System modeling based on machine learning for anomaly detection and predictive maintenance in industrial plants

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***Abstract*—Electricity, water or air are some Industrial energy carriers which are struggling under the prices of primary energy carriers. The European Union for example used more 20.000.000 GWh electricity in 2011 based on the IEA Report [1]. Cyber Physical Production Systems (CPPS) are able to reduce this amount, but they also help to increase the efficiency of machines above expectations which results in a more cost efficient production. Especially in the field of improving industrial plants, one of the challenges is the implementation of anomaly detection systems. For example as wear-level detection, which improves maintenance cycles and thus leads to a better energy usage.**

This paper presents an approach that uses timed hybrid automata of the machines normal behavior for a predictive maintenance of industrial plants. This hybrid model reduces discrete and continuous signals (e.g. energy data) to individual states, which refer to either the present condition of the machines. This allows an effective anomaly detection by implementing a combined data acquisition and anomaly detection approach, and the outlook for other applications, such as a predictive maintenance planning. Finally, this methodology is verified by three different industrial applications

I. Introduction

When considering Cyber Physical Production Systems [2] or ISO 50001 [3] certifications, both topics summarizes a reliable data acquisition, analysis and detection of anomal behavior. Regarding each of those topic alone, there are numerous approaches for specialized problems. For example acquiring and analyzing data from one device of a machine. But when going to a more broader view, by considering complete machines or even production lines instead of single devices, there is a lack of solutions following the whole tool chain.

Detailed, in the field of data acquisition there are countless systems for acquiring data, but synchronization solutions or data warehousing are often considered separately. But, especially in industry automation, data from production machines has a different nature than for example data from social networks. Here, data comes from real-time networks like PROFINET or similar. Those networks specify certain requirements, e.g. cycle-times or reliability. When combining data from different networks a synchronized data acquisition is inevitable [4], to be able to capture a system-wide status.

The next step on the tool chain is data-analysis. Specialized algorithms can be applied to model devices like motors or actuators. These algorithms are very matured and are often used on the shop floor. Still, there is a lack of algorithms which consider the system as a whole and try to recognize for example system-wide anomalies or wear level. Finally, data has to be presented in a manner which is easy understandable especially for the machine operators. Also new arisen policies like BYOD (Bring your own device) should be considered.

The contribution of this paper is beside the in [5] published framework the consideration of noise and simulation inaccuracies for improved modeling of the normal behavior. Summarized the framework features a (*i*) time synchronized data-acquisition using OPC UA as semantic data interface, (*ii*) the automatic learning of hybrid automata for representing the normal behavior of systems as well the modeling of continous data with regresssion analysis and kalman filter as outlined in [6] and (*iii*) the detection of anomal behavior in discrete and continuous-values. Finally, the results are presented via OPC UA and SingalR on cellphones and other devices. The applications are e.g. wear-level detection, impurity and therefore they are an essential step for machine forecasting.

The paper is organized as follows: After the Introduction, a brief state of the art for each considered part follows. Section III describes the system in detail including the used algorithms. After the system description in Section IV a proof of concept is conducted. Section V concludes this contribution.

II. State of the Art

This section describes the current scientific research areas in the field of data acquisition, data processing and model-based anomaly detection. Finally, current approaches for data representation based on human machine interfaces are presented.

A. Data Acquisition

Productions plants are built from various assets, which consist of a multitude of different components. In order to realize suitable results from data processing, a much more reliable data acquisition is necessary. As only time synchronized data for example allows an accurate system status on a given timeframe, outlined in [4]. In order to realize the synchronization of different nodes within the accuracy of nanoseconds, the Precision Time Protocol ([7]) was introduced. Considering time synchronization in wireless sensor networks, they differ completely from cable based networks, as they for example struggling under the issues of higher latency and different signal runtimes. Related works in this field are the Flooding Time Synchronization Protocol (FTSP) [8] and the Reference Broadcast Synchronization (RBS) [9]. Additionally, the Network Time Protocol (NTP) approach [10] allows a reliable time information distribution over networks with variable packet delay.

Process and energy data acquisition in distributed systems like manufacturing plants is an interesting field of research. As outlined in [4] real-time measurements must be exactly record to analyze these energy data. Therefore, in recent years, different approaches for data acquisition in industrial plants have been proposed. For example, using IEC 61131-3 function blocks on the IO or PLC level are widely used for communication, as outlined in [4]. Various projects have been approved to offer solutions for distributing systems in a wide variety of automation applications (see comprehensive overview in [11]).

With special energy profiles for real-time Ethernet protocols like ProfiEnergy, it is possible to transfer acquired energy data without further manual engineering. As the real-time communication already features a network wide time synchronization, here the data acquisition could be eased.

B. Data Processing

Most industrial facilities consist of hybrid systems that can only be described with continuous models or discrete event systems. In order to model timing information, Verwer has introduced in [12] a splitting process of the system states. In [13] a new algorithm was introduced, which is able to learn a timed hybrid automaton extending the previous considerations.

These algorithms are able to tackle the issues of manual modeling of industrial plants, which is rendered unrealistic when considering cyber-physical-production-systems.

In general, two classes of algorithmic approaches exist for the detection of anomalous or suboptimal plant configurations:

I. Phenomenological Approach: The system output including its sensors, data and its energy consumption is directly classified as correct or anomalous.

II. Model-based Approach: A model is used to simulate the normal behavior of a plant. For this, the simulation model needs all inputs of the plant, e.g. product information, plant configuration, plant status, etc. If the actual measurements vary significantly from the simulation results, the behavior is classified as anomalous.

While phenomenological approaches are often more straight-forward and do not require a system model, they have one major inherent drawback: They must deduce against the direction of causality since they deduce from measurements (i.e. symptoms) to anomalies. For complex distributed systems with many interdependencies between components and complex causalities, this leads to several problems: (*i*) The classification rules need a high number of measurement variables including the measurements history to detect anomalies. (*ii*) A high number of classification rules is needed to capture the effect of different input combinations and again all combinations over time may be needed. Since the analysis of a plant‘s behavior depends on a high number of input data and normally deals with distributed plants and automation systems, a model-based approach is a highly suitable option in this case and used for the implementation of the framework.

With this algorithm mentioned above, it is possible to model the behavior of systems, which are composed from different sub-systems. In [6] is outlined how the training of behavior models for the analyzed system in two steps can be carried out. The functionality of the algorithm can be divided into two crucial phases:

I. Learning Phase: A timed automaton is trained by a state-based application, which are based on the above mentioned algorithms. During this step, no knowledge is required about the automaton structure and the number of automaton states.

II. Operation Phase: Similar automaton states are merged and thereby produce a compact and significant timed hybrid automaton of the system.

1) Model-Based Anomaly Detection: The virtual planning, simulation and commissioning of equipment (“Digital Factory“) is the scientific trend the last years (see [14]): By using system simulations in the early design phase, effort can be saved. For example commissioning time system integrators and plant operators can be minimized (*i*) , it reduces the risk of errors in the system (*ii*) and optimizes the system design and configuration (*iii*) . For this approach, often standard tools such as *Dassault's Dymola* or *TheMathwork's Simulink* are used.

Disturbances in hybrid systems can not be avoided although nowadays the technical standard has matured enormously. In [15] the author describes in detail the classification of these disturbances in permanent and non-permanent faults wherein the duration of their effects the classification crucial influenced. The approach of model-based anomaly detection is chosen because it has some individual advantages: fast enough for medium-sized problems, easily maintainable, directly supports reusability, and has a well-founded theory ([16]). The model-based design allows an early test of the components to be developed. Methods of model-based anomaly detection can be classified according to [17] in supervised and unsupervised techniques. The supervised techniques involve models which are generated on the basis of training data. Unsupervised techniques include models without training data and with semi-supervised methods.

So far, significant steps in the application of model-based anomaly detections have been achieved for discrete systems. Different types of automatons for different cases were developed (e.g. non-deterministic, timed, probabilistic, hybrid). An overview to the main formalisms can be found in [18].

For example, in the case of finite state automaton, an anomaly occurs from the current state, which should be triggered by the observed event, i.e. if the sequence of control signals (events) is incorrect [19]. Concurrently to the previously described approach, a lot of research in the field *model-based anomaly detection of strictly continuous systems using continuous model* has been carried out. Conventional methods are (*i*) K-means, (*ii*) agglomerative hierarchical clustering, (*ii*) fuzzy clustering, (*iv*) graph-based clustering or the application of (*v*) self-organizing maps (SOM) (see [17] for details). A comprehensive description of possible assignments of SOMs for anomaly detection is described in more detail in [20].

The statistical approaches of anomaly detection are mainly based on the construction of a probability distribution model, and become visible how likely objects with this model are. State space equations are used in the most common approaches, thus it is possible to model the temporal transition of hidden process variables. Estimates of the hidden process variables can be carried out either by Kalman filter-based observers (e.g. [21], [22], [23], and [24]) and particle filter (see e.g. [25]).

C. Human-Machine Interfaces

A survey about agent-based control and holonic manufacturing systems (HMS) can be found in [26]. In this context, often systems such as OPC (Classic DA, UA, HDA, etc.) or simply the OPC Unified Architecture are mentioned. In [27] it is shown how to implement the OPC Unified Architecture to a programmable logic controller (PLC). This architecture can be used in order to realize a faster energy and data collection process. A series of projects based on particular web services and their DPWS (Device Profile for web service) as outlined in [28], [29].

III. Framework Components

The framework consists of the following components: (*i*) OPC UA server, (*ii*) evaluating module and (*iii*) front-end.

The OPC UA server is a standard implementation from the OPC Foundation and not further explained at this point, as due to the compatibility all OPC UA servers are compatible at this point. Considerable, here is the implementation of a custom information model, which provides a data interface to all modules. The OPC UA server guarantees that this information is comprehensible by all client devices, even if they are not tackled by this project.

The evaluating module handles the anomaly detection and modeling of the continuous dynamics of the system. Due to the uniform interface provided by the OPC UA Server, semantic objects are saved on the server for data transportation introduced in [4], therefore this allows the creation of a boundless vertical integration into a given industrial system.

The requirement for learning the normal behavior of machines and for anomaly detection, are the following: (*i*) Energy or process data must be acquired synchronously to the process and (*ii*) comprehensive over multiple processes. As the bulk of today's industry machines are using bus systems like PROFINET or similar, in [4] a synchronous data acquisition was introduced.

This concept is able to cover the majority of systems. However the ISO 50001 also claims that especially older machines near the end of their life-cycle has to arm with such data acquisition techniques. For covering those types of machines or finding a flexible approach to expand industry machines in the course of the associated project, a wireless system was build as introduced in [30].

The main motivation of using a Wireless Sensor Network [31] for this purpose are the low installation costs. The used sensors originally belong to the field of home automation. Here, the sensor nodes are used for measuring the power consumption of the machine components and transmit the

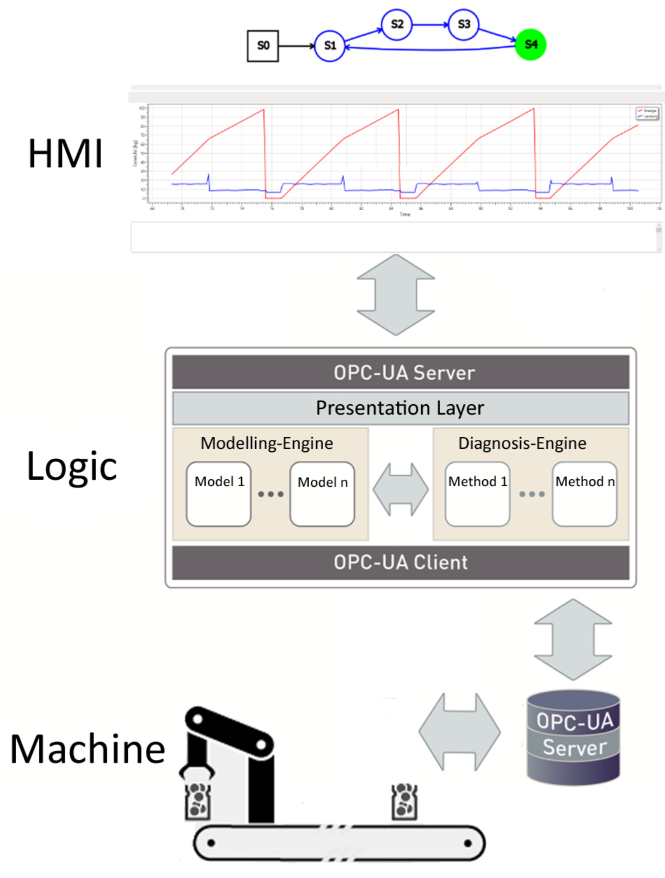

Fig. 1. System components.

data to a gateway-node which tranfers the data to the OPC UA server. The physical network layer is based on the IEEE 802.15.4 standard, 6LoWPAN allows IPv6 communication with the nodes and the nodes are synchronized with the FTSP algorithm [8]. On the OPC UA server, the data is saved in a semantic data model. This model features value types, sensor locations, descriptions and historic values in a most uniform way to enable other system like MES or ERP systems to acquire and understand the data afterwards for other purposes.

The framework outlines two operation phases. In the **Learning Phase**, the machine must operate at normal state and the software is learning the behavior. In the **Operation Phase** all data from the previous phase is used, to compare it with the actual data. In the following sections these two phases are described in detail, moreover Figure 2 is intended to provide a overview of the respective steps.

Data Acquisition
In this step the data are captured in the system. The network traffic is passively recorded and subsequently afflicted with the necessary semantics (signal-to-variable assignment). The recorded data is stored in a database.

Noise Handling
One of the problems when acquiring data is the noise handling between purely mechanical driven operations and cycle based data acquisition. As the cycle of the data acquisition and the switch operation of the machine are not synchronized and the

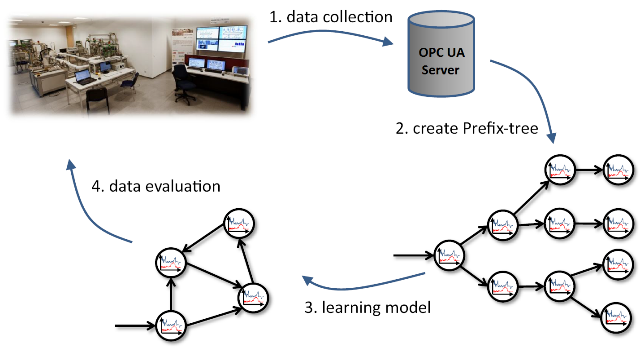

Fig. 2. Learning concept.

data is used without filtering afterwards, the noise distracts the ability to abstract the process. Therefore the learned automaton are not resilient and as a result anomaly detection algorithms are not able to identify anomal behavior for this specific state. The problem is depicted in figure 3, here a data value switches between different cycles, which lowers the accuracy when detecting anomal behavior. When this data is used in the modeling process it will result in at least two different states which are redundand.

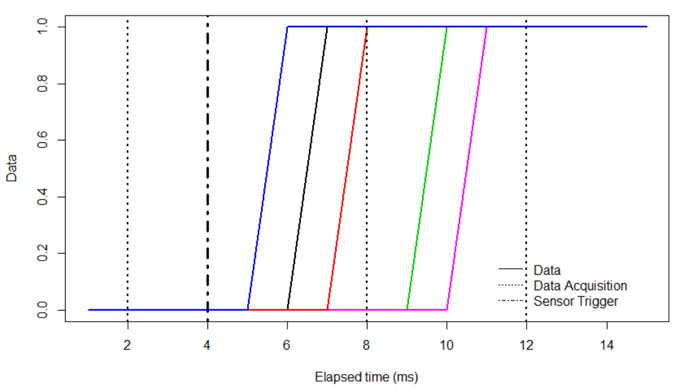

Fig. 3. Sampling noise.

This specific problem was tackled by the usage of dynamic thresholds, which summarizes multiple data acquisition cycles before and after a state change. This delays the anomaly detection only by some (in most cases 2-3) network cycle times, which could be for example 12ms. Due to this case anomalies could be detected 12-36ms later than their occurrence. In normal machine operation this is acceptable.

Learning Phase

When a sufficient quantity of measurements is reached, they are summarized in a Prefix-tree. With a bottom up approach introduced in [32] the Prefix-tree is merged until the final behavior models of the particular plant components are trained. After the training of the discrete dynamic of the system all continuous data is separated based on the state space model trained before.

Summarized, the model (and its structure) is learned from the training data with as little a-priori knowledge as possible. This approach avoids a complex manual modeling. Therefore, the installation effort can be reduced so that anomaly detection approaches are even possible where rule-based approaches are infeasible.

Simulation Inaccuracies

When considering simulation inaccuracies in terms of modeling in Cyber Physical Production Systems, they are at the first glance inaccuracies in the learned models. This is often result from insufficient learning data and therefore a model which only abstracts parts of the whole system dynamic.

While the HyBUTLA (Hybrid Bottom Up Timing Learning Algorithm) algorithm are able to abstract the system in a good way, it is not possible to determine the amount of data which is needed until for the learning convergence of the system. By using a combination of the offline HyBUTLA algorithm and the online algorithm Otala (Online Timed Automation Learning Algorithm) [33], it is possible to exactly determine the amount of data.

In detail the process could be measured based on the number of states, the numbers of transitions and changes in time boundaries. This curve is shown in Figure 4, where the number of changes is shown versus the number of events. As simple consideration a threshold of 1000 incoming events without changes was chosen as convergence criteria.

After the convergence the online model is discarded and the results from the HyBUTLA algorithm is used for further usage. The preliminary results show clearly, that in most cases even by expert the needed amount of data for modeling a system dynamic was underestimated and with the combination much better models could be learned.

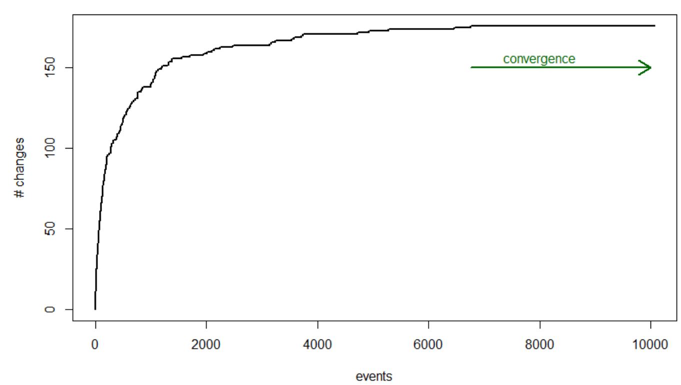

Fig. 4. Learning convergence for test data using Otala.

Operation Phase

The next step is to determine whether simulation predictions and measurements should vary significantly enough to form an anomaly. In this phase, the learned process models are used for anomaly detection. With this method two different types of errors can be detected: (*i*) a faulty behavior in the logical end of the investment process, and (*ii*) faulty timing of the process. For every observed event in the system, a comparison with the model prediction is made. If a transition between event occurs in the system which cannot be performed by the model, a system fault is signaled. The observed transition does not only track the discrete behavior, furthermore timing issues and anomal energy behavior are detected. The Kalman-filter introduced in [34] is used in addition to regression formalisms to recognize anomalies in energy data. Beside the detection of anomal behavior, the statistical informations of state changes are able to keep track of the wear level of the system. Based on statistical parameters which are either learned from maintenance cycles or a-prioi knowledge, warnings are created by reaching these thresholds.

Human Machine Interface

In this context, as part of further research activities in the field of mobile platforms a first application for data analysis was prototypically implemented. The communication between the system and device was realized using *SignalR*. This library enables to add real-time web functionality to the applications used on mobile platforms. With this technology it is possible to deliver data in a most transparent way and without loosing the most important data information. Otherwise it is not possible to kept the data structure, real-time capability and data quality information which are stated by the OPC communication.

IV. Proof of Concept

An extensive evaluation of the proposed learning framework was conducted and tested on three separate evaluation platforms. These are: (*i*) Smart Factory OWL, (*ii*) Intralogistic test platform and (*ii*) Chemical test platform. In the following subsections these platforms are described and explained more detailed.

The test results are described by the Pearson product-moment correlation coefficient (PCC) defined in equation 1, which describes the linear correlation between variables as indicator for the usage of input variables for the system. If no correlation between the input and the output is given, a-priori knowledge could be used instead to define input variables. Afterwards with the analysis of variance (ANOVA) which is defined in equation 2 to 5 the data is analyzed and the statistical variance is calculated and presented as percentage value of the given variance.

$$\varrho(x,y) := r_{xy} := \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \cdot \sum_{i=1}^{n}(y_i-\bar{y})^2}} \quad (1)$$

$$s_{1,2}^2 = \frac{1}{(n_1-1)} \sum_{i=1}^{n} 1(x_1 j - x_1^{`})^2 \quad (2)$$

$$QA = n_1(X_1 - X..)^2 + n_2(X_2 - X..)^2 \quad (3)$$

$$QB = \frac{((n_1-1)s_1^2 + (n_2-1)s_1^2)}{n_1+n_2-2} \quad (4)$$

$$F = \frac{QA}{QB} \quad (5)$$

A. *Smart Factory OWL*

The Smart Factory OWL is a demonstration plant which consist of multiple transportation and processing modules. The tested system modules are described detailed in [34] and summarized consist of eight modules, which are four different transport, storage, weight, filling and production. The production module is shown in Figure 5. The modules consist of heterogeneous systems like PLCs, communication interfaces, and IO modules from different vendors for demonstration purpose. The here tested production module consists of a heating module, a blowing fan, including with raw and processed material container. In [34] the module is explained as follows: "The popping machine of the Smart Factory receives raw material (corn), and activates the air heater. A fan blows the hot air towards the raw material container. Popcorn is obtained as a result of this processing. The described process represents one production cycle."

The used data was acquired with a cycle time of 1 second and the maximal energy consumption goes up to 1200 watts. The model learned from 50 cycles enables the system to predict the power consumption with the observed signals.

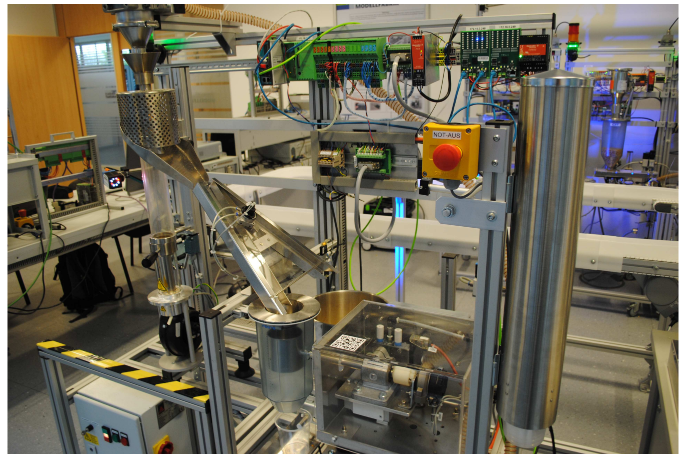

Fig. 5. Production module of the Smart Factory OWL.

As in [34] outlined, the concept targets the following faults: Signal Zero Values, signal drops and jumps. The calculated f-measure which summarizes the test results. The tests where performed 100 times for each fault and the results show that the sensitivity, specificity and accuracy rates of 100% were obtained for signal drops and jumps by 10%. Even signal drops and jumps of 2.5% led to the same results. This denotes the results obtained in [35] by 10%.

B. *Intralogistic Test Platform*

This section describes the physical process of the Intralogistic test platform, shown in Figure 6. Its structure consists of an active transport process (linear conveyor) and a passive transport process (roadway). The work piece (metal ball) is transported to a specific position. The process flow starts with the transfer of the metal ball at the bottom of the roadway by the magnet. The linear conveyor lifts up the metal ball to the dropping range and drops it. Once the metal ball and the magnet are back in their starting position (bottom of the roadway) a transport process is completed and the next transport process can start. The automaton which was learned with this framework is described detailed in [5]. Apart from the discrete sensors of the test platform, the process also includes two continuous types of data: (*i*) the data from the movement of the magnet and (*ii*) the accumulation of the energy used by the magnet when switched on. The entire power consumption of the process can be mapped on the basis of this data. The calculated coefficient of determination of the learned data based on the original data is roughly above 80%. This shows that the learned behavior equate with the original data.

C. *Chemical Test Platform*

As highly non-linear energy consumption is clearly recognized, a follow-up evaluation was carried out using a different

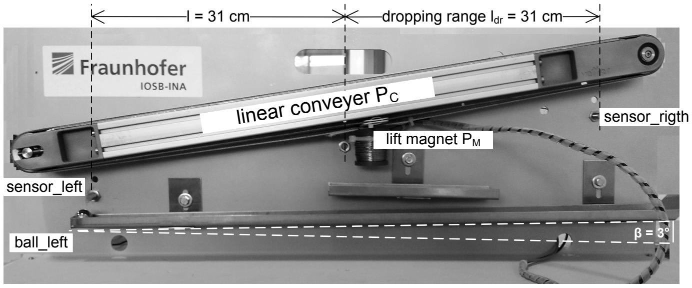

Fig. 6. Intralogistic test platform.

model plant so that algorithm can evaluate the other types of energy consumption.

The production process is different to the one used in the Smart Factory OWL. A reactor is used for mixing water with different acids to create specific acid concentrations, afterwards they are filled into bottles and stored. To produce these acids it is critical to have a specific flow of water between the reactor and the pattern basin, as this directly influence the resulting product.

The signal of one production cycle combined with the predicted signal and the associated hybrid system are shown in Figure 7. Using the same approach as in [35] specified, the detection accuracy of more than 93% is verified.

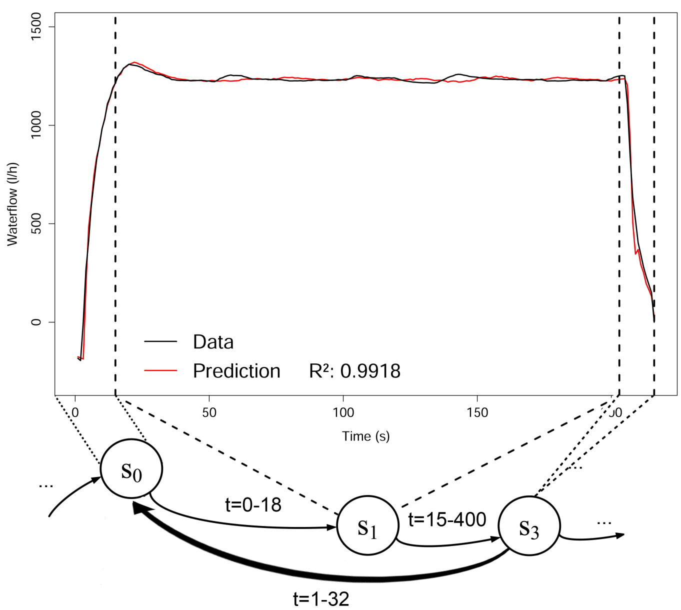

Fig. 7. Learned hybrid automaton.

D. Discussion

This contribution investigates anomaly detection and predictive maintenance in hybrid systems with an approach based on stochastic timed hybrid automata. Also the usage of sensor data to learn hybrid automata of the machines normal behavior was introduced. This subsection summarize the achieved results and build a basis for discussions about the advancement within this research field. When considering the results shown in table I the accuracy of the learned model of the Smart Factory OWL looking quite high. But when considering the used data acquisition, which directly derives data from the network, including timestamps in the range of nanoseconds. The learned automata are able to cope even with cycle times up to 10ms, but the results are only feasible under this controlled prototypical environment. When system are used, like the energy demonstrator or the test platform, where the data acquisition for example already involving filtering or an overall much worse acquisition, the quality (of the learned automata) slightly decreases. This will be still a subject of research, which data quality could be measured as threshold for a feasible trade off between the cost of data acquisition, quality of learned automata (and therefore the ability to identify anomal behavior) and the final results, which are able to lead to better utilization of machines.

TABLE I. RESULT OVERVIEW

Platform	Model accuracy
Smart Factory OWL	$\sim 100\%$, $var > 2,5\%$
Intralogistic Test Platform	$\sim 80\%$
Chemical Test Platform	$\sim 90\%$

V. CONCLUSION

With technologies for data acquisition and middleware technologies, combined with new anomaly detection algorithms, it is possible to solve another step depicted by the vision of Cyber Physical Production Systems. The implemented Framework is able to identify anomal behavior by abstracting from the learned state space model and the continuous dynamic of a system. Such anomal behavior are for example timing errors and degeneration effects which are not recognized by PLCs. Advantage of this method over a traditional, static limit testing, is a model of the whole continuous dynamics, which is reducing it to separately modeled state vectors. In addition, this allows flexible adaption when the system has changed, e.g. to learn new waveforms or new system dynamics. Especially, in the field of modular machines or systems that produce a very large number of different products, even with small batch sizes. Here, the flexibility of the used algorithms is crucial.

The key features addressed in this paper and prototypically implemented as framework are summarized:

- Synchronized data acquisition
- Learned timed hybrid automata

Those features could lead to a new generation of a software based predictive maintenance system, which continuously monitors the system to give optimal maintenance intervals. However, several open issues like modeling of sole continuous systems or finding initial thresholds for maintenance cycles remain and they are still a subject of research.

As future work, the fully functional implementation will be further discussed and released in terms of the project for practical usage.

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REFERENCES

[1] IEA, "Key world energy statistics," Tech. Rep., 2012. [Online]. Available: http://www.iea.org/publications/freepublications/publication/kwes.pdf

[2] E. Lee, "Cyber physical systems: Design challenges," in *Object Oriented Real-Time Distributed Computing (ISORC), 2008 11th IEEE International Symposium on*, 2008, pp. 363–369.

[3] "Energiemanagementsysteme - anforderungen mit anleitung zur anwendung (iso 50001:2011)," 2011.

[4] F. Pethig, B. Kroll, O. Niggemann, A. Maier, T. Tack, and M. Maag, "A generic synchronized data acquisition solution for distributed automation systems," in *17th IEEE International Conf. on Emerging Technologies and Factory Automation ETFA'2012*, Krakow, Poland, 2012.

[5] B. Kroll, S. Schriegel, S. Schramm, and O. Niggemann, "A software architecture for the analysis of energy- and process-data," in *18th IEEE International Conf. on Emerging Technologies and Factory Automation ETFA'2013*, Cagliari, Italy, 2013.

[6] O. Niggemann, B. Stein, A. Vodenčarević, A. Maier, and H. Kleine Büning, "Learning behavior models for hybrid timed systems," in *Twenty-Sixth Conference on Artificial Intelligence (AAAI-12)*, Toronto, Ontario, Canada, 2012, pp. 1083–1090.

[7] IEEE, "Standard for a Precision Clock Synchronization Protocol for Networked Measurement and Control Systems," IEEE Std 1588-2008 (Revision of IEEE Std 1588-2002), 2008.

[8] M. Maróti, B. Kusy, G. Simon, and A. Lédeczi, "The flooding time synchronization protocol," in *Proceedings of the 2nd international conference on Embedded networked sensor systems*, ser. SenSys '04. New York, NY, USA: ACM, 2004. [Online]. Available: http://doi.acm.org/10.1145/1031495.1031501

[9] J. Elson, L. Girod, and D. Estrin, "Fine-grained network time synchronization using reference broadcasts," *SIGOPS Oper. Syst. Rev.*, vol. 36, no. SI, pp. 147–163, Dec. 2002. [Online]. Available: http://doi.acm.org/10.1145/844128.844143

[10] S. Ganeriwal, R. Kumar, S. Adlakha, and M. Srivastava, "Network-wide time synchronization in sensor networks," Networked and Embedded Systems Lab (NESL), Electrical Engineering Department, UCLA, Tech. Rep., 2003.

[11] W. Emmerich, M. Aoyama, and J. Sventek, "The Impact of Research on the Development of Middleware Technology," *ACM Transactions on Software Engineering and Methodology*, vol. 17, no. 4, pp. 19:1–19:48, 2008.

[12] S. Verwer, M. de Weerdt, and C. Witteveen, "A likelihood-ratio test for identifying probabilistic deterministic real-time automata from positive data," in *Grammatical Inference: Theoretical Results and Applications*, ser. Lecture Notes in Computer Science, J. Sempere and P. Garca, Eds. Springer Berlin / Heidelberg, 2010.

[13] A. Maier, O. Niggemann, A. Vodenčarević, R. Just, and M. Jaeger, "Anomaly detection in production plants using timed automata," in *8th International Conference on Informatics in Control, Automation and Robotics (ICINCO)*. Noordwijkerhout, The Netherlands, Jul 2011.

[14] W. Kühn, "Digital factory: simulation enhancing the product and production engineering process," in *WSC '06: Proceedings of the 38th conference on Winter simulation*. Winter Simulation Conference, 2006, pp. 1899–1906.

[15] R. Mohammadi, "Fault diagnosis of hybrid systems with applications to gas turbine engines," Ph.D. dissertation, Concordia University, Montreal, Canada, 2009.

[16] B. Peischl and F. Wotawa, "Model-based diagnosis or reasoning from first principles," *IEEE Intelligent Systems*, vol. 18, no. 3, pp. 32–37, 2003.

[17] P.-N. Tan, M. Steinbach, and V. Kumar, *Introduction to Data Mining*. Addison-Wesley, 2006.

[18] B. Kumar, O. Niggemann, and J. Jasperneite, "Statistical models of network traffic," in *International Conference on Computer, Electrical and Systems Science*. Cape Town, South Africa, Jan 2010.

[19] A. Vodenčarević, H. Kleine Buning, O. Niggemann, and A. Maier, "Identifying behavior models for process plants," in *Emerging Technologies & Factory Automation (ETFA), 2011 IEEE 16th Conference on*, 2011, pp. 1–8.

[20] C. Frey, "Diagnosis and monitoring of complex industrial processes based on self-organizing maps and watershed transformations," in *Computational Intelligence for Measurement Systems and Applications, 2008. CIMSA 2008. 2008 IEEE International Conference on*, july 2008, pp. 87 –92.

[21] M. W. Hofbaur and B. C. Williams, "Mode estimation of probabilistic hybrid systems," in *In Intl. Conf. on Hybrid Systems: Computation and Control*. Springer Verlag, 2002, pp. 253–266.

[22] S. Narasimhan and G. Biswas, "Model-based diagnosis of hybrid systems," *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, vol. 37, no. 3, pp. 348 –361, May 2007.

[23] B. C. Williams and M. M. Henry, "Model-based estimation of probabilistic hybrid automata," Tech. Rep., 2002.

[24] F. Zhao, X. D. Koutsoukos, H. W. Haussecker, J. Reich, and P. Cheung, "Monitoring and fault diagnosis of hybrid systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part B*, vol. 35, no. 6, pp. 1225–1240, 2005.

[25] M. Wang and R. Dearden, "Detecting and Learning Unknown Fault States in Hybrid Diagnosis," in *Proceedings of the 20th International Workshop on Principles of Diagnosis, DX09*, Stockholm, Sweden, 2009, pp. 19–26.

[26] P. Leitao, "Agent-based distributed manufacturing control: A state-of-the-art survey," *Engineering Applications of Artificial Intelligence*, vol. 22, pp. 979–991, 2009.

[27] L. Dürkop, J. Imtiaz, H. Trsek, L. Wisniewski, and J. Jasperneite, "Using opc-ua for the autoconfiguration of real-time ethernet systems," in *11th International IEEE Conference on Industrial Informatics*, Bochum, Germany, Jul 2013.

[28] S. Faltinski, O. Niggemann, and J. Jeschin, "Evaluation of Different Middleware Approaches for Industrial Automation," inIT - Institut Industrial IT, Hochschule Ostwestfalen-Lippe, Fraunhofer IOSB-INA Kompetenzzentrum Industrial Automation, Tech. Rep., 2010.

[29] G. Candido, F. Jammes, J. de Oliveira, and A. Colombo, "Soa at device level in the industrial domain: Assessment of opc ua and dpws specifications," in *8th IEEE International Conference on Industrial Informatics (INDIN)*, 2010, pp. 598–603.

[30] T. Bian, R. Venkatesan, and C. Li, "Adaptive time synchronization for wireless sensor networks with self-calibration," in *Communications, 2009. ICC '09. IEEE International Conference on*, 2009, pp. 1–5.

[31] T. Rossbach, A. Schreiber, S. Engelhardt, W. Kattanek, and E. Chervakova, "Long-life sensor modules - challenges for hardware design and MAC algorithms," in *Proceedings 54. Internationales Wissenschaftliches Kolloquium*. TU Ilmenau, September 2009.

[32] S. Faltinski, H. Flatt, F. Pethig, B. Kroll, A. Vodenčarević, A. Maier, and O. Niggemann, "Detecting anomalous energy consumptions in distributed manufacturing systems (in press)," in *IEEE 10th International Conference on Industrial Informatics INDIN, Beijing, China*, 2012.

[33] A. Maier, "Online passive learning of timed automata for cyber-physical production systems," in *The 12th IEEE International Conference on Industrial Informatics (INDIN 2014)*. Porto Alegre, Brazil, Jul 2014.

[34] S. Windmann, S. Jiao, O. Niggemann, and H. Borcherding, "A stochastic method for the detection of anomalous energy consumption in hybrid industrial systems," in *INDIN*, 2013.

[35] A. Vodenčarević, H. Kleine Büning, O. Niggemann, and A. Maier, "Using behavior models for anomaly detection in hybrid systems," in *Information, Communication and Automation Technologies (ICAT), 2011 XXIII International Symposium on*, 2011, pp. 1–8.