Cloud-based Control Approach in Discrete Manufacturing Using a Self-Learning Architecture

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Abstract: Process anomalies and fluctuations in product quality are widespread problems in discrete manufacturing. There have been various control approaches to tackle the challenge. This paper presents a cross-process control approach that combines engineering knowledge and data analytics techniques. An initial rule basis is generated by experts using simulation models. To achieve a data driven enhancement concerning process and product quality, a PLC-based connector is developed to record and unify real process data from heterogeneous data sources. The data is processed in the cloud and inferred using online modeling techniques. Neural networks with autoencoder structure are applied to extract unknown features, to iteratively refine the knowledge base and thus to optimize quality control.

Keywords: Data fusion and data mining; Process control, manufacturing; Intelligent systems and instrumentation (smart systems, sensors, actuators and distributed systems)

1. INTRODUCTION

Unexpected failures and abnormal behavior of manufacturing systems and processes are problems that lead to increased machine downtimes and fluctuant product quality. A better understanding of the system's behavior with the aid of data is the key to improve reliability and process stability. Smart data acquisition infrastructures, e.g. intelligent sensor networks and smart tag technologies, enable data driven modeling, cloud-based control and optimization of processes, systems and quality. Recent approaches focus on self-learning techniques to extract features and to discover knowledge within data. The approaches show decent results concerning single processes and systems but do not consider sets of multiple interconnected processes. Due to the fact that potential interdependencies between processes are not captured adequately, the approaches lack in precision and extensibility for high-dimensional systems.

This paper presents an approach that differs from previous self-learning approaches in four concerns. Firstly, expert knowledge from process engineers is transformed and integrated in the data driven system modeling. An inference system is used to reason on the basis of the rule-based knowledge. Secondly, a chain of interdependent processes is considered. Thus, interconnected multidimensional data models are generated to represent processes. The models are the basis to apply the inference system and to control the whole process chain. Thirdly, new knowledge gained from data analytics with recurrent neural networks is used to refine the knowledge base. The neural networks are trained to reduce dimensionality and to extract features which represent abnormal behavior. Fourthly, the proposed system is constructed as cloud-based architecture that enables the multi-loop control of the process chain.

This paper is organized as follows. Section 2 overviews the state of the art and points out the general approach. Section 3 proposes a generic data acquisition and data modeling concept that enables flexible cloud-based data processing. Section 4 introduces the self-learning control system and its components. Furthermore, the generation of an initial rule basis with expert knowledge from metal forming is described. The paper is concluded in section 5.

2. STATE OF THE ART

2.1 Knowledge-based and Self-learning Systems

Knowledge-based systems have been widely used in control and manufacturing. These systems are often realized in terms of inference systems due to the fact that linguistic expert knowledge can be integrated. There have been various application-oriented extensions over the last years. For instance, Tettey and Marwala (2006) developed a method to extract and translate fuzzy rules for transparent interpretation. Hence, the forecast of conflicts occurring in automation systems could be enhanced. Mahdaoui et al. (2012) uses computational intelligence techniques, e.g. a temporal fuzzy inference system (FIS), to improve online control and fault diagnosis of manufacturing systems. Bramhane et al. (2014) utilizes a neuro-fuzzy system (NFS) to control logistic processes between various manufacturing systems and to optimize the priority scheduling of incoming jobs.

To refine knowledge and to gain new knowledge from large amounts of process data, inference systems are further extended and coupled with big data analytics techniques. The root cause analysis proposed in Abele et al. (2013) consists of two separate layers, namely a knowledge-based layer and a machine learning layer. A predefined rule basis is continuously refined using a Bayesian classifier. Denkena and Dittrich (2016) present a self-optimizing system for industrial cutting processes that refines expert knowledge based on support vector machines. In Andonovski et al. (2016) a mechanism for the identification of sparsely active and less informative rules is presented. The knowledge basis is frequently updated based on the density structure of the recorded data.

2.2 Control Approaches in Discrete Manufacturing

To combine knowledge-based and self-learning approaches and to apply them to the field of discrete manufacturing, alignments and further extensions have to be undertaken to incorporate domain-specific surrounding conditions. There have been studies to use the aforementioned concepts in automatic control of discrete manufacturing process chains. Endelt et al. (2010) presents an iterative learning and control approach (ILC) that aims to reduce long-term disturbances and failures along a process chain. Two control loops are defined, namely an inner loop that controls during processing and an outer loop that incrementally learns from part to part.

Allwood et al. (2016) present well-founded research in the specific field of automatic control in metal forming. Metal forming is characterized by uncertainty due to parameter variation and unknown process relations. Product quality parameters are the controlled variables that are adjusted applying a closed-loop approach. Havinga et al. (2014) and Fischer et al. (2016) research the optimal control strategy for the quality outcome depending on material properties but failed to establish a self-learning control architecture. Consequently, this paper introduces a remote and self-learning control architecture in discrete manufacturing that unites expert knowledge as well as data analytics techniques and realizes a cross-process control.

2.3 General Approach

There are various well-researched control approaches in discrete manufacturing that are applied to single processes, e.g. Endelt and Volk (2013). The major contribution of this paper is the concept and implementation of a cross-process control applied to a set of interconnected processes. There are several challenges that occur. To connect processes along a process chain, data has to be retrieved from single measuring units and has to be transferred and merged on an external server that runs the controller. Thus, a generic data acquisition concept is needed to deal with the variety of data sources in the field level. This paper introduces a connector that tackles this challenge. On this basis, we propose a cloud-based approach that includes a multidimensional modeling concept to process the data. To achieve an accurate control, engineering knowledge and data analytics techniques are combined in one system. Engineering knowledge is formalized and an inference system is used for deductive reasoning. Neural networks are utilized to extract new knowledge from recorded data. The system is tested with a model process chain in metal forming. It consists of an initial preparation of raw material, heating, two-step hot forging including preforming operation, cooling and quality control. The control strategies can be realized "real-time" (the same part), "inline" (the next part) and "offline" (future parts). The architecture of the cloud-based system and the synergy of its components are depict in figure 1.

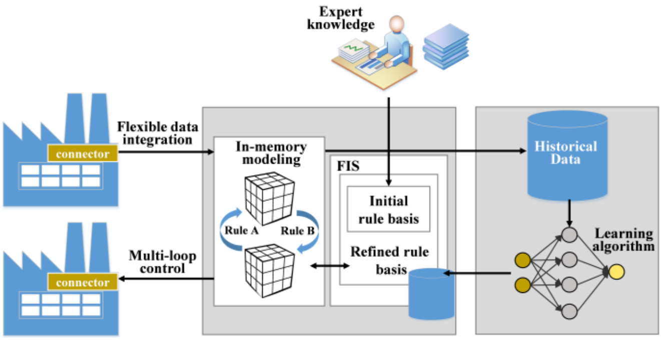


Fig. 1. Overview of the system architecture.

3. DATA ACQUISITION AND MODELING

3.1 Remote Sensor Data Acquisition

Endelt et al. (2013) identify the ability to sample highly accurate process data as a limitation in the industrial implementation of advanced and learning control algorithms. The heterogeneity of data sources is a major challenge that has to be tackled. Hence, we propose a connector to extract data from different data sources in the field level and to uniformly transfer the collected data to the cloud. The connector consists of two parts. The first part provides an individual interface for each data source and the second one provides a standardized interface to further process the data. The concept rests on the work of Faul et al. (2016).

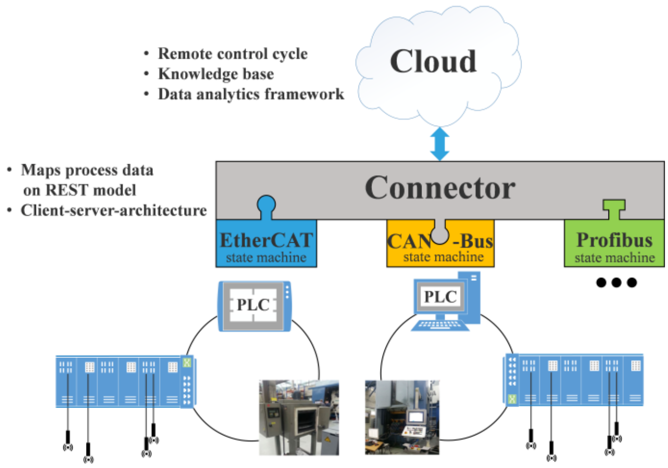


Fig. 2. Realization of the remote data acquisition.

The connector is realized in a distributed architecture where individual interfaces run on control devices and the standardized interface runs in the cloud. The individual interface is implemented as Mealy machine being cyclically called by the PLC. The „read“-state is individually implemented depending on the bus system. It scans the protocol structure and separates data and metadata. To capture and store the data for further processing, extracted input and output signals are mapped to global variables. The „write“-state cyclically posts all variables to the external server by using a generic REST model. The major part of process data recorded from manufacturing systems is time series data. Thus, sensor values are converted and mapped onto the REST model containing time stamp, metadata and the corresponding data alternately. This component can be reused. The standardized interface runs in the cloud and forwards the data according to the cycle time of the PLC (every 7ms). The time span between the conduction of two consecutive process steps eases time requirements. The realization is depict in figure 2.

3.2 Multidimensional Modeling and Flexible ETL-Stack

In this paper, a multidimensional modeling approach based on online analytical processing (OLAP) is applied to handle process data in the cloud. It extends the approach described in Shin et al. (2014). The multidimensional model includes dimensions that consist of an internal, hierarchical structure. The branching of each structure path is described by an element. The granularity of the description increases with hierarchy depth. The innermost layer of a dimension contains basic elements that are associated with data vectors. Heterogeneous data can be integrated into one homogeneous model due to the fact that different layers with different granularities can be connected. The modeling approach is visualized as cube in figure 3. The possibility of an automated integration of multiple process steps and the corresponding data structures marks an important factor regarding the flexibility of the whole data processing system. Hence, an ETL stack (Extract - Transform - Load) is implemented based on three fundamental dimensions, namely time, space and product information.

The product information dimension covers order, batch and product identification number as well as product type.

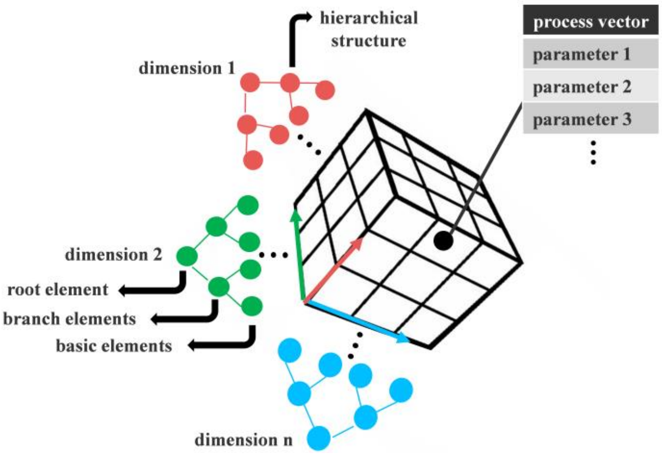


Fig. 3. Multidimensional modeling of process data.

In case of a new product being produced on a different production route, the ETL stack maps the new information on the hierarchical dimension structures. As a result of the mapping process, new elements are generated within the hierarchy for the identified changes, namely the product type. The corresponding process data is assigned to the new subspace of the cube respectively. The integration of new data is flexible due to the generic REST model and the described projection on the overarching dimensions. Therefore, different process data structures of varying product types can be adapted by the ETL stack. The same flexibility applies to any other element of any other layer in the hierarchical dimension structure. Hence, the data cube extends itself and adapts changes automatically based on the extracted metadata. The whole ETL process is cyclically executed and GPU-supported to enable parallel computing. Thus, ad-hoc calculations on the models and online data processing can be realized.

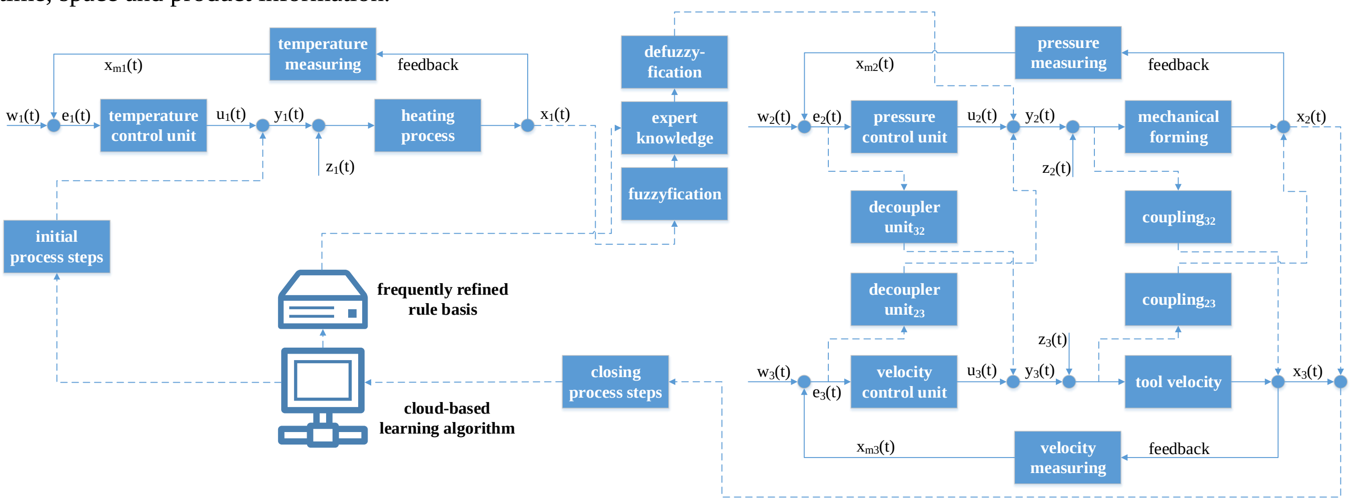


Fig. 4. Control logic and FIS: Example of heating and forming process with multiple inputs and outputs to the system.

4. SELF-LEARNING CONTROL ARCHITECTURE

In this chapter, a novel self-learning control approach in discrete manufacturing is introduced. Firstly, an approach to combine online data processing (chapter 3) and FIS-based control is presented. Secondly, a rule basis is defined and integrated in the modeling system. Subsequently, a multi-loop control architecture is constructed as depict in figure 4. Thirdly, the rule-based control is extended by new knowledge from data analytics. General regression neural networks (GRNN) with recurrences based on radial basis functions are applied on the pre-structured data.

4.1 Combining Online Modeling and FIS

To tackle the initially mentioned challenges concerning interdependencies between processes, multidimensional data models are connected through a joint rule basis. The multidimensional approach allows the separate modeling of each process, system or subsystem. A set of data models which represent subsystems of a system can be composed to generate the model of the system. Inversely, process specific information can be separated from a process chain model. The concept is illustrated in figure 5.

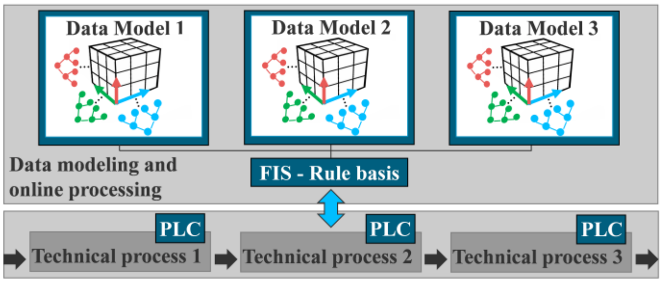


Fig. 5. Digital twins of interconnected process steps.

To assign specific properties to the cube data, we define a separate cube that serves as metamodel. This meta cube consists of the same multidimensional and hierarchical structures as the original data cube. Each cell of the cube contains an n-dimensional vector that defines n properties assigned to the data in the corresponding cell of the original cube. Thus, we are able to define specific thresholds, complex rules or any other properties for all hierarchical layers of the model. This circumstance enables the integration of expert knowledge. Consequently, a FIS is designed that is predicated on the multidimensional modeling approach and is inspired by the vector and matrix control strategy of Mihai (2008). The multidimensional data structure is predestined to construct control systems with multiple inputs and outputs. The control logic is illustrated in figure 4. The FIS connects the inner control loops of single processes, e.g. heating and forming process. It controls various measures resulting in a multi-loop control cycle. The rule premises and conclusions include logic expressions consisting of elements of various hierarchical levels. Accordingly, the proposed rules can be formalized as follows:

$$\mu_I[\vec{x}(n), w, \vec{y}(n)] = \mu_P[x_1(n), \ldots, x_m(n)] \cdot w \cdot \mu_C[\vec{y}(n)]. \tag{1}$$

Expression μ_P denotes the composition of fuzzy sets described by an m-digit membership function. It is the premise set, μ_C the fuzzy conclusion set, w the weight, $\vec{x}(n)$ the input and $\vec{y}(n)$ the output parameters. The interference set μ_I is generated using compositions $\cdot$. The membership functions are radial basis functions:

$$f_{act}(f_{in}[\vec{x}(n)]) = 0{,}5 \cdot \left(1 + \cos\left(\frac{f_{in}[\vec{x}(n)] - (r_1 - r_2)}{2r_2}\pi\right)\right). \tag{2}$$

It applies to the input space of $r_1 - r_2 \le f_{in}[\vec{x}(n)] < r_1 + r_2$ and describes one side of the symmetric function. Parameter $x_i(n)$ denotes the input value i of part n, r_1 determines the upper inflection point of the cosine and r_2 the length corresponding to 90°. The values in the border areas are 1 for $f_{in}[\vec{x}(n)] < r_1 - r_2$ and 0 for $f_{in}[\vec{x}(n)] \ge r_1 + r_2$.

4.2 Integration of Expert Knowledge

Control logic for discrete manufacturing processes such as forming processes is basically based on a metamodel which is constructed using finite element simulations of the process. The approach rests on Bonte et al. (2007). Since a metal forming process is highly nonlinear it is difficult to build a corresponding model in terms of differential equations. For processes of the process chain which have a reduced number of parameters, fit-functions can be used as representative models if satisfactory fitting functions are available.

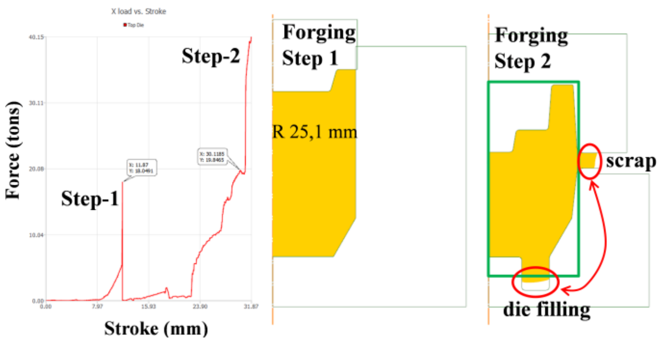
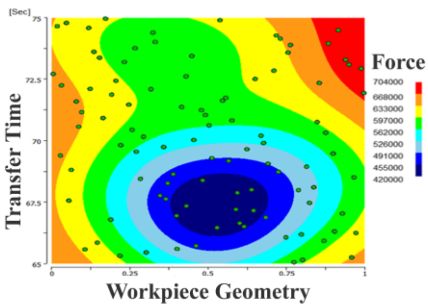


Fig. 6. Above: Finite element simulation of the forming process. Below: Result of parameter variation.



As an example for the complex process behaviour, the result of the finite element simulations in figure 6 can be considered. The aluminium material has a strain rate dependent behaviour in hot forming conditions. The die filling is a quality criterion for the success of the process. In an unexpected manner the amount of die filling can be controlled purely by controlling the forging speed. In general, the behaviour of the whole system can be represented by value-n-tuples discretely covering the scattered values of input parameters and realisable ranges for actuated variables. This general data set can be used to build a metamodel of the process.

The creation of the initial data set for the metamodel is based on the simulation of the process chain which has inbuilt sensors and actors in a similar manner as the real system. The hydraulic press allows alteration of punch displacement and velocity for each part. Automated execution of the designed virtual experiments is possible by the DEFORM finite element simulation program. In figure 6 maximum tool forces are demonstrated in colour with respect to workpiece size and transfer time from one forming station to another including geometry measurement with laser profilometer and lubrication time. Process parameters are varied within the allowed range. Since the tool loading is important in getting higher tool life, it could be logical to control the process such that the parameters remain within the ranges where maximum tool forces are low (blue regions). Such rules and further an initial rule basis can be retrieved from the metamodel data set. To enhance the system's performance in terms of accuracy, new knowledge is extracted from real sensor data using a neural network with autoencoder structure.

4.3 Integration of New Knowledge

The integration of new knowledge extracted by GRNN is conducted by extending an iterative algorithm that is proposed by Fischer et al. (2009). The initial input to the algorithm is the rule basis created in chapter 4.2. To refine the nonlinear approximation, the loading of existing rules compared to new findings is referenced. All predefined rules are weighted according to their degree of certainty. The certainty is described in terms of an equivalent number of samples.

The relation between recorded in- and outputs consist of a stochastic nonlinear and a systematic nonlinear portion that we intend to approximate. The following expression describes the estimated output for a cluster center:

$$y_{i\_new}[c_i(\vec{x})] = \frac{\sum_{k=1}^{s-1} w_k \cdot y_{i\_old}[c_i(\vec{x})] + w_{meas} \cdot y_{meas}}{\sum_{k=1}^{s-1} w_k + w_{meas}}. \qquad (1)$$

Parameter c_i marks the center of cluster i, $\vec{x}$ the measured input data, s the number of corresponding samples, w_k / w_{meas} the weights and y_{i_old} / y_{i_new} the nonlinear approximation before and after the integration of new knowledge. Nonlinearities are described using a normalized distribution A_i, following Rau (2003). The normalization improves the approximation accuracy due to a better monotonicity behaviour. The output values are calculated based on all current clusters p that are weighted with b:

$$y_i[\vec{x}(n)] = \vec{b}A_i[\vec{x}(n)] \text{ with } A_i = \frac{f_{act}(f_{in}[\vec{x}(n)])_i}{\sum_{k=1}^{p} f_{act}(f_{in}[\vec{x}(n)])_k}. \qquad (2)$$

The method completes three steps to integrate new knowledge: affected outputs are transformed into m deterministic outputs according to the current number of fuzzy conclusions. Consequently, the new relation is separated into m relations. The new conclusion values are calculated according to (1) and integrated in the knowledge base. The second step is the recalculation of weights after a denormalization. To conclude, the cluster centers are recalculated using weights and input vectors from the data sample. This step can cause the creation and deletion of rules. Thus, the knowledge base is refined and an adaptive and self-learning control is achieved.

4.4 Empirical Results

Figure 7 shows the time course of the pressure that is generated from pumps of the press during the forging process (green line). The accuracy of the pumps is one essential factor being responsible for the quality of process and product. Thus, a slinking deviation from the normal behaviour over time is a main driver for quality fluctuations and has to be adapted for an optimal control along the process chain. A deviation extracted from real sensor data is depict by the violet line. The real sensor data has a size of 1 TB. The main part of the data represents healthy machine conditions apart from the mentioned course. Additionally, artificial anomaly scenarios that occurred in the past and that have been manually examined by experts are integrated (red, blue, black, magenta) to further validate the approach.

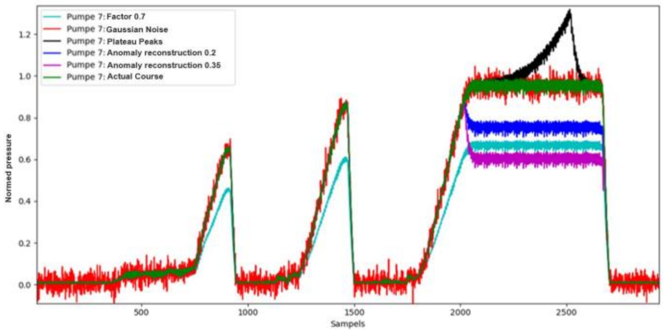


Fig. 7. Measured pressure (green), measured anomaly (violet) and artificial anomalies (other colours) of one cycle.

Based on the described data set a GRNN with autoencoder structure is applied to learn a model and to integrate the new knowledge using the algorithm described in chapter 4.3. The empirical results are shown in figure 8 and 9. Figure 8 depicts the reconstruction error of the learned model with test data from the described anomaly scenarios. Figure 9 illustrates the capability of the optimized knowledge base to detect the slinking deviation process. The anomaly linearly increased over 30 days to the final shape (blue, right). The according response of the model is depict on the left and shows an exponential behaviour over time. The flat line on the left is the model response in case of no anomaly. Due to the refined knowledge base, an optimized adjustment of the actuating variables of the process and consecutive process steps is possible depending on the model output.

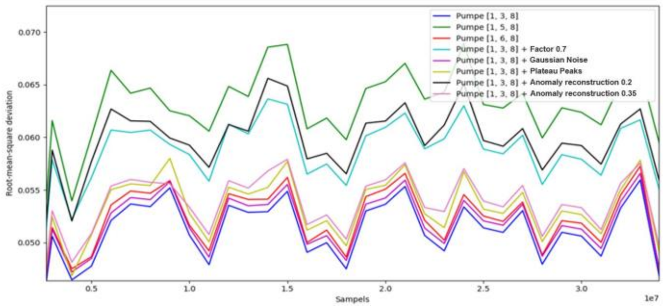


Fig. 8. Averaged reconstruction error over time sequences of the described anomaly scenarios.

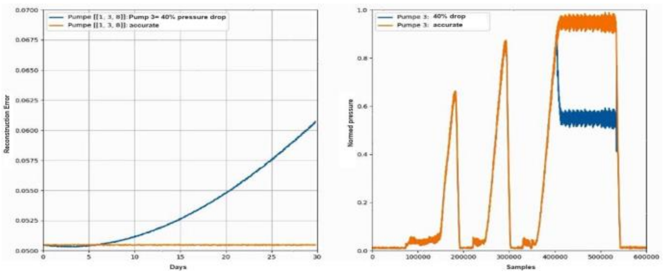


Fig. 9. Slinking deviation over time (blue, right) and normal behaviour (orange, right) and the model output (left).

5. CONCLUSION AND FUTURE WORK

The present paper focused on designing a novel self-learning assistance system in discrete manufacturing. The whole system and its components, namely the connector, the online modelling and the learning structure, have been tested successfully. Empirical results using the explained learning structure underline the capability of the described approach. The main finding is an exponentially behaving sensitivity of autoencoder structures based on linearly behaving anomalies. In future work, the proposed approach will be further tested on larger data sets considering including a wider range of abnormal process behaviour that we intend to control.

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