View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by Technische Universität Dresden: Qucosa

peer reviewed

PREDICTIVE MAINTENANCE WITH A MINIMUM OF SENSORS USING PNEUMATIC CLAMPS AS AN EXAMPLE

Wolfgang Gauchel*, Thilo Streichert, Yannick Wilhelm

Festo AG & Co. KG, Ruiter Straße 82, 73734 Esslingen, Germany

* Corresponding author: E-mail address: wolfgang.gauchel@festo.com

ABSTRACT

In standard pneumatics, the available signals for data analytics are very limited. As a rule, no continuous status information is available. Usually only the reaching of the end position is indicated - by means of a digital signal of a proximity sensor. This paper examines whether these limited data can be used to derive usable and useful information for predictive maintenance. Pneumatic clamps in body-in-white construction were chosen as application example. The paper describes a continuous run to investigate the basic feasibility of predictability. In the following chapters, possibilities for error classification are discussed. Finally, the implementation of the findings in a field test is described.

Keywords: Predictive Maintenenace, Clamping Units, Pneumatics

1. INTRODUCTION AND PROBLEM DESCRIPTION

In the course of digitization the automation world, predictive maintenance is becoming more and more important. Thanks to continuous measurement and analysis, predictive maintenance makes it possible to forecast the remaining service life of machine components [1].

One of the most promising approaches to realize predictive maintenance is machine learning. Machine learning deals with algorithms, that learn from data and predict outcomes that will occur with a certain probability [2].

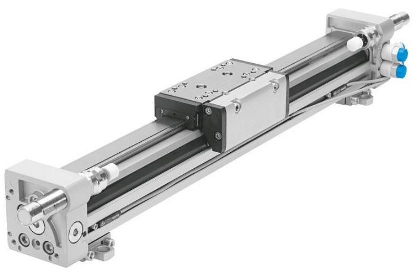

Figure 1: Typical sensor equipment in pneumatics: Linear drives DGC with two proximity sensors SMT.

This paper focuses on the question, whether a maintenance requirement for pneumatic standard systems using a minimum of sensors can be predicted with the help of machine learning algorithms. A double acting cylinder is normally equipped with an proximity sensor in every end position (cp. **Figure 1**). Does such a system with a minimum of sensors generate enough data, containing sufficient information about the health state of the underlying process and component so that is applicable for predictive maintenance?

From the perspective of control engineering, this is rather not possible. A system consisting of two limit switches cannot be observed.

A system is called observable if the initial value of the system state at the beginning of the time interval can be calculated from the temporal course of the output and input signals in a finite period of time [3]. If this holds for any initial state and not only for a limited set of initial states, the system is called complete observable [3, 4]. (Föllinger [4] supplements this definition by a "no matter where this [initial state] lies").

It is obvious that this definition is not fulfilled by a pneumatic cylinder with only two proximity sensors. If, for example, the initial state is somewhere in the motion phase, the first information one receives about the system state is reaching the next end position - i.e. location information at a defined point in time. With this information however, it is not possible to calculate in which position the cylinder has started or even which pressures were prevailing in the cylinder chambers at the start time. An observability of the considered pneumatic system is therefore not given. The “free flight” between the end positions without any sensor information makes observation impossible.

However, it should be noted that this definition of observability is based on a classical control engineering understanding of a system model. This assumes, that state variables such as pressure or position can be described continuously over time. Another type of model, in which e.g. only the average travel speed is described, can be derived from the existing digital signals. This raises the question whether a prediction of possible failures is possible based on such rudimentary observability.

To investigate this, chapter 2 describes the state of the art in predictive maintenance. In chapter 3, the selected application example - pneumatic clamps in body-in-white construction - is explained. Chapter 4 describes an endurance run with pneumatic clamps in order to fulfill the basic proof of predictibility. To generate useful information for maintenance personnel in addition to a simple "there is a risk of failure", chapter 5 deals with possibilities for fault localization. Finally, chapter 6 describes a field test in automotive production. The paper ends with a summary and outlook in chapter 7.

2. STATE OF THE ART IN PREDICTIVE MAINTENANCE TECHNOLOGY

Predictive maintenance is a subgroup of condition-based maintenance, in which known operating conditions, that can lead to condition changes, are preferentially monitored and corrected after detection with the objective of preventing machine failures. The changing operating conditions are identified by root cause analysis. Before faulty operating conditions can be diagnosed, anomalous process states and failures must be detected by comparing them to a normal reference condition (fault detection) [5, 6].

Subsequently the fault diagnosis identifies the type of the fault, localizes the fault in the system and quantifies the magnitude of the fault effect [5, 6].

Fault detection and fault diagnosis for pneumatic actuators using sensor systems is a well-known topic in scientific literature. In [7] the dynamic performance of an industrial globe control valve unit is monitored via a temperature sensor, a pressure transducer, a displacement sensor and a flow transmitter. For fault diagnosis they analyze waveform characteristics based on main statistical properties of the data, captured by the sensors. Subbaraj and Kannapiran investigated fault detection in pneumatic actuator valves for cooler water spray systems in cement industry by using principle component analysis for input feature dimension reduction [8] and an artificial neural network (ANN) model for classification [8, 9]. Further investigations on fault detection for pneumatic actuators in control valves using ANNs are described in [10, 11]. In [12] three different types of cylinder leakages are considered by an ANN approach to predict the leakage orifice. The input features are captured by two proximity sensors, one working pressure sensor, two pressure transducers in each cylinder chamber and a differential pressure transducer for air flow determination. Mahmoud et al. [13] use sensor-detected acoustic emissions of microstructural changes in the material of pneumatic cylinders for condition monitoring. The average energy of the acoustic emission signal is used as metric for fault detection. None of these works investigated a minimal sensor use, consisting of only two proximity sensors at the end positions of a linear pneumatic cylinder towards the practicability of predictive maintenance.

Predictive maintenance is not only a relevant topic in the scientific world, also many companies have already presented solutions or offer corresponding products. Examples at component level are the monitoring of roller bearings [14], plastic plain bearings and drag chains [14] as well as pumps [16] or electric motors [16, 17]. What all these examples have in common is, that sensors are available for condition monitoring, some of which are even supplemented separately. An example is the addition of a sound sensor [18].

Pneumatic companies also have shown first examples for predictive maintenance, e.g. the monitoring of shock absorber functions or cylinder speeds based on an electro-pneumatic valve system [19]. In this case, only the digital information of a standard pneumatic system is used.

3. APPLICATION EXAMPLE PNEUMATIC CLAMPS

Pneumatic clamping systems were selected as an application example to investigate whether sufficient data is available in standard pneumatics that allow statements about the operating conditions of the drive system. Such clamps are widely used in body-in-white construction (cp. **Figure 2**). From a pneumatic point of view clamps are double acting cylinders with oval piston. The piston is part of a toggle joint mechanism (cp. **Figure 3**).

Clamps are an interesting example, because the price pressure for such pneumatic components is very high. The willingness of automobile manufacturers to pay for additional sensor technology for the clamps tends towards zero. That’s why in the foreseeable future the minimum sensor technology will be installed only. On the other hand, a plant shutdown is very expensive for manufacturers due to the loss of production.

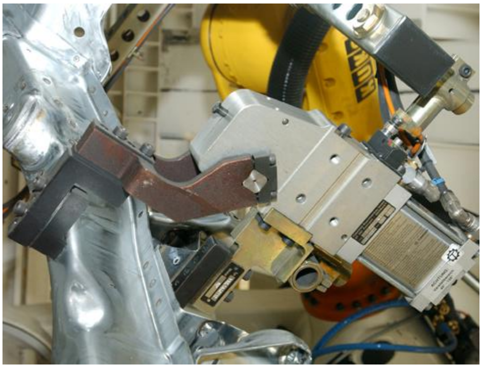

Figure 2: Pneumatic clamps in body-in-white construction [20].

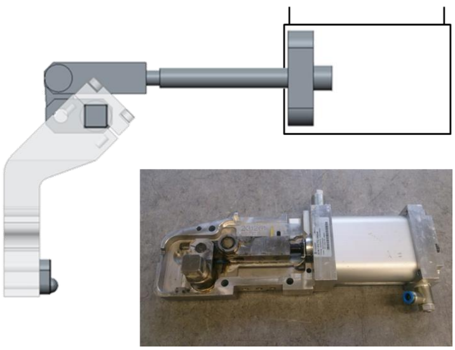

Figure 3: Structure of a pneumatic toggle level clamp.

Furthermore, clamping units offer relatively clearly defined conditions: All clamps perform a very similar movement, the main differences in the clamps lie in the size, the angle range and the clamping arm used. Thus, the application example is very suitable for investigating and generalizing the feasibility of predictive maintenance for pneumatic linear actuators with a minimal sensor use.

4. ENDURANCE TEST WITH CLAMPING UNITS

In a first step, an endurance run was started in which a total of six clamps were tested until end of life (cp. **Figure 4**). The recorded data was used to determine whether any changes in the available data could be detected before a failure. And if so, how far in advance.

Figure 4: Picture of endurance test with six clamps.

In **Figure 5** the corresponding circuit diagram of the endurance run is depicted. It shows that the six clamps are only controlled by three valves. The first valve switches one clamp, the second valve switches two clamps and the third valve switches three clamps. This is quite common in real body-in-white production. Here, one valve controls a number of 1 to 7 clamps.

Only the valve shifting signal and the two signals from the proximity sensors are included in the signal evaluation for each clamp. Two times each for closing and opening the clamp can be derived from these three digital signals, thus in sum four times (cp. **Figure 6**).

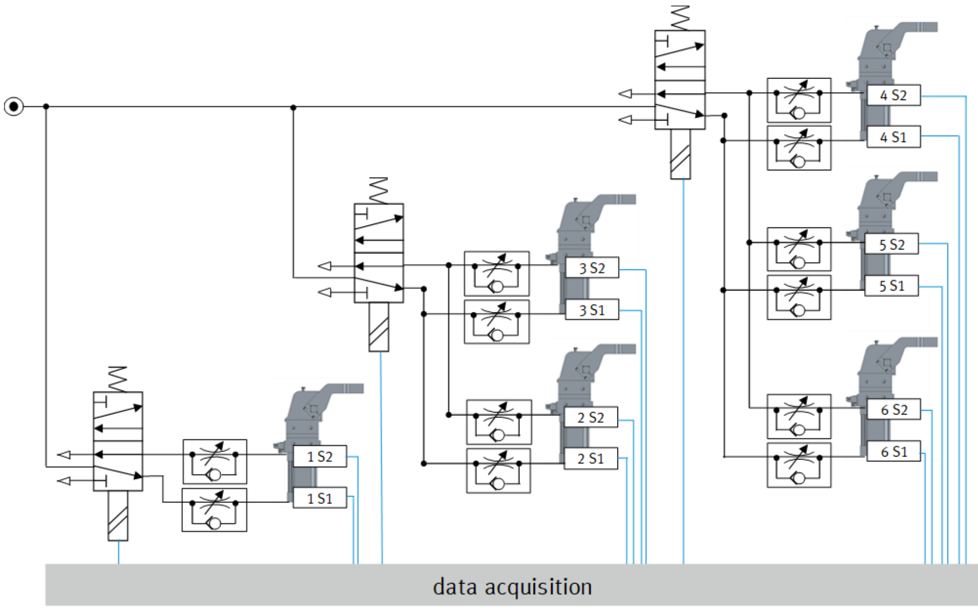

Figure 5: Circuit diagram and data acquisition of endurance test.

- The **reaction time** is the time between the valve signal and leaving the first end position.
- The **travelling time** is the time between leaving the first end position and reaching the second end position.

The results of this endurance run can be summarized as followed: With a lead time of 2 to 4 days changes occur in the four times described. As an example, **Figure 7** shows the signal characteristics of the travelling times for closing (extracting of clamp) and opening (retracting of clamp) before failure. Minimum, maximum and mean values are given for each direction.

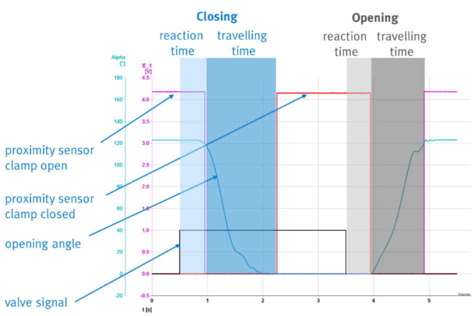

Figure 6: Time definitions.

The endurance run was operated at a higher frequency than actually occurs in a production line in automotive engineering. Thus, there is a chance to make a maintenance recommendation sufficiently early by monitoring the clamps.

Furthermore, the results underline why a machine learning approach for clamp monitoring makes sense. Although the design was very similar for each clamp e.g., same installation position and same lever arm, there are individual times for each clamp which must be learned separately.

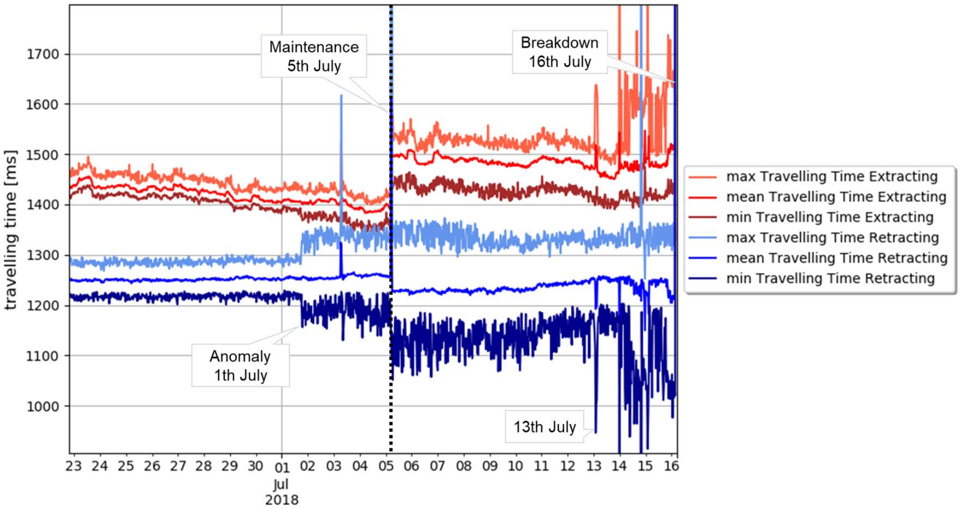

Figure 7: Exemplary signal characteristics of the travelling time in case of failure of a clamp.

5. FAULT CLASSIFICATION

The endurance run has shown that one can (hopefully) derive information from the digital signals in time, that the operating conditions have changed compared to the normal process states at the beginning of data recording. The next step is to ask in the sense of fault diagnosis whether one can also read from the data what is the root cause of the changing in the operating condition beheavior. This aimed at fault localization and/or fault description, both of which can be helpful for targeted and faster maintenance.

First of all, fault classification takes place at component level. Using known information from the circuit diagram, it can be concluded which of the components involved is out of order. If, for example, all clamps connected to the same valve extend with a delay, this is probably due to a cause affecting the whole pneumatic drive system, e.g., the valve, the pressure supply or leakage. If only one of the clamps extends with a delay, it is probably due to a problem with this specific clamp.

Furthermore, fault classification is possible at function level of the clamp or the valve. To investigate this, a test bench with a single clamping unit was created (cp. **Figure 8**) where defined errors easily can be added to the system.

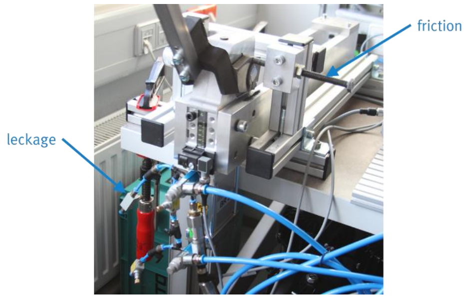

Figure 8: Test bench to add defined errors.

This is a procedure well-known from condition monitoring investigations (cp. [6, 21, 22]).

In the following subsections, two faults are described as examples: A leakage at the upper cylinder chamber (chapter 5.1) and a friction at the clamping arm (chapter 5.2). The conclusions of the test bench results are presented in chapter 5.3.

5.1. Leakage at the upper cylinder chamber

Leakage is one of the well-known possible faults of pneumatic systems. Leakage can theoretically occur in all pneumatic components: In tubes, fittings, valves, one-way flow control valves and cylinders. In cylinders (and valves), a distinction can be made between internal leakage from one

Table 1: Influence of a leakage at the upper cylinder chamber on reaction and travelling time (normalized)

	closing		**opening**	
	reaction time	travelling time	reaction time	travelling time
leakage 0 %	100 %	100 %	100 %	100 %
leakage 6 %	94 %	93 %	103 %	99 %
leakage 36 %	77 %	72 %	111 %	97 %
leakage 100 %	62 %	51 %	137 %	89 %

Table 2: Influence of friction at the clamping arm on reaction and travelling time (normalized)

	closing		**opening**	
	reaction time	travelling time	reaction time	travelling time
friction 0 %	100 %	100 %	100 %	100 %
friction 25 %	136 %	97 %	99 %	107 %
friction 50 %	216 %	99 %	104 %	115 %
friction 100 %	225 %	133 %	115 %	130 %

chamber to another and external leakage from one chamber to the environment.

As an example, external leakage at the upper cylinder chamber of a clamp is investigated below. For this purpose, a precisely adjustable throttle is integrated between the cylinder chamber and the associated throttle check valve, which vents the chamber into the environment (cp. **Figure 9**). For the measurements, the throttle is set to a desired leakage flow at a given inlet pressure.

The changes in the four times considered for different leakages are shown in **Table 1**. The results are explained below.

In the open position of the clamp (cp. **Figure 9**), the upper cylinder chamber is connected to the supply pressure, the lower cylinder chamber to the environment. The added leakage slightly reduces the pressure in the upper cylinder chamber in this position. If the valve is switched, the upper cylinder chamber is exhausted. The leakage causes a larger amount of air flowing out of the chamber, the pressure drop is faster. Thus, the cylinder movement starts faster, i.e. the reaction time when closing is reduced. During the movement, the leakage acts here like a larger opening of the throttle check valve, too. The movement time when closing the clamp is therefore also reduced.

In the closed clamping position (cp. **Figure 9**), the upper cylinder chamber is exhausted, and the lower chamber is filled with supply pressure. After shifting the valve, the upper chamber must

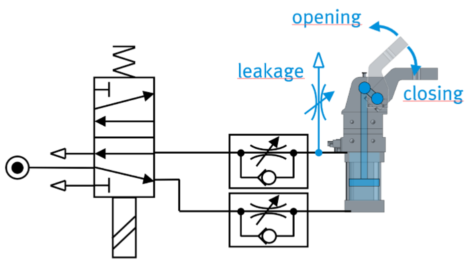

Figure 9: Leakage at the upper cylinder chamber.

be filled with pressure. This pressure build-up is slowed down due to the leakage, so the reaction time during opening is slightly increased. However, as long as the leakage remains limited, the travelling speed hardly changes. Because of the supercritical flow through the exhaust air throttle, the movement is initially independent of fluctuations in the drive pressure. If, however, the leakage in the upper chamber is increased to such an extent that the cylinder breaks away much later, the chamber pressure in the lower chamber drops further and further. This significantly increases the movement speed at the beginning of the return stroke, which results in a shorter travelling time.

5.2. Friction at the clamping arm

Changes in friction behavior is a second category of possible defects that is important in practice. Changes in friction can essentially occur at the valve spool or at the dynamic seals of the cylinder (clamp). Furthermore, the clamping arm can grind, which corresponds to increased friction on the load side of the toggle lever gear. This case is described in more detail now. On the test bench, a screw is placed on the clamping arm so that it grinds past the screw (cp. **Figure 8**). Even if this looks rather rough, a grinding of the clamping arm is still a case of damage, which occurs in rare cases in automobile production.

It should be noted that the change in friction force cannot be adjusted as precisely with the test setup as the change in leakage. For this purpose, a force sensor and an additional drive would have had to be integrated. This effort has not been made. Accordingly, the results of the friction change shown in **Table 2** are to be considered rather qualitatively.

The increased friction on the clamping arm has the greatest effect at the start of the closing movement of the clamp. The closing movement does not begin until the increased static friction has been overcome. In order to generate the necessary pressure difference, a reaction time that increases with increasing friction is necessary. With lower friction forces, the travelling time is then initially independent of the friction; only with very high friction forces does the travelling time increase. This is the result of the super-critical pneumatic movement, which is at first approximation independent of the load.

The influence on the reaction time during opening is considerably lower than during closing. At the beginning of the opening movement, the main load of the drive is the overcoming of the toggle lever. Therefore, noticeable changes in reaction times only occur when friction forces are high. The following movement shows a clear dependence: the higher the friction, the longer the travelling time. The difference between opening and closing travelling times can be explained, among other things, by the different influence of the weight force depending on the direction of movement. This means that the mounting situation of the clamp has a relevant influence on the travelling times.

5.3. Conclusion of the test bench results

As the description of the two test cases leakage at the upper cylinder chamber and increased friction at the clamping arm have shown, the introduced errors have a very different effect on the four considered times resulting from the few available digital signals. The result is an error-typical pattern in the times that can be used for predictive maintenance. In the same way as for the two example errors, a pattern can also be identified for other faults such as leakage or friction elsewhere, obstructed throttle or changes in supply pressure. Fortunately, these are indeed specific patterns that can be explained using mechanical and pneumatic expertise.

The example also shows, that condition-based monitoring with limit and trend checking of just single sensor signals cannot provide an appropriate and exact fault discrimination for fault diagnosis.

Due to the large number of faults, the intensity of the effect depending on the degree of error as well as the fault interdependencies between various sensor signals, more complex methods of fault detection and diagnosis are needed to describe the anomaly and failure behavior. And this is exactly what machine learning can guarantee. The strength of this data analytic techniques lies in learning complex patterns and assigning them to normal and anomalous states.

6. FIELD TRIAL

Due to the promising results, a pilot project was started at a car manufacturer to investigate the feasibility of the laboratory results in practice. Details of the results are subject to confidentiality. The tests are still ongoing. In the following section, however, the concept for implementing data acquisition and machine learning can be briefly discussed.

Acquiring data can be done on several system levels with a different granularity (see **Figure 10**). On the very lowest level – the field level – data like shifting time of limit switches and valves can be directly read from a valve terminal via the field bus. This could be a solution for retrofitting scenarios where the PLC should not be modified. If this restriction does not exist, it is also possible to directly contact the PLC for acquiring the necessary data. In both cases, a so-called edge-device or IoT-Gateway is typically capable in receiving this data. On the other hand, a plant PC is typically installed close to a machine cell which receives data from the PLC.

With this in mind, two possible targets exist for executing analytic models, i.e. an edge-device/IoT-gateway or the plant PC.

While the edge-device can be installed without interference of the machine, some software installations are necessary at the plant PC. In our approach, we distinguish between model execution and training. The training phase requires large data batches with historical data and the model execution typically has real-time constraints and requires streaming data from the machine. Therefore, the configuration and training of analytic models is implemented on an engineering PC or in a cloud platform. This has the advantage that only during a training phase data needs to be sent to the cloud and later on, only analytic results from e.g. the edge-device will be transmitted. This reduces the cost for data transmission because the high-frequent traffic is processed close to the machine.

Once the model is trained and loaded to the computational resource close to the machine, it can be executed and will produce results. In such a setup, several methods exist for providing results to the operator:

1. via dashboards in a cloud,
2. via a PLC to an MES system or
3. via a panel installed to the machine cell.

7. CONCLUSION AND OUTLOOK

The paper shows that even with the limited number of data from a minimum of sensor use in standard pneumatics, valuable information about the operation process states can be derived. The acquired data is sufficient for accurate fault detection and fault diagnosis. An endurance run with pneumatic clamps has shown that changes can be seen in the reaction and travelling times about 2 to 4 days before failure. In addition, a test bench was used to prove that typical faults in the pneumatic system lead to different patterns in the four calculated times. Thus, these data can be used for a more detailed fault description and localization. Finally, a current field test was described in which the findings are tested in practice. If the practical test is successful, the predictive maintenance of the clamps will be commercialized.

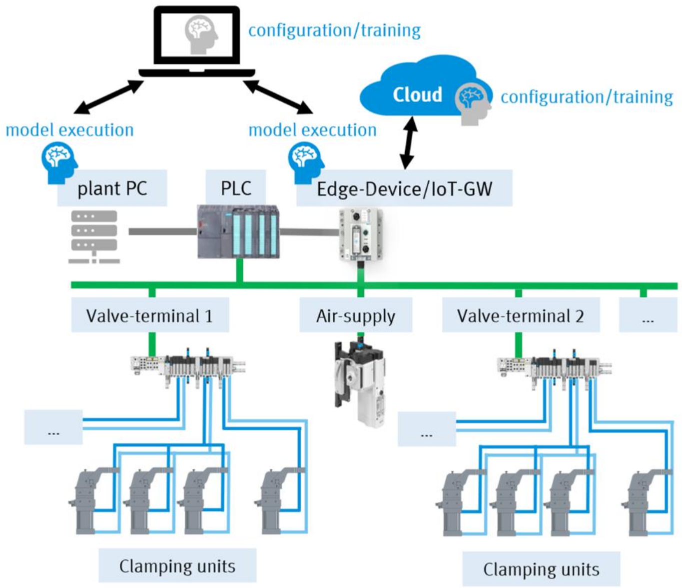

Figure 10: Concepts for data acquiring.

REFERENCES

[1] Predictive Maintenance - Servicing tomorrow - and where we are really at today, VDMA, April 2017

[2] Quick Guide Machine Learning in Mechanical and Plant Engineering, VDMA, 2018

[3] J. Lunze, Regelungstechnik 2. Berlin, Heidelberg: Springer Berlin Heidelberg, 2014.

[4] O. Föllinger, „Regelungstechnik“, 11. Auflage, 2013, VDE Verlag, Berlin Offenbach

[5] DIN/VDI-Normenausschuss Akustik, Lärmminderung und Schwingungstechnik, „Condition monitoring and diagnostics of machines – General guidelines (ISO 17359:2018)“, DIN ISO 17359:2018-05, 2018

[6] S. Fritz, "Verfahren zur Erkennung sowie Diagnose von Fehlern in pneumatischen Systemen und Komponenten", PhD Thesis, RWTH Aachen, 2011

[7] M. A. Sharif und R. I. Grosvenor, „Sensor-based performance monitoring of a control valve unit“, Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng., Bd. 213, Nr. 2, S. 71–84, Mai 1999.

[8] P. Subbaraj und B. Kannapiran, „Artificial Neural Network Approach for Fault Detection in Pneumatic Valve in Cooler Water Spray System“, Int. J. Comput. Appl., Bd. 9, Nr. 7, S. 43–52, Nov. 2010.

[9] P. Subbaraj und B. Kannapiran, „Fault Diagnosis of Pneumatic Valve Using PCA and ANN Techniques“, in Trends in Computer Science, Engineering and Information Technology, 2011, S. 404–413.

[10] J. F. Gomes De Freitas und I. M. Macleod, „Neural Networks For Pneumatic Actuator Fault Detection“, Trans. South Afr. Inst. Electr. Eng., Bd. 90, 1999.

[11] M. Karpenko und N. Sepehri, „Neural network classifiers applied to condition monitoring of a pneumatic process valve actuator“, Eng. Appl. Artif. Intell., Bd. 15, Nr. 3–4, S. 273–283, Juni 2002.

[12] Ž. Nakutis und P. Kaškonas, „Application of ANN for pneumatic cylinder leakage diagnostics“, S. 6, 2005.

[13] H. Mahmoud, P. Mazal, F. Vlasic, und M. Jana, „Condition Monitoring of Pneumatic Cylinders by Acoustic Emission“, in Applicaion of Contemporary Non-Destructive Testing in Engineering, Bernardin, Slovenia, 2017, S. 8.

[14] A. Tiede, „Der spannende Weg von Predictive Maintenance zu Industrie 4.0“, Accessed 05/08/2019 https://www.easyfairs.com/fileadmin/groups/9/maintenance/Dortmund_2018/PDF/17_Tiede_Schaeffler.pdf

[15] IGUS GmbH, „Smart plastics“, Accessed 05/08/2019, https://www.igus.at/_Product_Files/Download/pdf/DE_smart_plastics_2019_screen.pdf

[16] Phoenix Contact, „Predictive Maintenance - Lösungen für die Überwachung von Pumpen und Motoren“, Accessed 05/08/2019, https://www.phoenixcontact.com/assets/downloads_ed/global/web_dwl_promotion/1065451_DE_DE_PumpMonitor_LoRes.pdf

[17] R. Näther, „Vernetzte Elektromotoren für Predictive Maintenance“, Accessed 05/08/2019, https://www.elektrotechnik.vogel.de/vernetzte-elektromotoren-fuer-predictive-maintenance-a-774056/

[18] Neuron Soundware, „Machine Whisperer“, Accessed 05/08/2019 https://www.neuronsw.com/machine-whisperer-neuron-soundware-presents-three-world-firsts-at-hannover-messe/

[19] Aventics, "Intelligent Pneumatics Drives Predictive Maintenance Forward", Accessed 05/08/2019 https://www.aventics.com/media/about_us/AVENTICS_at_a_glance/Press/Pressemitteilungen/Aventics_PI_005_17_HMI_Predictive_Maintenance_EN.pdf

[20] Tünkers, "Standardspanner", Accessed 18/12/2019 https://www.tuenkers.de/publish/binarydata/service/download/standardspanner_de.pdf

[21] S. Mundry, „Zustandsüberwachung an Prozessventilen mit intelligenten Stellungsreglern“, PhD Thesis, RWTH Aachen, 2002

[22] R. Gutiérrez González, "Development of a diagnostic concept for pneumatic systems and components", PhD Thesis, RWTH Aachen, 2012