Knowledge-Based Maintenance as an Enabler and Driver of Efficient and Sustainable Production Management

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Maintenance for Sustainable Production Management (1/2)

As-Is State: How OEMs and Machine Users May Gain Benefits from Data?

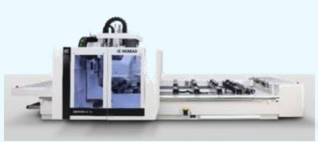
Reliability and durability to comply with specifications over useful life time.

Availability (Uptime) to be able to perform required functions at time *t*, *A(t)*, or over a stated period of time, A_{av}.

What is the link between data-driven approaches, RAM KPIs and sustainability factors?

Products (Complex Industrial Systems) are **used** under various environmental and operational conditions in industrial value chains.


CNC-Lathe S45 @ EMCO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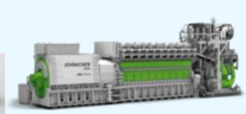
Gas Engine J920 FleXtra @ INNIO Jenbacher GmbH & Co OG

Intelligent functions for integrative analysis and modeling along value-added chain

RAM (t)*

***RAM** (Reliability, Availability, Maintainability)

Maintainability to be timely and efficiently retained in, or restored to a required functional state, after performing maintenance actions.

Integrative modeling and analysis

Reliability	Maintainability	Availability
↔ Constant	↓ Decreases	↓ Decreases
↔ Constant	↑ Increases	↑ Increases
↑ Increases	↔ Constant	↑ Increases
↓ Decreases	↔ Constant	↓ Decreases

KPI: Key Performance Indicator | **OEM:** Original Equipment Manufacturer

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Maintenance for Sustainable Production Management (2/2)

How does advancing maintenance approaches facilitate achieving sustainable production management?

- Problem space (objectives of sustainable production management):
  - Environmental Conservation: Reducing emission, Optimizing energy and resource consumptions
  - Economic Enhancement: Optimizing lifecycle costing
  - Social Efficiency: Improving workforce efficiency

⇨ **Maintenance is a key** for optimizing performance and efficiency of equipment and industrial machines

⚠ Only focusing on this contradicts partially with sustainability goals as physical, virtual and human resources are invested to create and operate a new machine in production facilities

- Solution space:
  - Design new generation of AI-enhanced machines (Maintenance-By-Design, Self-healing, etc.)
  - Optimizing maintenance of existing machines (Maintenance-By-Operation, etc.)

⇨ **Joint efforts of OEM's and Machine Users:** Extending Remaining Useful Life Time (RUL) and improving efficient operation of machines through data-driven approaches

Guiding research question: How can multiple data sources and existing prior knowledge and experiences be used for planning and optimizing maintenance (operational and tactical factors) and translating related KPIs into sustainability factors?

AI: Artificial Intelligence | **KPI:** Key Performance Indicator | **OEM:** Original Equipment Manufacturer

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Knowledge-Based Maintenance (KBM)

Interpretation and Challenges of KBM at the Age of Industry 4.0

- **Knowledge-Based Maintenance** is about integrating Predictive and Prescriptive Approaches …
  - **employing AI** (methodologies, methods, algorithms, tools, technologies) for analyzing, modeling, predicting and reducing the **likelihood or frequency of failures** and thus **increasing availability** in production systems, gaining benefits from multi-channel, multi-structured data sources and **prior and human experiential knowledge**.
- **What are the challenges (scientific and practical)?**
  - Proper use of **multiple data sources**
  - Suboptimal use of **multi-structured** data
  - **Multi-modality** of data (semantic correlation of information)
  - **Multiple** and overlapping reliability-centered and maintenance **strategies** and approaches
  - **Multi-dimensionality** of maintenance organization/actors/teams, processes and IT-systems

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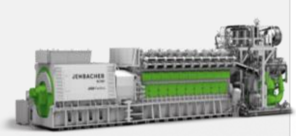

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* **AI:** Artificial Intelligence

F. Ansari, R. Glawar, & T. Nemeth, PriMa: a prescriptive maintenance model for cyber-physical production systems, *International Journal of Computer Integrated Manufacturing*, 2019.

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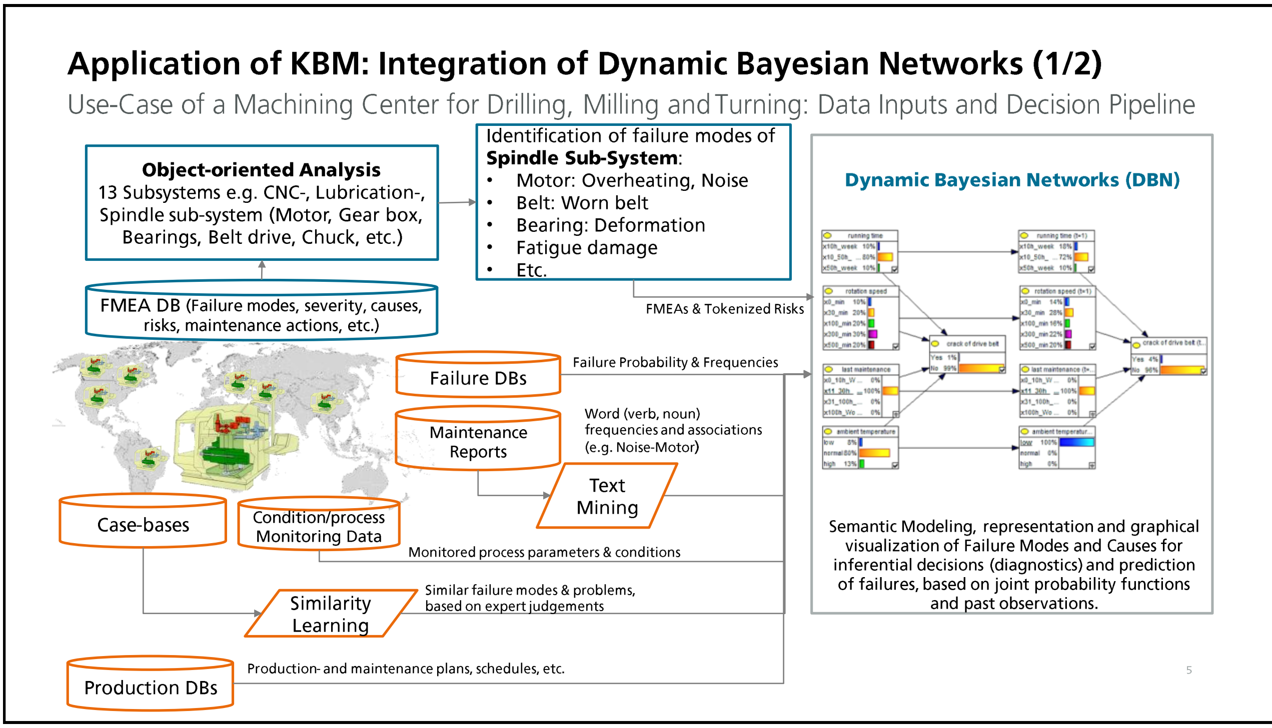
Application of KBM: Integration of Dynamic Bayesian Networks (1/2)
Use-Case of a Machining Center for Drilling, Milling and Turning: Data Inputs and Decision Pipeline
Object-oriented Analysis
13 Subsystems e.g. CNC-, Lubrication-, Spindle sub-system (Motor, Gear box, Bearings, Belt drive, Chuck, etc.)
Identification of failure modes of Spindle Sub-System:
• Motor: Overheating, Noise
• Belt: Worn belt
• Bearing: Deformation
• Fatigue damage
• Etc.
FMEA DB (Failure modes, severity, causes, risks, maintenance actions, etc.)
FMEAs & Tokenized Risks
Failure DBs
Failure Probability & Frequencies
Maintenance Reports
Word (verb, noun) frequencies and associations (e.g. Noise-Motor)
Text Mining
Case-bases
Condition/process Monitoring Data
Monitored process parameters & conditions
Similarity Learning
Similar failure modes & problems, based on expert judgements
Production DBs
Production- and maintenance plans, schedules, etc.
Dynamic Bayesian Networks (DBN)
Semantic Modeling, representation and graphical visualization of Failure Modes and Causes for inferential decisions (diagnostics) and prediction of failures, based on joint probability functions and past observations.
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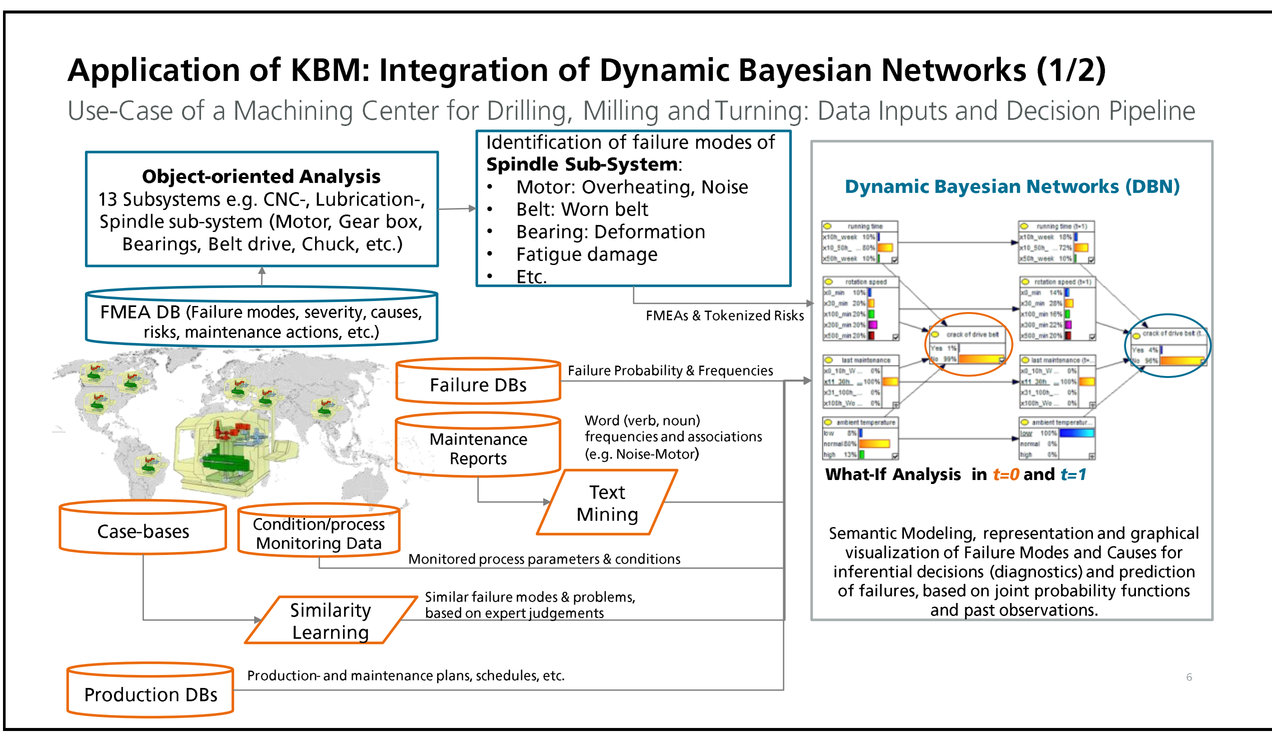
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What-If Analysis in t=0 and t=1
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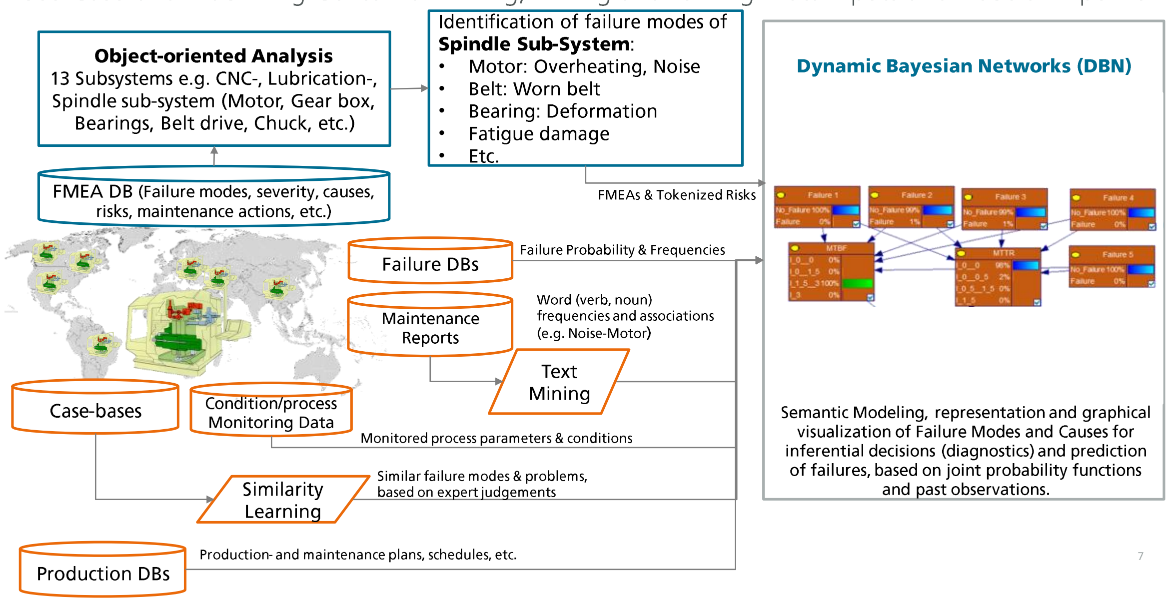

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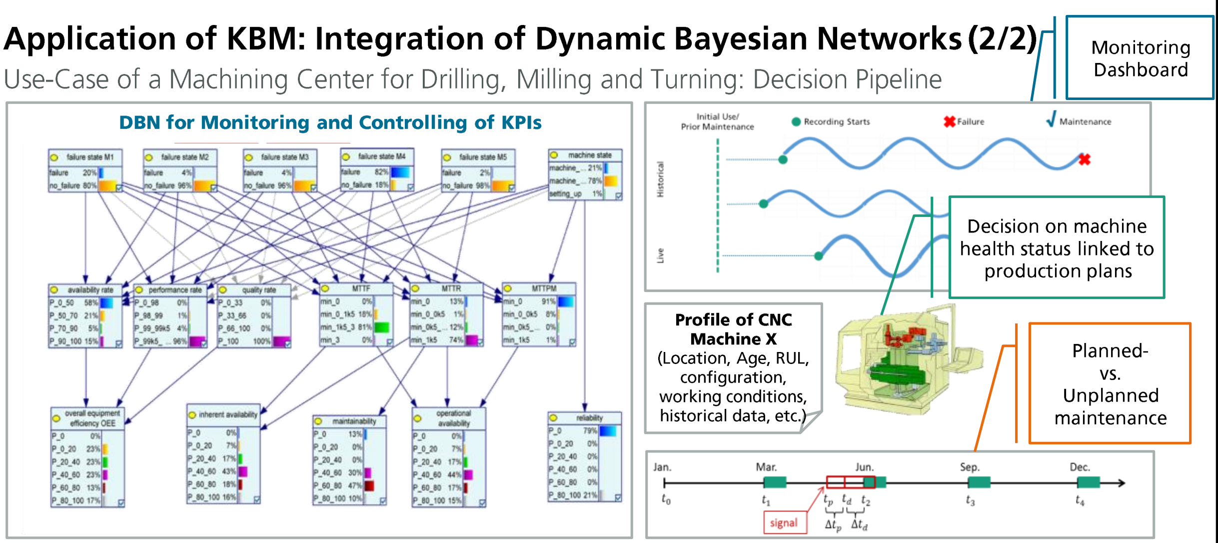
Application of KBM: Integration of Dynamic Bayesian Networks (2/2)

Use-Case of a Machining Center for Drilling, Milling and Turning: Decision Pipeline



Knowledge-based approach supports **informed decision-making** that may impact on **extending RUL** and improving **efficiency** in operations and maintenance management

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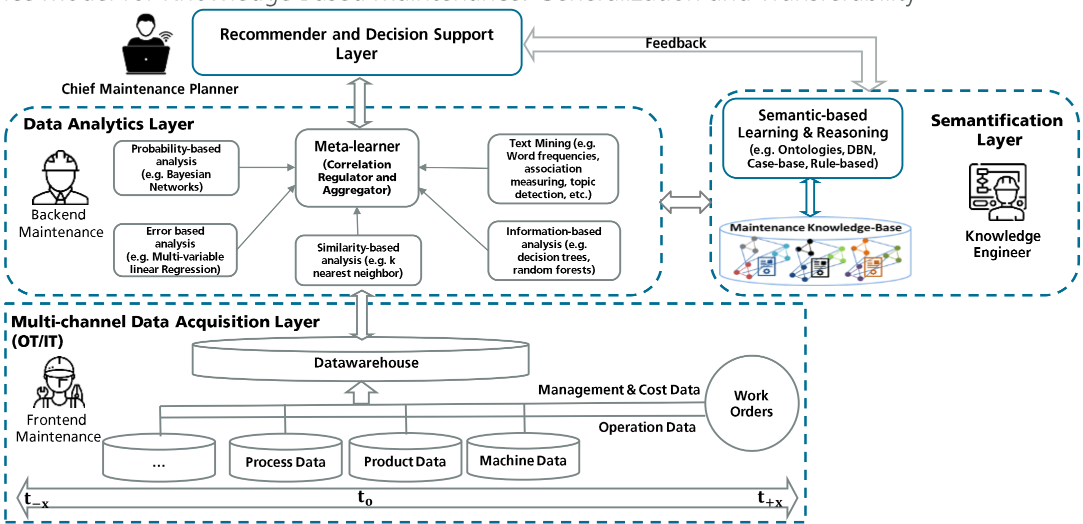
PriMa: Prescriptive Maintenance Model

Reference Model for Knowledge-Based Maintenance: Generalization and Transferability



F. Ansari, R. Glawar, & T. Nemeth, PriMa: a prescriptive maintenance model for cyber-physical production systems, *International Journal of Computer Integrated Manufacturing*, 2019.
F. Ansari & R. Glawar, Knowledge-Based Maintenance, Book Chapter, In Instandhaltungslogistik, K. Matyas (Ed.), 7th Edition, Carl Hanser Verlag, 12/2018, pp. 318-342.

Knowledge-Based Maintenance in Practice

Knowledge Graph-based Assistance System for Troubleshooting & Documentations

Ansari, F., Hold P., & Khobreh, M. (2020).A Knowledge-Based Approach for Representing Jobholder Profile toward Optimal Human-Machine Collaboration in Cyber Physical Production Systems, CIRP Journal of Manufacturing Science and Technology, Elsevier, Vol. 28, pp. 87-106.

Ansari, F., Kohl, L., Giner, J., & Meier, H. (2021). Text mining for AI enhanced failure detection and availability optimization in production systems. CIRP Annals, 70(1), 373-376.

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

Maintenance for Efficient and Sustainable Production Management

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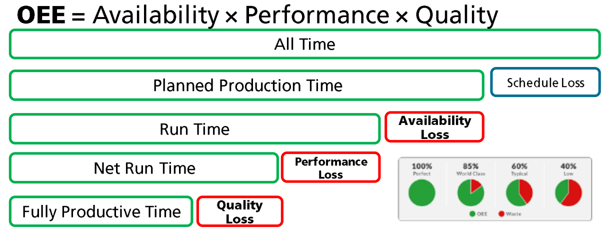
Overall Equipment Effectiveness (OEE)

Benchmark and Baseline KPI for Assessing Production Efficiency and Maintenance Competitiveness

- OEE is a **benchmark** to compare the performance of a given production asset to industry standards, to similar in-house assets, or to results for different shifts working on the same asset.
- OEE is a **baseline** to track progress over time in eliminating waste from a given production asset.
- It takes into account all losses, i.e. Stop Time Loss/Availability Loss, Speed Loss/Performance Loss, and Quality Loss, resulting in a measure of **truly productive manufacturing time**.
- Schedule Loss (shutdown, set-up) is not included in OEE
- Total Effective Equipment Performance (TEEP), adjusts OEE by considering %Utilization (scheduled loss)

OEE = Availability × Performance × Quality



Availability = Run Time / Planned Production Time

Run Time= Planned Production Time – Stop Time

Performance = (Ideal Cycle Time × Total Count) / Run Time

Quality = Good Count / Total Count

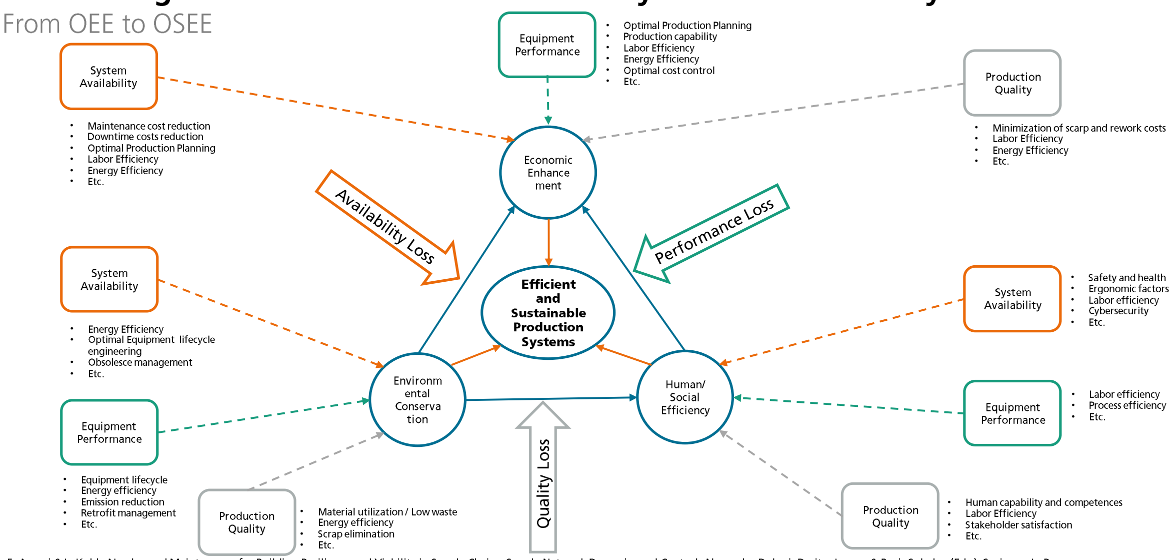
OEE = (Good Count × Ideal Cycle Time) / Planned Production Time

How can we correlate OEE Losses to Sustainability Factors and introduce a measure for lean and sustainable production?

J. Brenner, Lean Production: Praktische Umsetzung zur Erhöhung derWertschöpfung, Carl Hanser Verlag GmbH Co KG., 2018.

Translating OEE Measures to Production System Sustainability

From OEE to OSEE

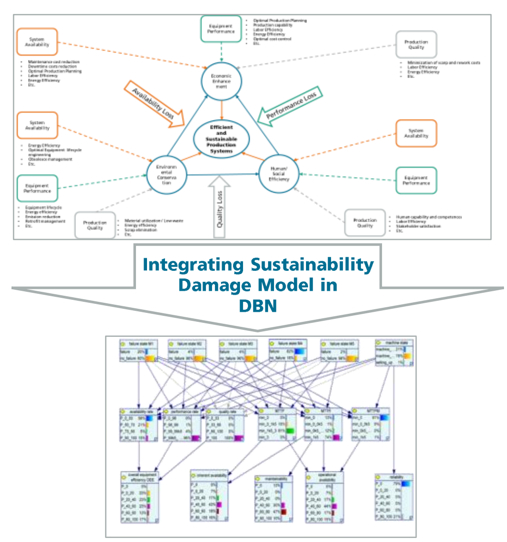


F. Ansari & L. Kohl, AI-enhanced Maintenance for Building Resilience and Viability in Supply Chains, Supply Network Dynamics and Control, Alexandre Dolgui, Dmitry Ivanov & Boris Sokolov (Eds.), Springer, In Press

Translating OEE Measures to Production System Sustainability

From OEE to OSEE

- **Overall Sustainable Equipment Effectiveness (OSEE = OEE × Sustainability)** can be calculated as the relationship between the OEE and sustainability parameters (**Damage/Loss Model**).
- For environmental sustainability most common way is to use **CO2 equivalents** due to emissions (e.g. based on methodologies for calculating environmental impacts Ecotax, Ecovalue08, Ecoindicator-99, and Ecoinvent 3, e.g. via SimaPro Liberary).
- **Other emission and environmental damage sources** e.g. waste, emissions by displacement, origin of raw material, etc.), correlating OEE losses and sustainability factors.
- **Economic and human factors** can be should **not be undermined** (Total Productive Maintenance and Lean Management).
- This should also facilitate rating maintenance activities in terms of sustainability as **low to high competitive.**
- Integrating sustainability damage model into decision pipeline.



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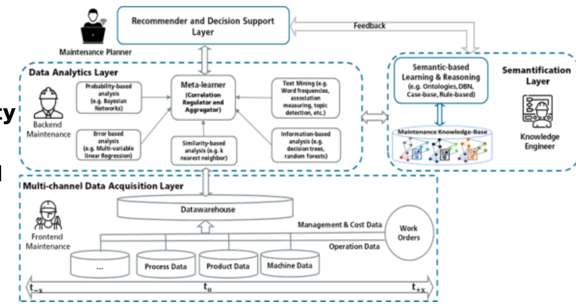
Transfer Possibilities into Industrial Contexts

What are the major challenges and pathways for future research?

- **Success of KBM for efficient and sustainable production systems in industrial context** is strongly dependent on
  - Existence of data (e.g. failure data) and evidences (observations)
  - Correctness and validity of data (**also sustainability data, especially from process level**)
  - **Correct interpretation** of data (by algorithms and human)
  - Explainability of algorithm's decision to humans
  - Modeling and incorporation of human knowledge/experiences
  - Employing simulation-based and physics-informed AI models



As industrial engineers, on the top of this, we should examine economic and technical plausibility of KBM in each industrial application.

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Technology for People!

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