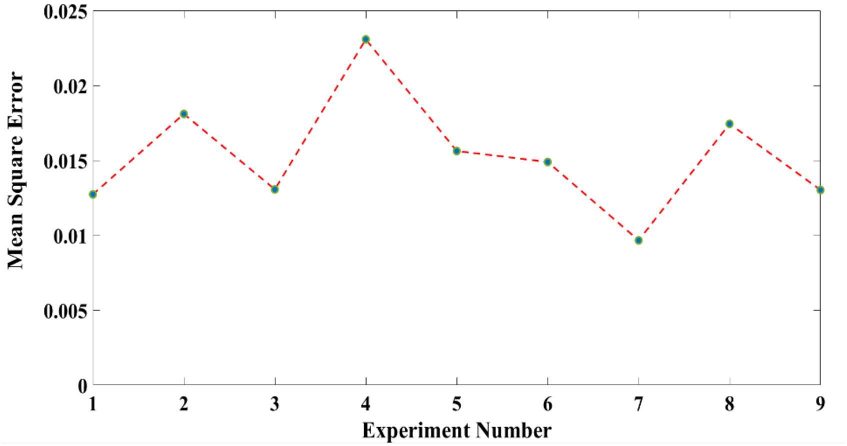
Railway Vehicle Suspension - Model Validation

- *The experiments and model showed similar results*
- *Vehicle velocity has a significant effect on the acceleration signal*

Bogie displacement



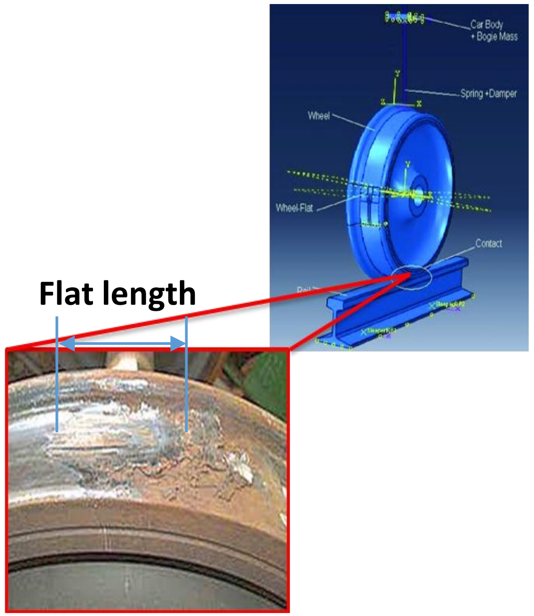
Mean Square Error (MSE)



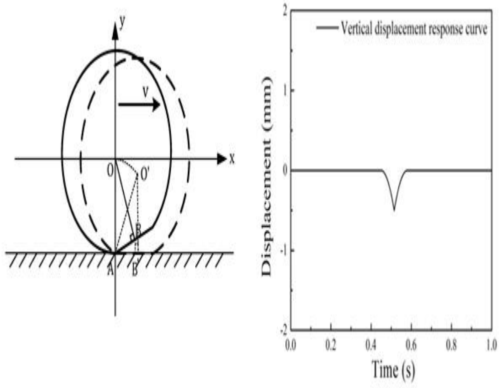
$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(measured\ (i) - simulated\ (i)\right)^2$$

Wheel Flats

- The main causes of wheel-flats are temporary or **complete wheel blocking**.
- wheel-flats pose risk to the safety of the rail vehicle ride.



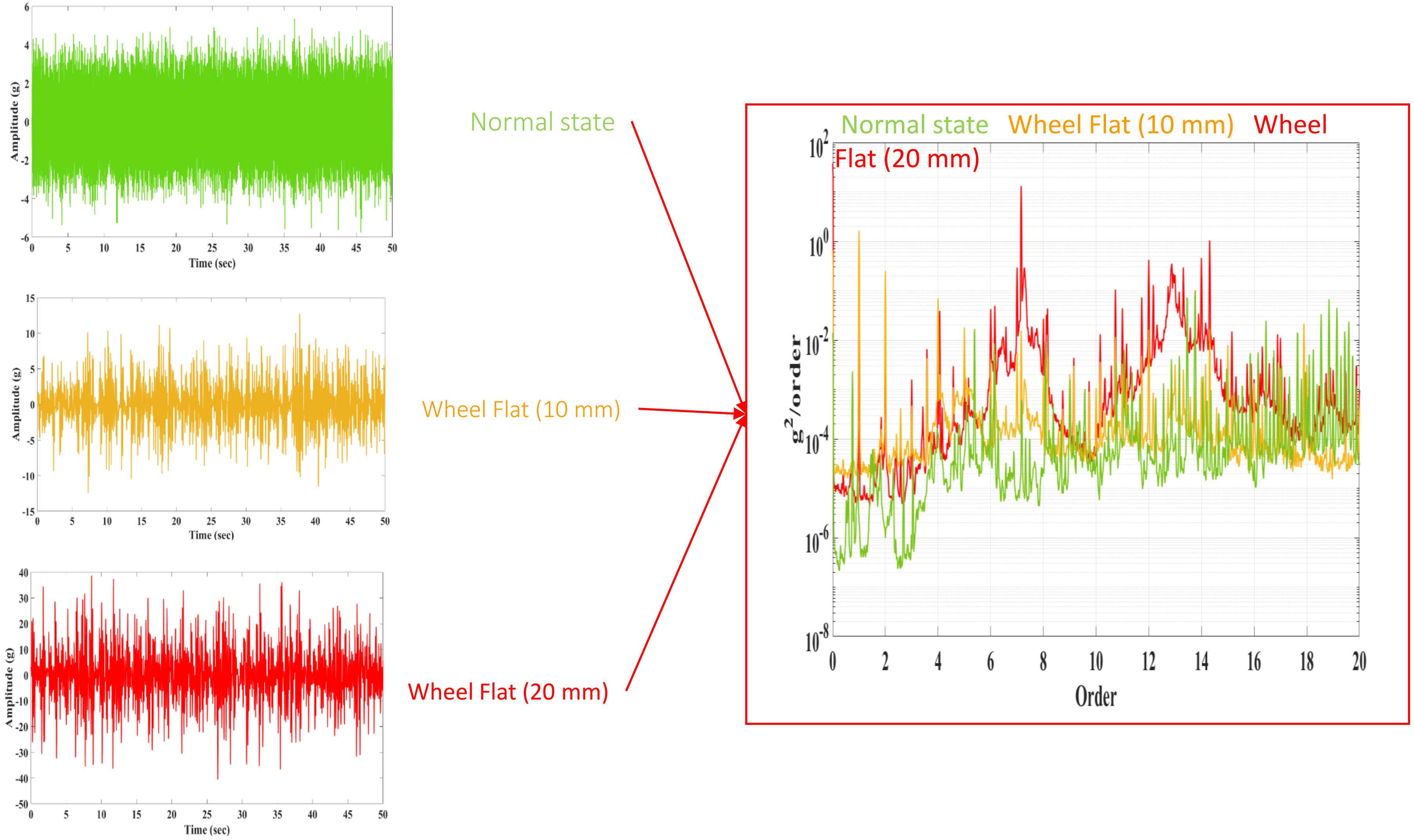
The vertical motion of a wheel flat:
(**a**) The geometry of a wheel flat;
(**b**) The vertical displacement response curve
of point *O*.



(a) (b)

Flat length (mm)	Speed (km/h)	Tone (Hz)
10, 20, 30, 40, 50	10	0.96
	40	3.86
	70	6.76
	100	9.66

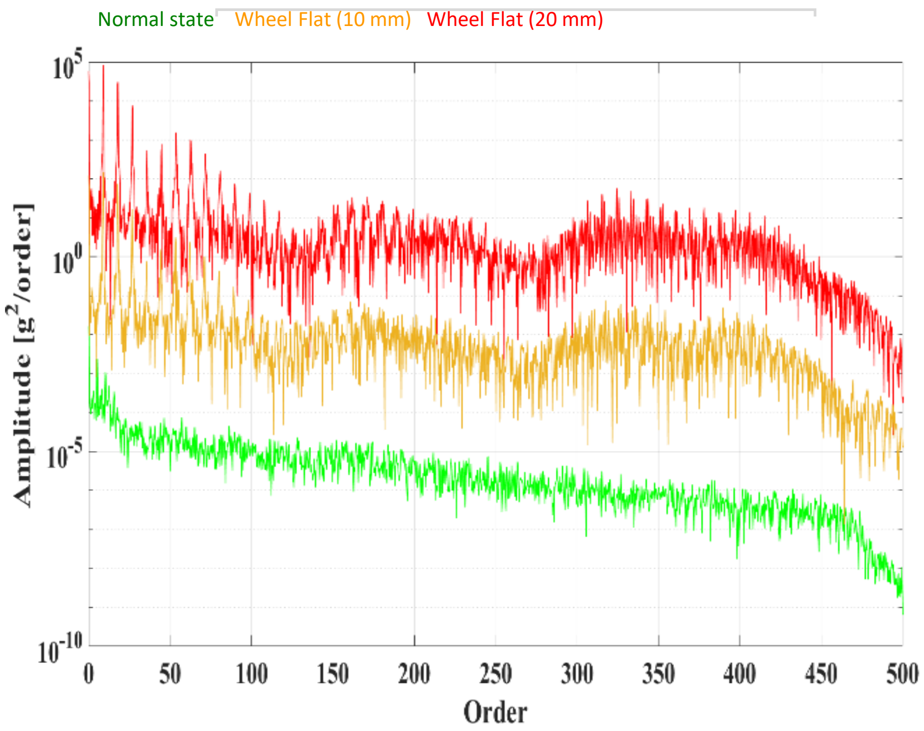
Railway Vehicle Suspension - Wheel Flat Detection

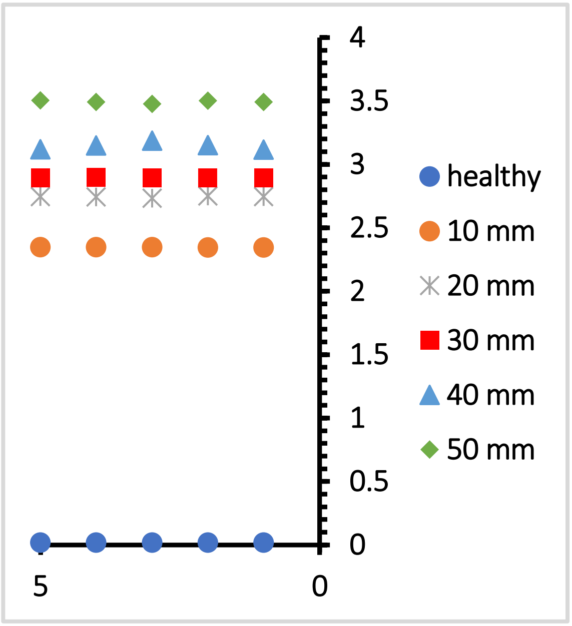


Railway Vehicle Suspension - Wheel Flat Detection

- *Peak Energy Concentration* $\quad PEC = \frac{\sum_i s_{O,i}}{RMS}, \forall i \in \mathbb{Z}_O$

PEC measures the energy percentage that is concentrated in the peaks





Fault Size (mm)	Healthy	10	20
PEC	0.012	2.312	2.744
Fault Size (mm)	30	40	50
PEC	2.891	3.152	3.545

Railway Vehicle Suspension - Fault diagnosis

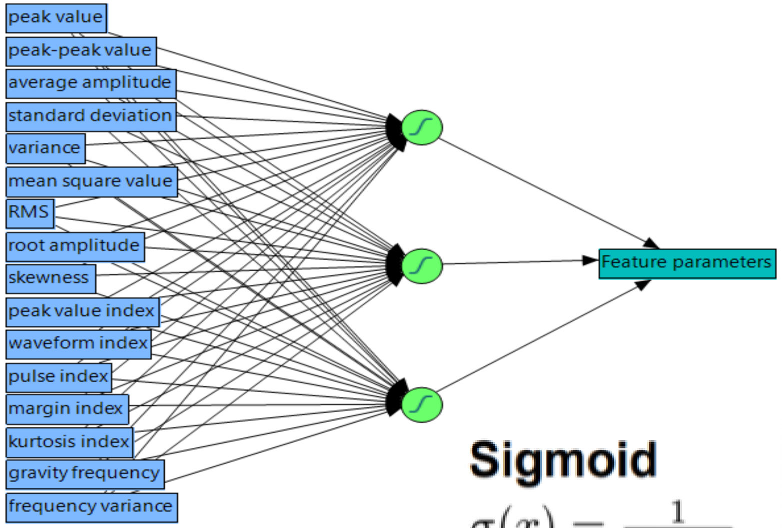
Time-domain and frequency-domain feature parameters of 4 states

Feature parameters	*peak value*	*peak-peak value*	*average amplitude*	*variance*	RMS	*skewness*	*kurtosis*	*standard deviation*
Normal state	0.30	0.59	0.17	0.15	0.47	0.87	1.34	0.39
Failure of lateral damper	0.32	0.69	0.14	4.93	0.32	1.13	0.88	2.22
Wheel flat	0.29	0.53	0.16	0.45	0.37	0.77	0.68	0.67
Failure of spring	0.28	0.58	0.15	0.51	0.26	0.43	0.66	0.46
Failure of spring & damper	0.31	0.63	0.18	0.74	0.64	1.21	0.75	0.84

Structure parameters of deep neural network

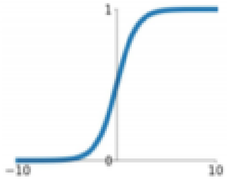
<table>
<tr><td>Nodes of input layer</td><td>Nodes of output layer</td><td>Nodes of hidden layer</td><td>Number of nerve cells in hidden layer</td></tr>
<tr><td>16</td><td>8</td><td>3</td><td>100</td></tr>
<tr><td>Non-supervision learning rate</td><td colspan="2">Fine-adjustment learning rate under supervision</td><td>Activation function</td></tr>
<tr><td>0.1</td><td colspan="2">0.01</td><td>Sigmoid function</td></tr>
</table>

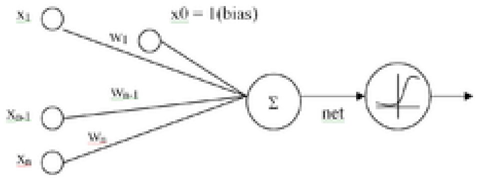
Railway Vehicle Suspension - Fault diagnosis



Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



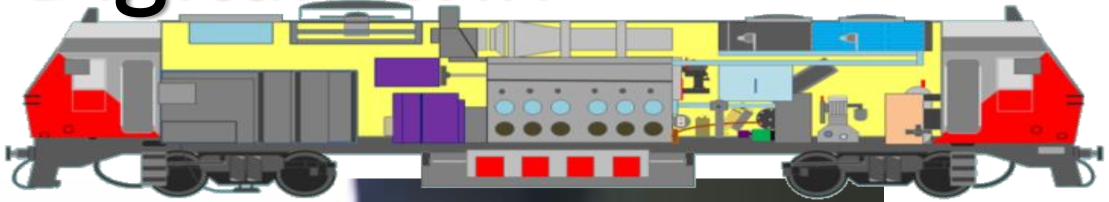


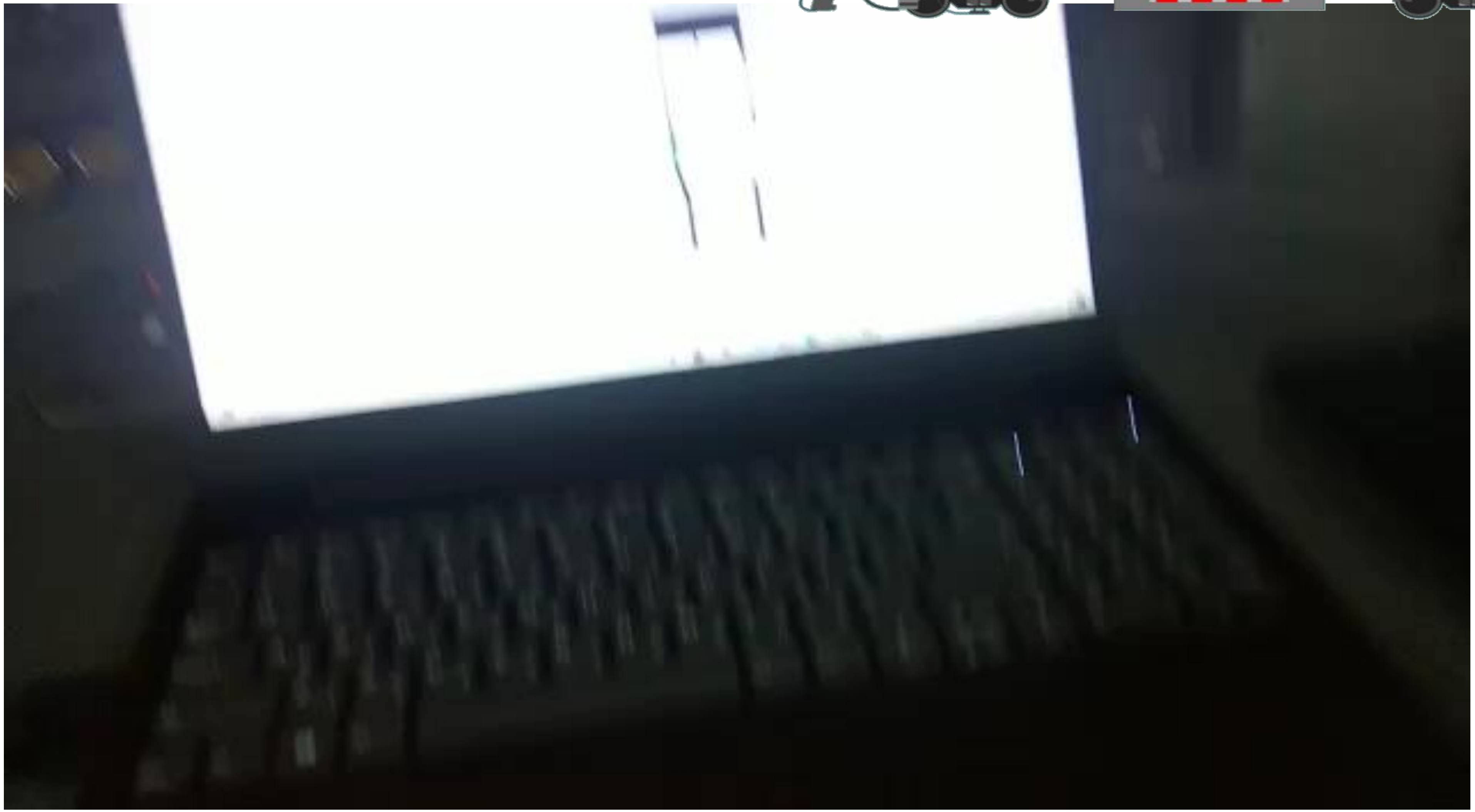
Features (16 in total) of the acceleration signature are extracted in both the time domain and frequency (Order) domain. Based on these, we can predict and classif the different faults using machine learning.

Structure parameters of deep neural network

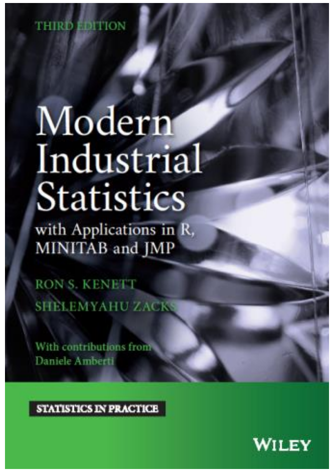
Nodes of input layer	Nodes of output layer	Nodes of hidden layer	Number of nerve cells in hidden layer
16	8	3	100
Non-supervision learning rate	Fine-adjustment learning rate under supervision		Activation function
0.1	0.01		Sigmoid function

Railway Safety Valve – Digital Twin

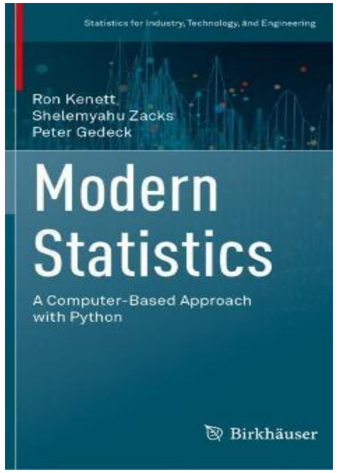




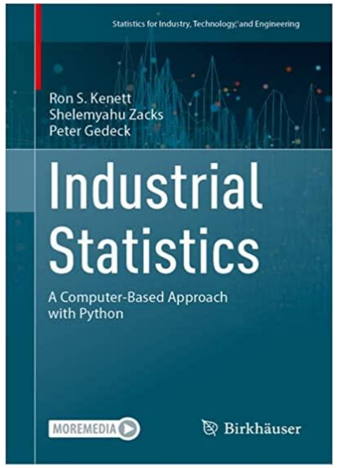
2021



2022



2023



The Challenge

"New engineering practices driven by the management of performance entail high expectations for predicting responses of systems of systems that are extremely large, extremely uncertain, extremely complex, **very accurately** and all this **in almost real-time**, for optimal decision-making.

The goal:

Certified Performance by Design"

Thank you for your attention