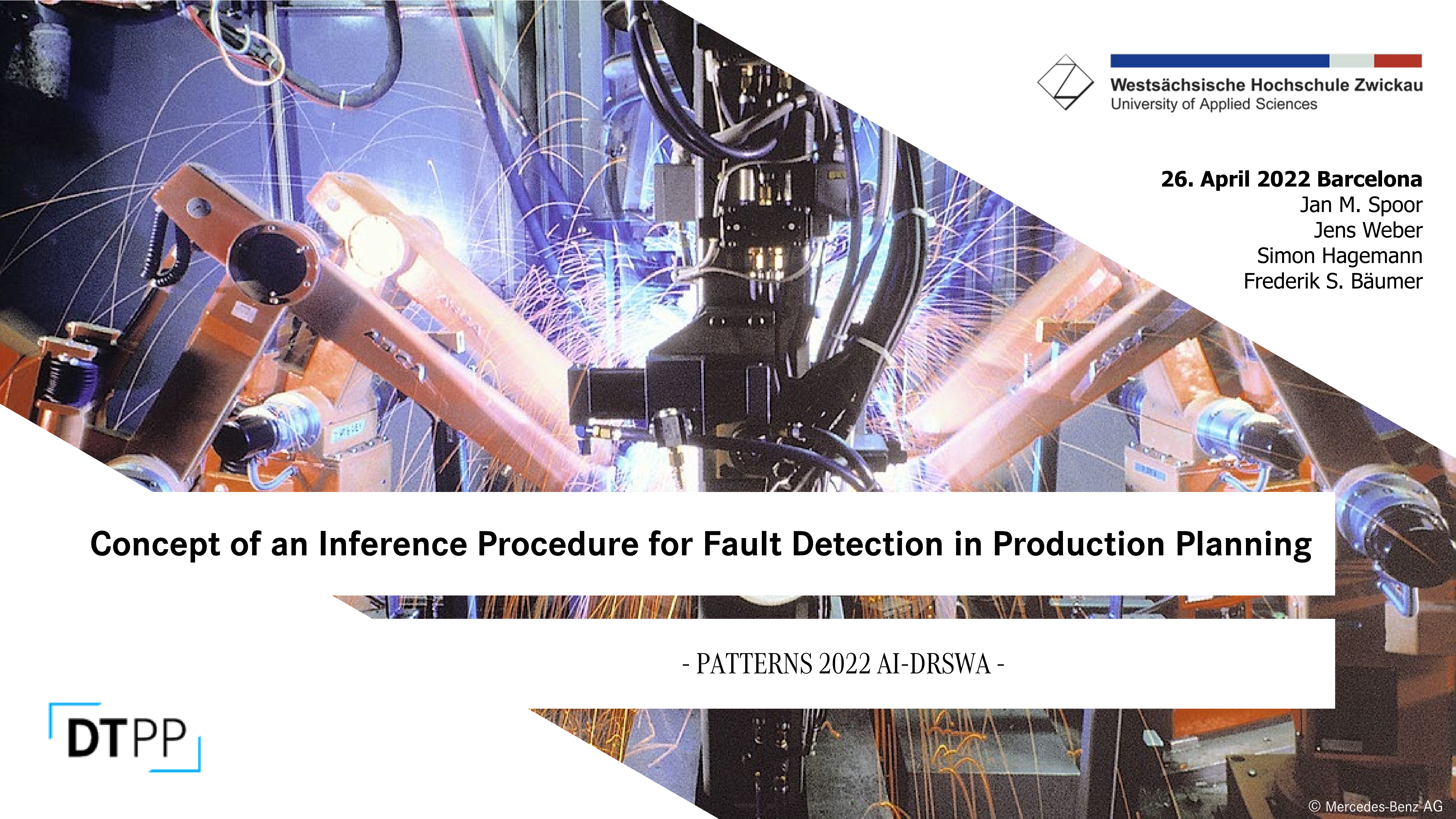

Westsächsische Hochschule Zwickau
University of Applied Sciences

26. April 2022 Barcelona

Jan M. Spoor
Jens Weber
Simon Hagemann
Frederik S. Bäumer

Concept of an Inference Procedure for Fault Detection in Production Planning

- PATTERNS 2022 AI-DRSWA -

DTPP

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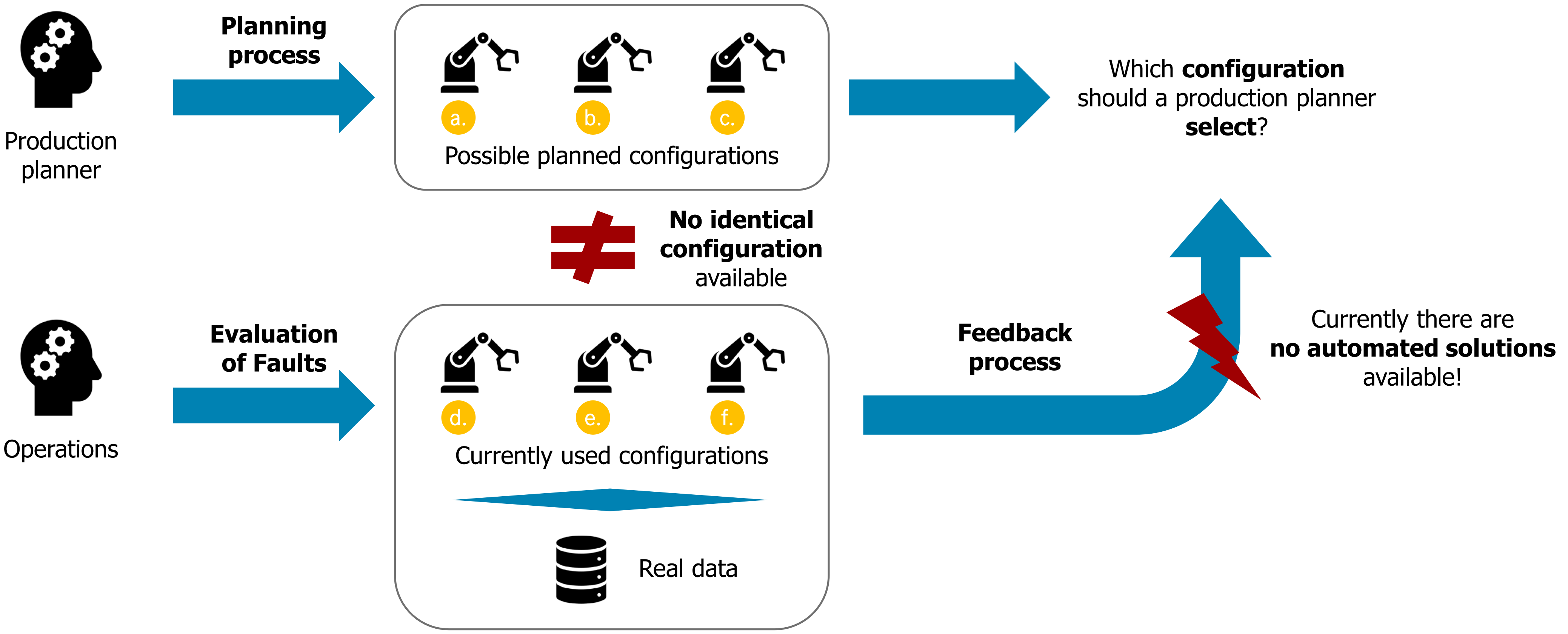
Current challenges & problems | There currently exists no coherent inference procedure from operation back to production planning

Sketch of the challenges in the planning process



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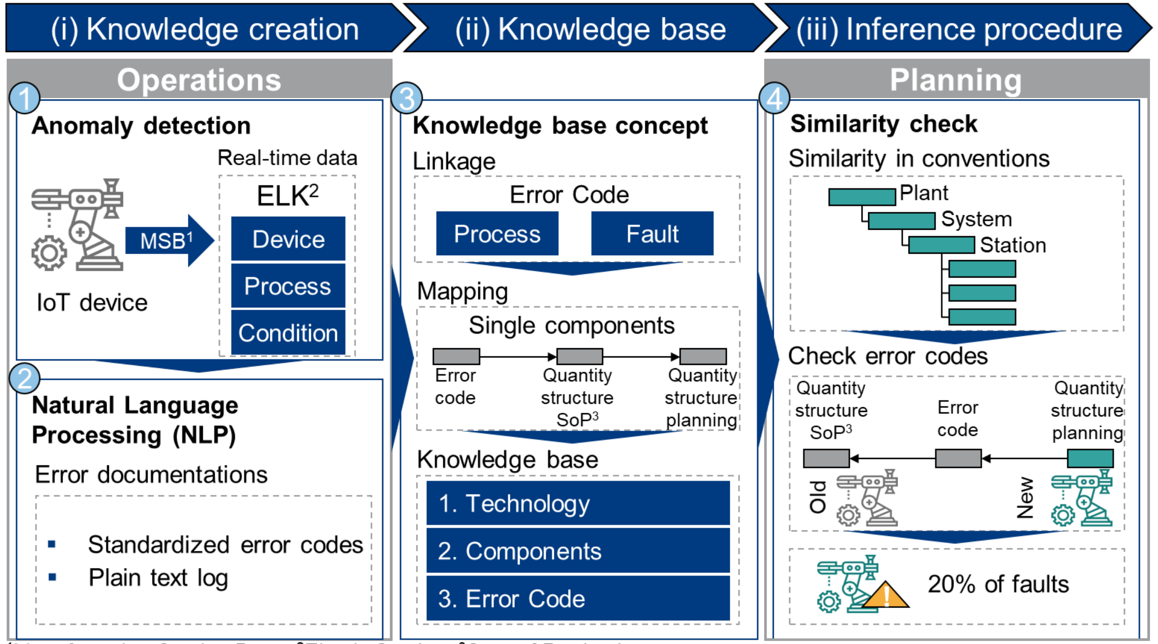
Former ideas & concepts | A former concepts by Gelwer et al. proposed i. knowledge creation, ii. knowledge base and iii. inference procure steps

Preceding Concept by Gelwer et al.



¹Manufacturing Service Bus ²Elastic Stack ³Start of Production

Concept for data consistency checks between operation and production planning enabling an improved knowledge of past errors in planning by Gelwer et al. (1)

Description of Concept

i. Knowledge Creation
- **Anomaly detection** is conducted
- Usage of data from **Internet of Things** (IoT) devices
- Data provided by a **Manufacturing Service Bus** (MSB)
- **Natural Language Processing** (NLP) is applied for analyzing the error documentation
- Described faults within shift logs should then be **classified using standardized error codes**

ii. Knowledge Base
- Linkage of the **technical description** of the occurred faults and the **affected processes** within the **error codes**
- Error codes are mapped with the **hierarchical quantity structure**
- Adding of **further contextual information**

iii. Inference Procedure
- **Quantity structure** in production planning **is compared to the documented faults** in similar quantity structures after start of production (SoP)

Limitations of the former concept | Major problems were already detected during the fault detection – this required a new approach

Found limitations during implementations studies | i. Knowledge Creation

High amount of different data types, faults, and needed methods

- **No** so-called **jack-of-all-trades algorithm** or method for a **consistent anomaly detection** exists
- Using the typology of Foorthuis (2) out of 9 types with 63 subtypes of anomalies, **38 different subtypes** from all 9 types **of anomalies** are expected within the data
- Used algorithms **heavily relied** on **well-labeled data**, **test datasets**, or **required an extensive amount of prior investigation** for setting up valid parameters

Error states are very rare

- Error states are only **occasionally and not consistently labeled**
- We estimate more than an **additional decade of runtime** using same configurations, as comparability is necessary, for creating sufficient error instances

NLP is only limited usable

- **Limited amount of shift log** entries exist, but a high training data size is required (3)
- Documentation often **lacks the required details** in delimitation of the different types of faults or error codes due to **implicit knowledge** of the workers
- Shift logs could be used to **determine if an error occurred** but not what error occurred

Real-time streaming data is difficult to implement

- **Technically complicated** to implement (4)
- Not necessary since **no short-term, and quick call** for action is given

Limitations of the former concept | Major problems were already detected during the fault detection – this required a new approach

Found limitations during implementations studies | ii. Knowledge Base

Fault and machinery patterns are not documented

- **Linking patterns** might help to identify the specific error more precisely
- Enables a **comparison** it with **similar faults**, a comparison of solutions for these similar faults, and in conclusion enables targeted countermeasures
- Patterns could be **transferred and reused** in stage (i)

Only the quantity structure offers little information about the component

- **Position, usage, and linked processes are changing** during the **production planning process** that renders the reasoning behind the choice unclear
- Important **contextual information is not documented** within the quantity structure during production planning and start of production
- A component might cause **comparable errors within different quantity structures**
- **Contextual information** about technologies, parts, usage, processes, and products might offer more explanatory value in describing errors

Limitations of the former concept | Major problems were already detected during the fault detection – this required a new approach

Found limitations during implementations studies | iii. Inference Procedure

A fleshed-out ontology is needed

- **Quantity structure** itself, even if tracked within start of production and production planning, is **not enough to detect similar set-ups**
- **Different quantity structures share comparable faults**, and solving the faults in these different quantity structures might offer very important insights and enable solutions
- Provide **additional information** about types, linkages, relations, and the interaction of product, process, and resources
- Domain information needs to be **embedded in an ontology**

No metric exists to determine similarity

- The proposed ontology must offer the **possibility to apply a quantifiable similarity measure**
- **Similar setups** and their respective faults should be given **more weight**
- The **predicted error-proneness** of the new configuration is **correlated to the distance measure** between the new and past configuration

Contents

Derived principles | Using the found limitation, we were able to derive 6 relevant principles for future concepts

The relevant findings from the discussion of the preceding concept can be expressed by the following six principles:

1. A normal model needs to be defined, and all data deviating from the normal model should be classified as generic faults
   - Since faults are rare in the data, an approach using labeled faults requires more labeled training data than currently available
   - The use of only supervised approaches is not recommended

2. Since shift logs can be used to identify if any error occurred
   - Enable spotting of time frames of interest for finding error patterns
   - Not all data are analyzed but data occurring during days with entries in the shift logs are

3. The classified patterns are the classification criteria for all anomalies
   - Using the deviations from the normal data, these findings can then be compared regarding their unique patterns
   - Building a new fault classification structure

4. Configuration must be enriched with contextual data
   - Fault patterns might be highly individual for each configuration
   - Enables a deeper contextual anomaly detection and a real causality analysis

5. An additional ontology must be created
   - Configurations are currently solely dependent on their quantity structure
   - Make configurations more specific and comparable beyond the quantity structure

6. A metric must be developed
   - Comparing the similarity of configurations independently of their hierarchical position
   - Based on the newly created ontology

Problem definition | The risk assessment of a new configuration depends on the current configuration risk and a similarity measure

To address the requirements discussed, we build a fundamental logic on how to feed errors back

The risk of any error occurring in configuration k is then given as following expression:

$$r_k = \sum_{e_j \in E_k} P\left(e_j \mid \theta_k\right)$$

The metric should then give an approximation of the possible error states using the configuration k as base.

$$r_{k^*} \approx \sum_{e_j \in E_k} P\left(e_j \mid \Delta(\theta_{k^*}, \theta_k), \theta_k\right)$$

For each error, a relation between configuration k and k* dependent on the distance measure is assumed.

$$P\left(e_j \mid \Delta(\theta_{k^*}, \theta_k), \theta_k\right) \sim P\left(e_j \mid \theta_k\right) \circ \Delta(\theta_{k^*}, \theta_k)$$

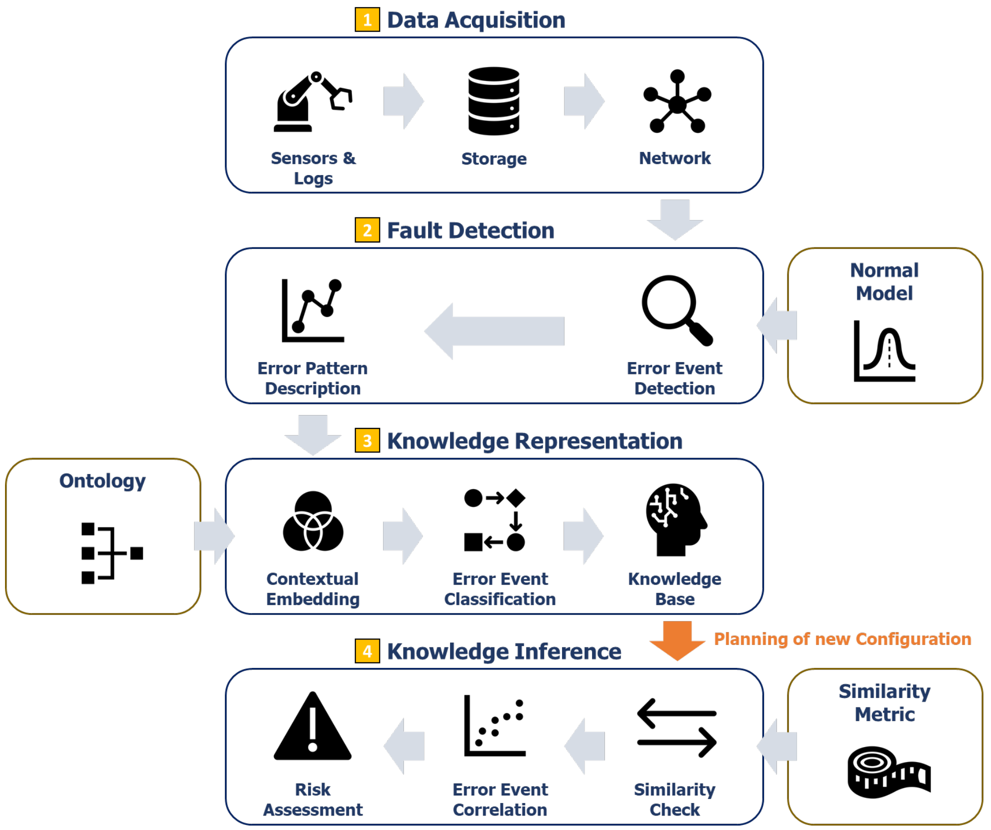
In order to conduct a risk assessment of a new configuration k*, the following challenges need to be addressed:

- The **risk assessment of base configuration k** is necessary
- There needs to be a **valid definition of a metric**
- Using the metric and risk assessment of k, a **risk assessment of k*** must be derived

Contents

Proposed concept | The concept uses 1. data acquisition, 2. fault detection, 3. knowledge representation, and 4. knowledge inference

Proposed concept



Description

1 Data Acquisition
- Process of collecting, processing, storing, and providing the data in order to conduct a fault detection

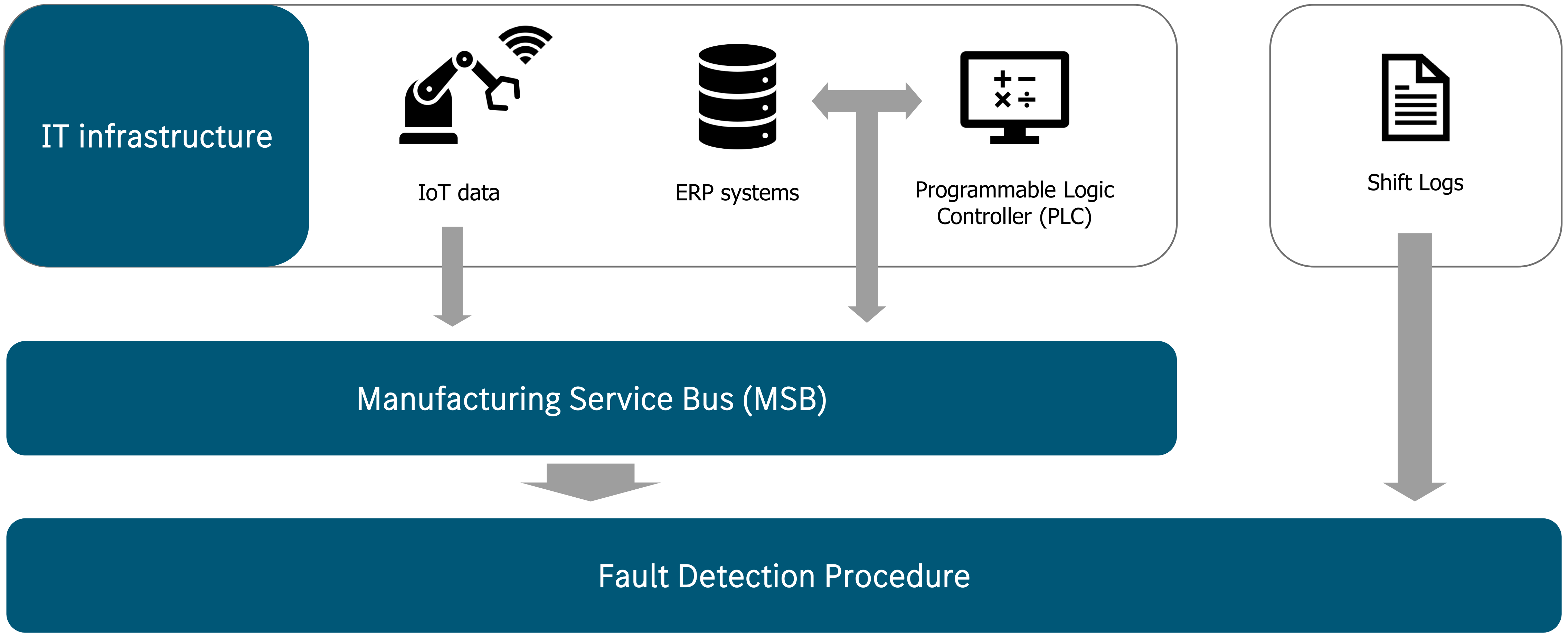
2 Fault Detection
- Accesses the normal model to use for a detection if any kind of event happened and to describe the event patterns
- Detecting if any event happened before classifying or describing the event

3 Knowledge Representation
- Pattern and error events are then embedded in the ontology of the configuration
- Events are documented by defined patterns and are occurring within delimited areas and applications
- The probability of occurrence can be determined by predictive pattern mining of the specific error event

4 Knowledge Inference
- A new planned configuration is compared to configurations in the knowledge base by applying the defined metric

1 Data acquisition | Data are provided via a MSB, which worked quite well in our implementation studies

Proposed concept for data acquisition



2 Fault detection | Since normal data are common, the normal model is applied as a base for the determination of a normal state and fault states

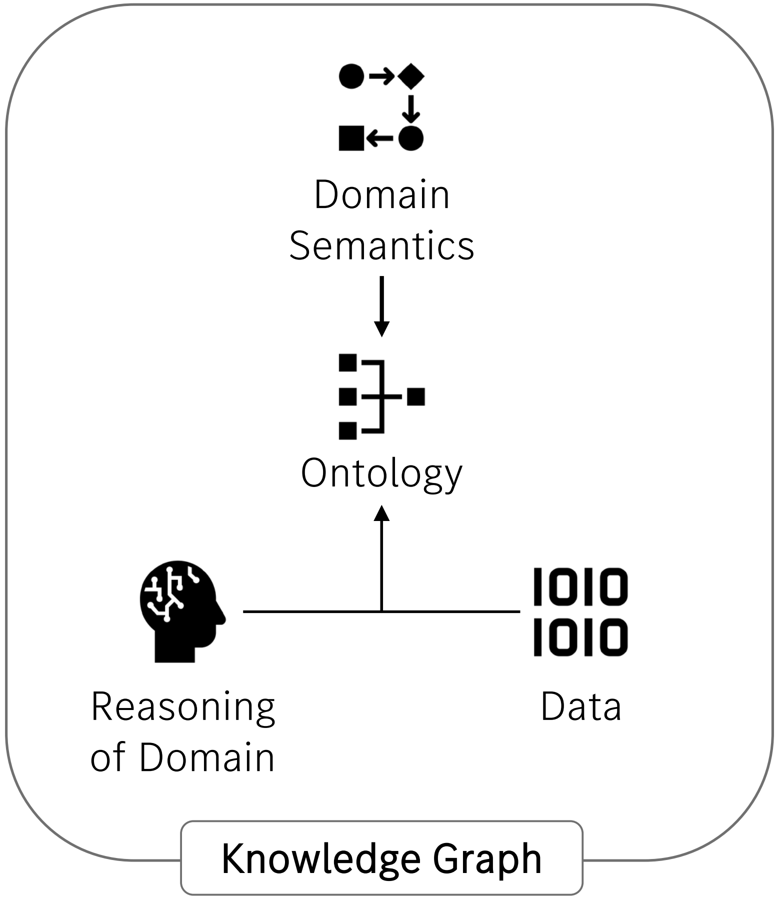
Possible solutions for anomaly detection

Further focus

Method	Advantages	Limits	Sources
Unsupervised learning	▪ Commonly used (LOF, etc.)	▪ High risk of falsely positive detection of noise in the data as faults	n.a.
One-class Support Vector Machine (SVM)	▪ Normal data is leading the classification	▪ Overfitting due to anomalies within the normal data	Schölkopf et al. (5)
Robust One-class SVM	▪ Normal data is leading the classification ▪ Less sensitive to outliers in the normal data then common one-class SVM	▪ High risk of falsely positive detection of noise in the data as faults	Yin et al. (6)
Kernel Principal Component Analysis (PCA)	▪ Normal data is leading the classification	▪ Overfitting due to anomalies within the normal data	Hoffmann (7)
Comprehensive Digital Twin (DT)	▪ Usage of simpler distance-based methods	▪ Requires extensive set-up of a DT	Tao et al. (8)
Autoregressive time series with distance-based metrics	▪ Usage of simpler distance-based methods	▪ Might be too imprecise ▪ Requires data as time series	Hau and Tong (9)
Cross correlation entropy	▪ Normal data is leading the classification ▪ No additional modelling, etc.	▪ Only identification of windows ▪ Requires data as time series	Wang et al. (10)

3 Knowledge representation | Since faults are very case specific, all information needs to be embedded in an ontology

Definition of Ontology and Knowledge Graph



Current challenges in applications

- Main challenges to solve for further implementations (11):
  1. Production models do **not follow the linked data principles** and require a **new vocabulary** instead of the re-usage of current used vocabularies
  2. The scope of currently used ontologies is **too application-specific** and not applicable in all areas of the production

- Most relevant for production planning in the automotive industry are the domains of **Product, Process, and Resources**, bundled in the **PPR concept** (12)

- Only the **linked and semantic description** of the faults are capable of setting up **contextual error identifications**

- An applicable ontology for the proposed concept must therefore combine:
  - Aspects of the **PPR concept**
  - Aspects of ontologies for a **contextual anomaly detection**
  - Aspects of **pattern mining**

3 Knowledge representation | Different domains, and information need to be analyzed for inclusion in the ontology

Overview of discussed ontologies

Sources	Domains								
	Product	Process	Resources	Component taxonomy	Quantity structure	Features	Time	Location	Sensor
PPR concept (12)	✓	✓	✓						
Ming et al. (13)	✓	✓		✓	✓	✓			
Agyapong-Kodua et al. (14)	✓	✓	✓						
Giustozzi et al. (15)	✓	✓	✓				✓	✓	✓

Further focus

4 Knowledge inference | To compare the risk and create a measure of fault probability, a metric needs to be developed

Current challenges in applications

- The concept should support a **rough planning** as the first step of the **production planning process**
- **Focus** of the rough planning is **more on resources than processes** since resources are main part of the cost calculation (16)
  - ➢ The similarity measure can **only be as good as the rough production planning**
  - ➢ During planning, more ontology types are added and **enable better similarity measures**
  - ➢ Ontology must be **imposed to planners, suppliers, and operation**

- In the definition of the metric a **contrary objective arises:**

The **metric must describes the error-proneness** of planned configurations based on current configurations	⟷	The **error-proneness** of the planned configurations **is itself derived from the distance measure** of the metric

- The metric to be defined is more likely a **fuzzy similarity assignment**, i.e., a probability that the configurations are similar

Contents

Conclusion | The concept is currently further researched at Mercedes-Benz Group AG - we hope to present the implementation studies soon

Accomplishments

- Six defined **principles** for future concepts
- Proposed **mathematical correlation definition** between the error-proneness of planned configurations based on current configurations
- Acknowledgment of the shortcomings of the former concept and proposal of an **advanced structure:**
  - **Data acquisition**
  - **Fault detection**
  - **Knowledge representation**
  - **Knowledge inference**
- These stages are enabled by the definition of:
  - **Normal model** as a basis for fault detection
  - **Ontology** for a valid representation
  - **Similarity metric** for target-oriented comparisons

Further research topics & challenges

- Set-up of a valid **ontology** within the manufacturing system
- Description and the derivation of a useful **metric** to determine similarity between configurations
- Selection of a useful **fault detection** method
- Set-up of a **use case oriented pattern mining**
- Analysis of the prosed **risk correlation**
- **Implementation** of the concept within an application at Mercedes-Benz Group AG

Contents

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