Smart Process Failure Analysis based on Bayesian Networks and Knowledge Graphs

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***Abstract*—In production, when it comes to quality defects or production disruptions, expert knowledge for root cause analysis is essential. This knowledge can be captured in a machine-readable format using ontologies and can then be probabilistically expanded in the next step. Bayesian networks can be employed to provide an estimate of the probability describing the cause of a production error. The aim of this work is, therefore, the development of a process diagnosis tool for an existing knowledge graph of a robot-based system, which relies on a Bayesian network to estimate potential error probabilities. For this purpose, the concept of the tool is developed and validated using the use case of robot-based glass panel assembly.**

***Keywords*—Knowledge Graphs, Bayesian networks, smart assistance**

I. Introduction

The globalization of production is driven by competition and is accompanied by increasing product individualization as well as shorter delivery times. This increases the complexity of production systems and the requirements for process control.Expertise can help establish and maintain the necessary infrastructure, but this comes with costs and risks. Individuals not only need to be trained and deployed, which is time-consuming and costly, but the transfer of internal knowledge about production facilities often happens unsystematically and is at risk of being lost. This leads to problems, particularly for small and medium-sized enterprises where specialized knowledge is distributed redundantly among fewer individuals.

The Industry 4.0 research initiative provides a solution by aiming to network human-machine systems. This includes the creation of assistance systems capable of preserving and efficiently and universally providing expert knowledge. [1] The necessary knowledge foundation for these assistance systems consists of a coherent digital network that contains production data semantically, adequately, and contextually in the appropriate granularity. To build this network, semantic technologies are used to work with machine data and process logic. This leads to the formation of Knowledge Graphs (KG), which connect terms and data points from the application context as nodes through edges. They are characterized, among other things, by their extensibility and can be used to infer implicit knowledge. The graph structure also allows for the application of other graphical models based on nodes and edges. For example, Bayesian networks (BN) can be generated from them, which allow for the probabilistic description of uncertain connections in the KG. This expands reasoning within the KG so that implicit knowledge and causal connections can be stochastically quantified. [2, 3]

With the goal of maintaining complex production systems independently of individuals by utilizing expert knowledge, it is necessary to determine probable causes for occurring process and product errors. This can help avoid long downtimes and more efficiently utilize scarce specialized personnel. Currently, there are no assistance solutions that allow for probabilistic reasoning based on any KG. This is where the present work comes in, aiming to develop a process diagnosis tool that fulfils this requirement by using BN

The remainder of this paper ist structured as follows: Section II provides a short overview about Bayesian networks in production, knowledge graphs and related works about decision supporting assistance systems based on a combination of BN with KG. In Section III, the concept of the smart failure diagnosis tool is explained. This followed by Section IV, where a proof of concept implementation is presented to evaluate the proposed communication service for a use case of a robot-based glass pane assembly process. Finally, the proposed smart failure diagnosis tool is discussed and an outlook on planned future work is given.

II. State of the Art

A. Bayesian networks in production

Bayesian Networks (BN) are Directed Acyclic Graphs in which nodes represent random variables and edges represent direct logical relationships between random variables. Each random variable in the BN has an associated probability table, which specifies the conditional probabilities of the associated node in relation to the states of its parent nodes. These probabilities are also called parameters and are algorithmically improved in the implementation of this paper [4]. If there is certainty about the state of some variables in the BN, a so called evidence is available. With this, the probability of the states of the unobserved nodes can be computed by using Bayes' theorem, the chain rule for BN, and other computational rules of statistics [5].

Conditional Probab.	$P(A\|B) = \frac{P(A \cap B)}{P(B)}$
Chainrule for BN	$P(V) = \prod_{v \in V} P(v\|\pi_v)$
Statistical marginal distribution	$P(X) = \sum_{V-X} P(V)$
Bayes' Theorem	$P(A\|B) = \frac{P(B\|A) \cdot P(A)}{P(B)}$
Law of total Probab.	$P(B) = P(B \cap A) + P(B \cap \bar{A}) = P(A) * P(B\|A) + P(\bar{A}) * P(B\|\bar{A})$

Fig. 1 Relevant formulas for computing in Bayesian Networks

Fig. 1 shows the main formulas for calculating probabilities in BN. Here, A and B represent two random variables that are modeled as nodes in BN. V is the total set of all nodes in the BN, X is a subset of them, and v represents a node from V. π_v denotes the parent nodes, i.e., the predecessor nodes of v.

To simplify complex BN and make them computable, algorithms like clustering algorithms can be used [6]. BNs are a way to represent and quantify causal relationships. Artificial neural networks are also suitable for this purpose [7], however, BN are more compatible with Knowledge Graphs (KG), since their structures are more similar. [8, 9] This makes it easier to form and use BN from existing KG. The mentioned algorithms for parameter learning and reasoning are located in the area of machine learning. Bayesian networks are modeling forms and can be used in the field of machine learning. They are a probabilistic modeling technique used to model uncertainty in data and solve inference problems. Fields of application are clustering, supervised classification, multi-dimensional supervised classification, anomaly detection. [10]

BNs are used to infer states of certain variables that cannot be observed, through existing knowledge. BNs are mainly used in medical diagnostics, genetic analysis or for failure analysis in production [11, 12]. Especially in Decision Support Systems (DSS) in production environments BN are applied, because they provide a quantified method for decision support. An DSS is a tool that enables users to obtain information about the production process and modify it with computer support [13]. It only supports human decision without making own decisions autonomously. At the end of the decision support, a decision is made, for example, on how to set the machine parameters or which parts need to be replaced to solve the problem. Unlike, for example, Root Cause Analysis, which makes qualitative statements about possible causes of errors [14], the calculation of state probabilities in BN makes it possible to determine a sequence of actions. This means that a sequence of the most probable causes of a fault is output, which are then processed one after the other in order to correct the corresponding fault in the most efficient way. [15]

If a BN consists of only two sets of nodes, it is called a bipartite graph. It is called complete if every single node of one set is connected to every node of the other set [16]. For error analysis of machines and processes, the two sets consist, for example, of errors and causes. An example is given in Fig. 2.

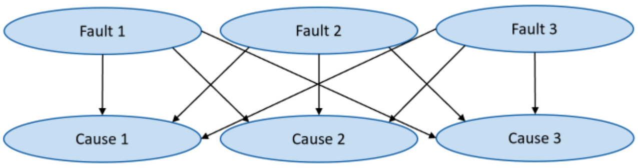

Fig. 2 Example of a complete bipartite graph

B. *Semantic technologies in production*

Cross-domain collaboration between humans and machines in production can be enabled by providing data from other sources and domains. To this end, this data must be semantically enhanced with metadata, i.e. context, so that it becomes machine-interpretable. For formal implementation, the World Wide Web Consortium (W3C) has defined standards that are applied in the Semantic Web. [17, p. 9]

One of these standards is the Resource Description Framework (RDF). The RDF model is composed of three components, Resources, Properties, and Statements. Statements are based on the subject-predicate-object principle and define the relationship between subject and object. These so-called triples can be used to create knowledge bases that enable the human- and machine-readable storage of knowledge in ontologies [17]. Ontologies in the informatic sense are systematic representations of knowledge and formalize the representation in a knowledge base [17, pp. 64-69]. Ontologies are created using, for example, RDF, or the Web Ontology Language (OWL). OWL is also a format defined by the W3C that is used to describe ontologies, as is RDF. In addition, OWL provides reasoning capabilities, among other things [17, pp. 127-128]. Ontologies are directed graphs that are created by multiple connected statements. If instances are added to the ontology, a so-called Knowledge Graph is created.

C. *Existing approaches of DSS based on bayesian networks and knowledge graphs*

There are a few approaches to implementing DSS using BN. Many of them deal with failure analysis in the engineering domain as addressed in part A. [18] Approaches that use KG and BN suggest to first extract information from the KG and databases, as well as expert knowledge to form BN. [3, 19] Especially Ungermann et al. approach is used in conceptualization and implementation.

DSS for fault analysis based on BN are for example GeNIe Modeler, BayesServer and UnBBayes [20–22]. In the existing DSS, BN are either learned from data or manually modeled. If the models are learned from data, historical data from production or patient data form the basis. Both the network itself and the network parameters are learned. If they are reproduced manually, causes, problems (symptoms) and tests are included in the model and connected. After complete modeling, the DSS allow to determine the most probable disease causing the observed symptoms or to find the most probable cause to a fault. It is also possible to determine the most useful tests to improve prognosis. However, automatic modeling of BN without past data is not possible, so that neither GeNIe Modeler nor BayesServer provide an interface to semantic models or KGs, respectively. Only UnBBayes allows a parallel modeling of KG and BN, but no possibility to automatically form a BN from an existing KG. UnBBayes

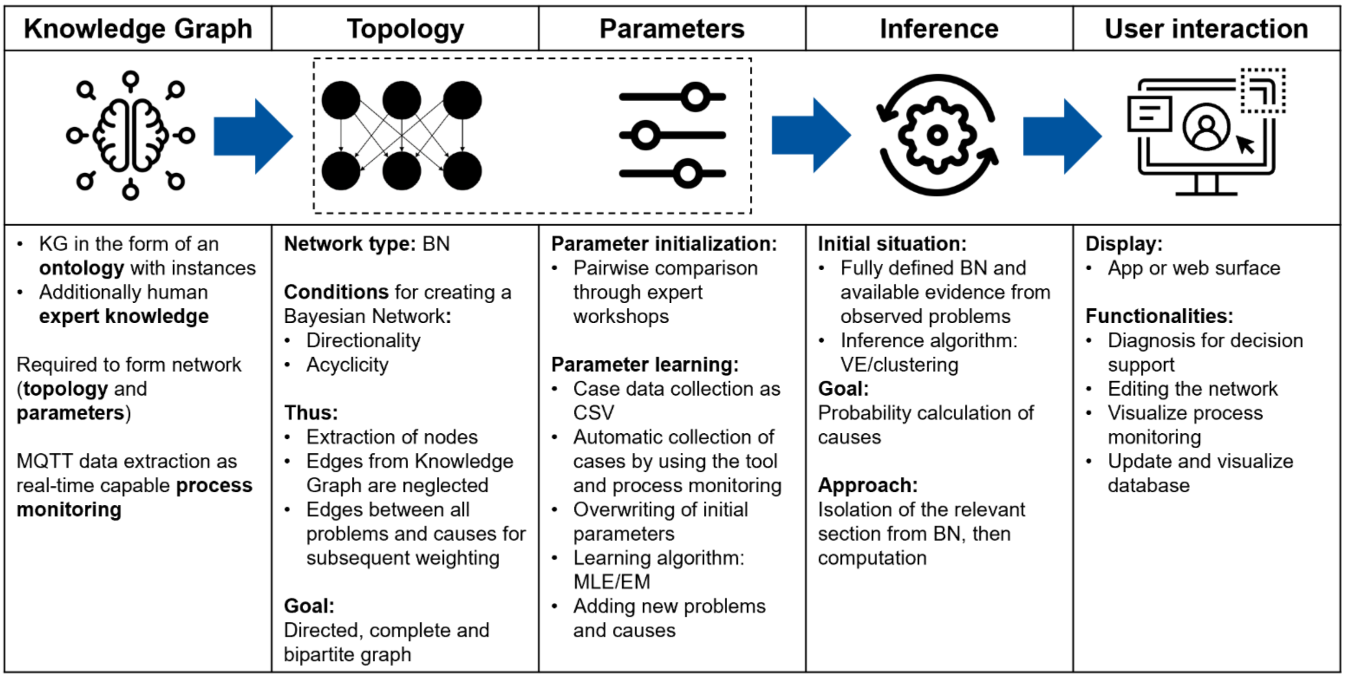

Fig. 3 Concept overview

also does not provide a user interface that can be used in the context of this work.

III. Concept Development

As shown in Fig. 3, a concept is developed to enable the transformation from any KG to a BN. The basis for this is an existing ontology enriched with process knowledge. In combination with human expert knowledge a DSS for failure analysis is generated. In addition, the DSS tool will monitor the production process live. MQTT data extraction will be used for this purpose. First, conditions for a topology, i.e., a node and edge arrangement, must be identified that allow reliable conversion from any KG to BN. These consist of:

1. Directionality
2. Acyclicity

Since KG and BN are directed graphs by definition, it is sufficient to find a provision to avoid acyclicity. In the given KG, faults and causes are instantiated from the corresponding classes “faults” and “causes”. Nodes and edges cannot be directly transferred from the KG to the BN to avoid cycles, so initially only the node sets from faults and causes are considered. The faults and causes are transformed into the form of a complete bipartite graph. For this purpose, all faults are connected to all causes, regardless of whether there is a causal relationship between them in the KG or not. By edge weighting, i.e. parameter determination, these connections are then switched on and off, as well as weighted.

This parameter determination is done in two steps. First, the parameters are initialized. For this purpose, expert workshops are held in which a preference matrix is set up by using pairwise comparison. This means that two individual causes for a fault or a fault combination are compared with each other. The more probable cause is marked. This is done for all causes and the number of markings is added up and put in relation to the total number of causes. This results in a ranking of probable causes and relative probabilities of the presence of a cause for the fault or fault combination. These relative probabilities are not to be seen absolutely, but allow a qualitative gradation of the cause probabilities. This makes it possible to recommend a correct sequence of actions to correct the fault, even if the probabilities calculated in the BN are not yet completely correct.

These probabilities are corrected by improving the parameters with data. For this purpose, case data are stored in a CSV file. Case data contains information about the errors that occurred, i.e. the evidence and the actual causes responsible for them. These are determined, for example, by workers during cause correction. Each time the diagnostic tool is used for failure analysis, these cases can be entered. In addition, cases are entered if errors were noticed by the MQTT process monitoring. For this purpose, MQTT messages are received from the subprocess steps and checked for errors in sequence or duration until the next message at the beginning or end of a subprocess step. If, for example, a sub-process is not initiated due to faulty communication with the controller, the cause of this, a network failure for example, can be detected. As a result of the fault detection, the DSS tool is automatically started to find the causes.

Using the CSV file, the parameters are then learned by applying Maximum Likelihood Estimator or Expectation Maximization to them. These algorithms determine the parameters in such a way as to maximize the probability of having generated the data at hand.

In the inference step, the completely defined BN including parameters is provided. Since the set of errors and causes can be very large, only the relevant errors and causes are obtained by clustering algorithms, for example variable elimination. This means that all unobserved faults are neglected and thus removed from the BN. Also causes, to the errors whose edges are weighted low by the parameter determination, are removed algorithmically. The principle is illustrated in Fig. 4. Possible faults are in the upper row and possible causes is the lower one.

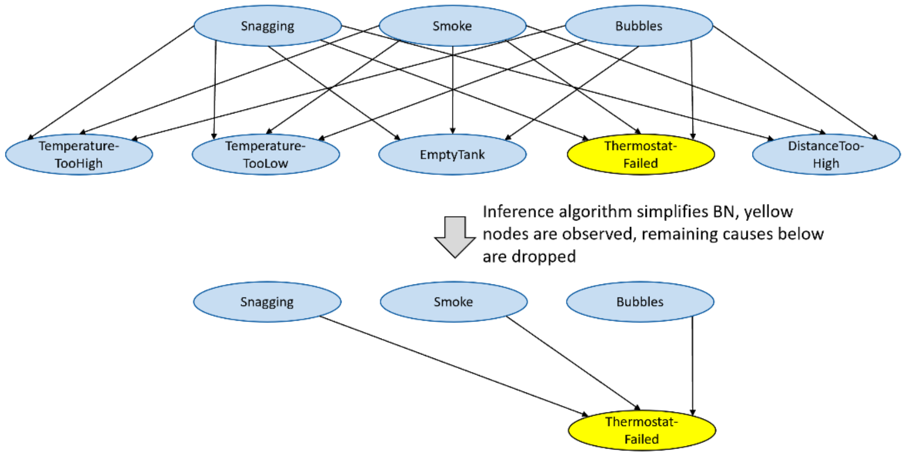

Fig. 4 BN simplification for given evidence

Subsequently, the computational steps from II.A are applied and the probability of occurrence is determined for each cause.

These calculated probabilities can then be graded and visualized in a user interface. This can be done on a web interface, for example. In addition, new errors and causes can be entered there that have not been observed before. Their parameters are initialized in such a way that all edge weights are very low, since they have never been observed before. Only after multiple occurrences and parameter learning, these weights are automatically increased. Furthermore, the user interface offers different possibilities to visualize the case data and to illustrate the process monitoring.

IV. Implementation and Validation

A. Demonstration scenario

The concept is applied in a robotic sub-process used in the assembly of glass panes for car windows, as shown in Fig. 5.

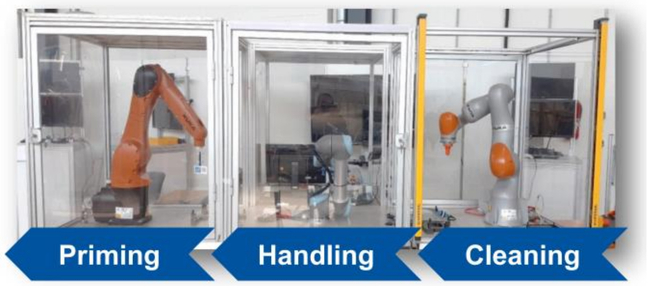

Fig. 5 Robot-based glass pane completion use case

In the first step of the process, a rear side window of a vehicle lying in a magazine is gripped by the so-called handler. The handler, a Universal Robot UR5 robotic arm with suction cups attachment, moves to the magazine and lifts out a pane after applying the negative pressure. This disc is moved to the cleaner cell where the disc is cleaned for adhesive application. In this step, the edge of the disc is swept by the Kuka Iiwa robot arm. During cleaning, the disc is held in place by a suction device. Then the handler picks up the pane again and moves it to the primer cell, where a KUKA Agilus KR6 R900 fivve drives along the edge of the pane using a gluing device with glue feed. The disk is held in the same way as in the cleaner cell. Finally, the pane is placed back into a magazine. The sub-process as described fits into the body assembly, which in turn is part of the assembly process of a truck.

The implementation is based on an ontology that was created in previous work. It contains information that is used for process time optimization as well as for finding causes for gluing faults. This means that in the ontology possible causes and solutions are connected with the corresponding gluing faults. However, there is no probabilistic assessment of the correlation level, which is why the process diagnosis tool has been developed. In Fig. 6 an excerpt from the ontology is shown.

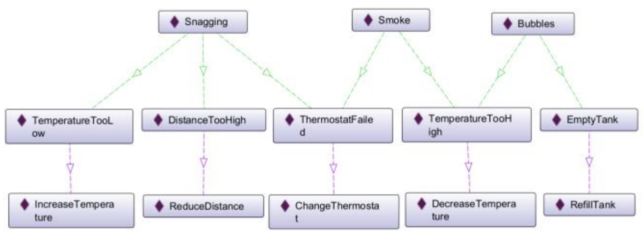

Fig. 6 Except from given ontology

In the ontology, possible gluing problems are given in the top row, possible causes in the middle, and solutions below. The connection between fault to cause is especially relevant.

B. Process diagnosis tool

The process diagnostic tool is the implementation for the DSS for finding the causes of faults. In the given ontology, only possible faults and causes resulting from gluing are specified. However, other failures such as process failures can also occur. For example, if the handler fails, it must be possible to determine the cause for this as well. For this purpose, the ontology was extended by classes and instances of the sub processes.

Fig. 7 shows the main function with the fault diagnosis. By using the previously defined BN, the probabilities for the error combination "Bubbles" and "Smoke", which can occur during the gluing process, are calculated. There is also the possibility to add new problems and causes. The parameters of the new nodes are initialized automatically and all edge weights are set to low as they have never been observed before.

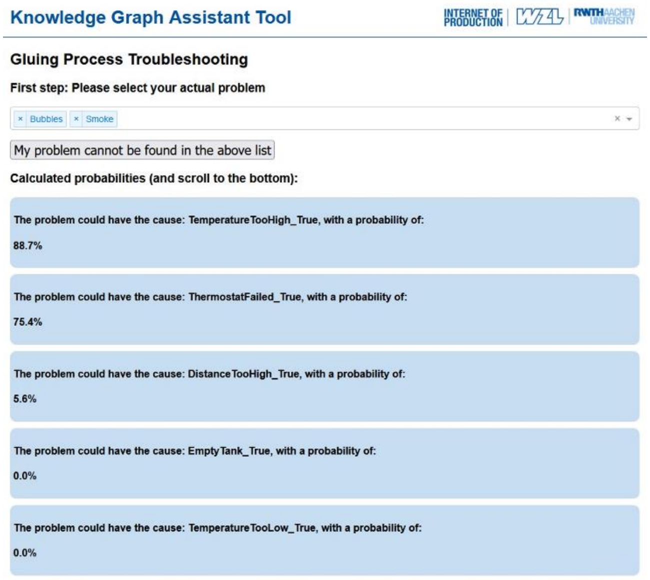

Fig. 7 Calculation of probabilities for causes of gluing fault

V. Summary and Outlook

In the context of this work, a concept for a smart failure diagnosis based on a combination of Bayesian networks and knowledge graphs was developed. The developed concept provides the framework for transferring any Knowledge Graphs based on OWL ontologies into Bayesian networks. For this purpose, the structure of the Bayesian network was defined as a complete, directed, bipartite graph to ensure compliance with the identified conditions of acyclicity and directedness. Furthermore, an objective parameter initialization method was developed through pairwise comparison to complete the network. In this step, expert knowledge is preserved. Additionally, an approach for storing case data was developed to improve the parameters and digitally evolve expert knowledge, so that an overall process performance can be approved by reducing reconfiguration time Furthermore, real-time process monitoring capability was established through MQTT data extraction. This enables the identification and treatment of process errors at the moment they occur. A framework was also created for investigating the causes of quality defects or process errors by suggesting a sequence of actions that lists and prioritizes potential causes. For this purpose, inference and learning algorithms were selected.

In future work, it could be advantageous to extend the diagnosis tool by all the available information of the control processes, such as sub steps of control actions. In the process monitoring through MQTT, not all incoming messages were analyzed, but only those at the beginning and end of the actions of individual cells. This way, the diagnostic tool can provide even better decision support. The number of errors and issues should also be expanded for the same reason, for which the prerequisites have been created. Furthermore, the algorithm is to be used as part of the assistance system to be developed for knowledge-based control process reconfiguration, in the context of the scientific project described above.

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