PRODUCTION STATE IDENTIFICATION USING RAW ETHERNET DATA OF TOTAL POWER CONSUMPTION IN A CYBER-PHYSICAL FACTORY

Meltem Dincer, Aleksei Kharitonov, Prof. Dr. Axel Zimmermann, Dr. Thomas Burghardt
Department of Industrial Engineering– Aalen University, Germany

axel.zimmermann@hs-aalen.de, aleksei.kharitonov@hs-aalen.de, thomas.burghardt@hs-aalen.de, meltemd@hotmail.de

Abstract: *Complex production systems are increasingly using Industrial Ethernet for connecting MES, PLCs, Touch Control, and even sensors and actors within the industrial control network. While today's production is still process driven under MES control, digitalization requires a data driven approach with cyber physical systems acting autonomously in a connected production world. Moving away from a centralized control architecture has the advantage of more flexibility but eliminates the implicit knowledge on global parameters such as the current condition or state of the overall machinery. This paper describes a methodology to retrieve these global parameters independently from any control system and fully transparent to the control network. A data sensor device is introduced that can listen to any Ethernet data traffic. Together with a specialized packet rules engine it is used to extract and combine information out of a raw Ethernet data stream to build up a virtual sensor device. A production state identification sensor is described as an example application of the virtual data sensor device.*

Keywords: CONDITION MONITORING, DATA ANALYSIS, DATA SENSOR, MAINTENANCE, VIRTUAL SENSOR

1. Introduction

Industrial control systems and process control systems are dominating today's factory floors. The centralized information on all production parameters enable supervisory functionality that is used to monitor the machinery condition for example [1]. However, migration to a smart cyber physical factory requires a more distributed control scenario and therefore prevents a centralized condition monitoring.

In this paper, we describe a way to retrieve virtually all relevant information on production parameters even in a smart cyber physical factory environment. As an example, we describe the identification of the working state on a drilling station in a cyber-physical factory (CP-Factory). An approach for transparent condition monitoring (CM) will be introduced. In order to permanently monitor the state of a system it is necessary to measure and analyze one or more physical values in real-time. Often the realization of a forward-looking state-oriented maintenance of an equipment is intended. The challenge in this strategy consists of the search of relevant sensor data, effective signal analysis, pattern recognition and control over the data flow. It was already shown that motor current signatures can be used to detect faults [2]. In this work, the application of a single physical energy data sensor for state identification is considered. The sensor measures the electrical power of all components in a production unit and provides periodically measured data on a digital interface to a cable-connected network (Ethernet). The energy sensor works as a Modbus Slave service and sends measured data upon request over Modbus/TCP protocol. [3] The goal is to reliably identify operational state and state transition from the total power consumption. For that purpose a data sensor (network sniffer) for the recognition of the MODBUS packets, their processing and evaluation of captured energy data was integrated at the network site. The electrical power for nine practice-oriented operational states was measured and saved as reference table values. Hereupon a data model for the state recognition and state transition was developed. It was implemented and validated in a user-friendly rule-based language in the data sensor. This rule-based interpreting language is a formal programming language for rule description and for analysis of the Ethernet data flow. In different tests, it was proven that the identification of an operational state was reliable with an error rate of 0.8 %. A use case of the application is the recognition of irregularities, detection of impermissible states and accordingly the identification of the state transition of a production module at the CP-Factory. The analysis- and evaluating tool consists of the data sensor with implemented rule interpreter. Thereby realizable data capture and evaluation can be implemented in existing networks. Further industrial use cases are discussed in this work.

2. Cyber-physical factory and virtual sensor

Cyber-physical factory (CPF) is a small-scale factory which is used for laboratory experiments and Industry 4.0 production process simulation. It offers a modular construction and modern communication between parts of the factory. The modular structure allows to composite the production process depending on the quickly changing manufacture requirements. Furthermore it allows to replace production units in a minimal time, reducing factory idling and avoid losses. It features radio frequency identification (RFID) for full control of the manufacturing process and to write production data directly onto the production unit, which enables to follow the whole production chain anytime in the future. Module units of the CPF are connected in a chain over industrial Ethernet. A manufacturing execution system (MES) is connected to the internal production network as well. The MES controls the manufacturing process of production units over all production steps. [4]

A power monitoring device SENTRON PAC3200 [5] is built into every production module.

Fig 2.1 Power monitoring device SENTRON PAC3200. [6]

It measures voltage and current, and based on these data it computes other electrical parameters such as total power consumption, active power consumption, etc. All data can be read on the front panel. The device provides all measured and calculated parameters to the Ethernet port over the Modbus/TCP protocol. It works in Modbus-slave mode and receives commands from Programmable Logic Controller (PLC), which has a Modbus-master role. The PLC monitors electrical values and reads them with a period of one second.

The data communication between PLC and Power monitoring device is sniffed using a data sensor device. Sniffing is fully transparent so that the original communication is not changed by any means. In addition to the sniffing capability a data sensor can also process the captured data, extract measurement values, and finally implement a virtual sensor functionality.

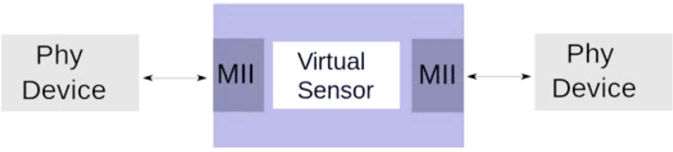

Fig. 2.3 Virtual sensor implemented in a data sensor device.

For implementing the capture unit and the virtual sensor an embedded XMOS parallel processor architecture is used. An embedded rule-based engine is developed on this platform, which makes it possible to define rules for every Ethernet packet of OSI layer 2. Thereby each of the passing Ethernet frames is going to be sequentially processed by the rules engine to filter out important information defined in the rules.

In the current work only the active power for the state monitoring was used, the rules for the Ethernet packets were written to filter out Modbus/TCP packets containing the value of the active power of the production module being monitored. In the next steps the encoded value of a floating point type was extracted from a specific place in an Ethernet frame. This preprocessing stage supplies the data for the further data analysis and for the state monitoring of the manufacturing module.

3. Solution of the examined problem

As a data sensor application example the identification of working states on a drilling machine in a cyber-physical factory was investigated. The working station consists of three actors, the conveyor and two drilling units, which can be moved in an X- and Z-direction. The working station detects a production part using light barrier sensor. The position of the production part is checked and the station can drill up to four holes on it. [4] The objective is the detection of the working states of the actors by measuring and analyzing the active electrical power of the drilling machine.

There are two possibilities to control the actuators, by the Manufacturing Execution System (MES) or manually via a touch panel. All working states are shown in figure 3.1. In state Z2, only the conveyor belt is switched on. During a drilling process, the conveyor belt runs and both drill units are active (state Z9). This corresponds to the production mode (order processing) when the plant is controlled by the MES. The permissible operating state transitions are also shown in green in the figure 3.1.

initial state \ final state		Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9
		base load	TB	B1	B2	B12	TB + B1	TB + B2	TB + B12	TB + drilling process
Z1	base load		+TB	+B1	+B2	+B12	+TB +B1	+TB +B2	+TB +B12	
Z2	TB	-TB		-TB +B1	-TB +B2	-TB +B12	+B1	+B2	+B12	+ drilling process
Z3	B1	-B1	-B1 +TB		-B1 +B2	+B2	-B1 +TB +B1	-B1 +TB +B2	+TB +B2	
Z4	B2	-B2	-B2 +TB	-B2 +B1		+B1	-B2 +TB +B1	-B2 +TB +B2	+TB +B1	
Z5	B12	-B12	-B12 +TB	-B2	-B1		-B2 +TB	-B1 +TB	-B12 +TB +B12	
Z6	TB + B1	-B1 -TB	-B1	-B1 -TB +B1	-B1 -TB +B2	+B2 -TB		-B1 +B2	+B2	
Z7	TB + B2	-B2 -TB	-B2	-B2 -TB +B1	-B2 -TB +B2	-TB +B1	-B2 +B1		+B1	
Z8	TB + B12	-B12 -TB	-B12	-TB -B2	-TB -B1	-B12 -TB +B12	-B2	-B1		
Z9	TB + drilling process		- drilling process							

permissible operating state transitions
impermissible operating state transitions
TB = conveyor belt, B1 = drill 1, B2 = drill 2, B12 = drill 1 and 2

Fig. 3.1 State table with permissible and impermissible state transitions.

For example a state transition from state 1 to state 2 is valid. A transition from state 2 to states 3 to 5 (shown in red) would not be permitted. This is caused by the fact that the conveyor belt and the two drilling units may not be simultaneously switched over due to different control mechanisms.

The energy measurement step includes the measuring of the active power of the production module in the nine operating states. For data collection the data sensor (network sniffer) was integrated into the data network running in forward mode. This has the task of detecting and forwarding the Modbus telegrams containing energy data to a desktop computer. In this phase no processing was done within the data sensor. On the desktop computer the energy data could be evaluated in offline mode with the software tool Wireshark.

With the help of Wireshark the collected energy data was exported into a text based network capture data format K12. In this data format every captured network data packet is saved into a single row in form of a time stamp and a sequence of bytes as hexadecimal numerical values represented in text form. In order to make this usable for state detection, data conversion from the hexadecimal to the decimal number system was performed. Finally the recorded data was exported to an Excel spreadsheet.

The data were recorded over a temporal measuring range of 15 to 30 minutes (see figure 3.2).

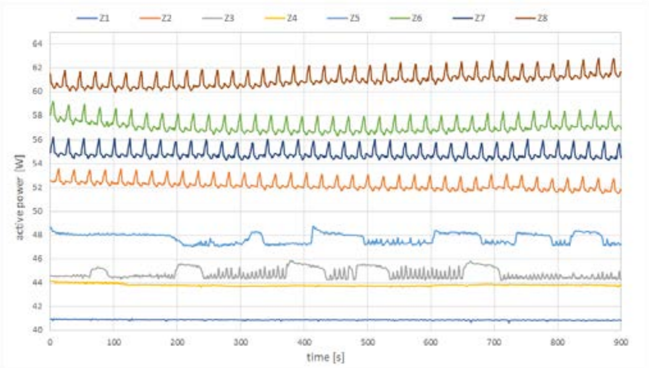

Fig. 3.2 Active power over a temporal measuring range of 15 minutes.

The procedure for measuring the energy values during the state transitions was identical. The active power during operating process and transitions between states were measured and recorded as reference values in tabular form.

A feature-based data model was developed for automatic state detection. For this purpose, the measured average active power values were used as characteristics of the states.

In the case of state transitions the differences between the individual states were calculated and recorded in a matrix.

In order to meet the cybernetic behavior of the plant, the recorded reference values were dynamically adjusted to current consumption in the nine operating states. Thus, possible fluctuations in energy consumption were counteracted. These may be due to load and temperature changes or mechanical wear. In order to enable robust state detection, the reference values have been adapted to the changes via the formation of the moving average.

The reference value of the current state as well as the reference values of the other directly accessible states are continuously adapted to the changes. Another challenge was to recognize the state transitions. For this purpose, the consumption in the operating conditions must be constantly measured and monitored for characteristic changes.

It has been found useful to aggregate the individual active powers readings over a short period of time from a few seconds to a mean value and to use them as a temporarily comparison value. If the difference between the comparison value and the reference value is outside a permissible range, a change of state is assumed. For safety, the status change is checked for validity by comparing it with the valid state changes.

In the second step for online analysis of production states, the above described model was implemented on the data sensor in a proprietary rule-based language with a total of 120 queries and instructions. The following is an explanation of the first two statements (see figure 3.3).

```
// intercept the relevant data packets
1."pass(if:*ETYPE=kIPV4; if:*I4PROTO=kTCP; if:*TCPSPORT=%502;
if:*MODBUSSIZE=%232; cont:%1)\0",
2."pass(set:$break=%1)\0",
```

Fig. 3.3 Example statements of the rule-based language.

The first nested statement checks whether the data packet is relevant to the model-based state detection. All IPv4 packets encapsulating the TCP protocol addressed to the port number 502 and having a length of 232 bytes are relevant. If all conditions are met, the cont:% 1 statement causes the 2nd statement to be skipped. Otherwise, statement 2 is executed, causing the next data packet to be analyzed. With these two commands, a filtering of relevant data packets is implemented. The subsequent instructions for the evaluation of relevant data packets are not explained in detail, as this would be beyond the scope of the present article.

4. Results and discussion

After the transformation of the model into an algorithm, it was implemented into the data sensor using the rule-based language. Following to that an evaluation regarding reliability of the state detection was performed. For this purpose, the data sensor was plugged into the Ethernet connection between the energy data sensor of the drilling station and the local Ethernet switch. The actual power values transmitted by the energy sensor in the data stream are detected by the data sensor and processed to conclude the current operating state of the drilling station.

In order to be able to fully validate the recognition of nine relevant states, all possible state transitions were carried out in a specific cycle during the test runs and production orders were commissioned via the MES. The deduced working states identified by the data sensor were compared with the actual operating states observed. (see figure 4.1 and 4.2).

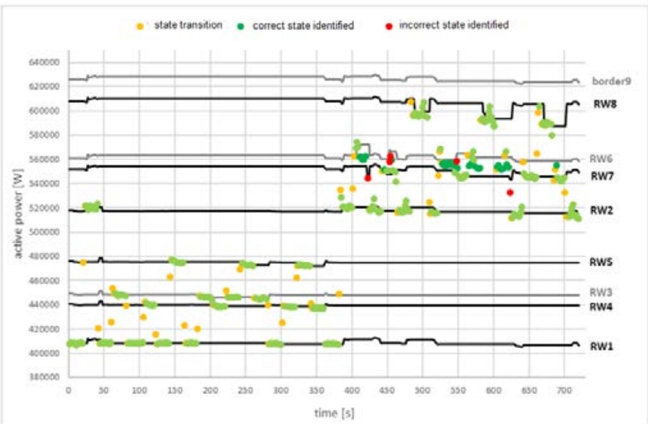

Fig. 4.1 Result of validation (states Z1 to Z8).

During the tests, 842 active power values were evaluated, wherein only 7 of them were identified incorrectly. Thus the error rate is 0.8%. Thereafter the state transition detection was tested. From the totally tested 68 state transitions 65 of them were recognized correctly, and besides none of them was classified as impermissible. The validation result of the commissioned production orders can also be shown: out of 14 orders, 13 were correctly recognized by the data sensor. In 12 of these orders, the data sensor could even distinguish between two different production order types.

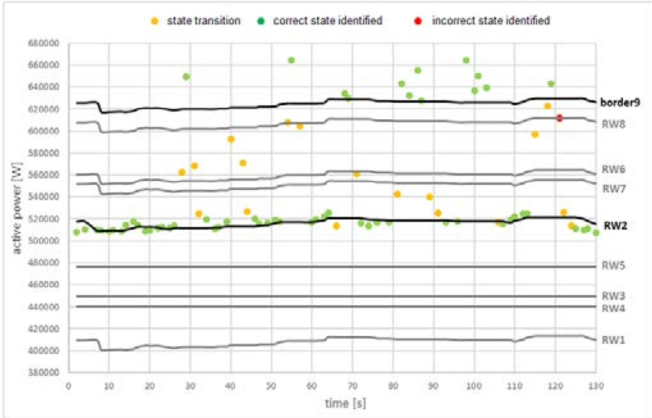

Fig. 4.2 Result of validation (states Z2 and Z9).

The validation result shows that in the case of sufficiently complex production processes, a condition monitoring system with certain level of reliability can be implemented by analyzing the Ethernet data with a single hardware.

5. Conclusion

In this work an algorithm for detection of operation states and state transitions was tested on a production line. Within this project, nine relevant operating states of the drilling station were defined. The total power consumption data of a drilling station in the cyber-physical factory was extensively analyzed and characteristics that represent a correlation between the energy data and the operating states were identified.

The analysis showed that using only the active total power value can be used to identify the operating state of the drilling station. In addition to that, a distinction between different production orders based on current power consumption and a time interval can be drawn. To develop a virtual sensor based on identified features and correlations, a model was derived. The model can recognize operating states and state transitions as well as distinguish between different production order types. In addition, the model includes the detection of impermissible state transitions, in which case an alarm message is issued.

To use the model in a real-time environment, the algorithm was implemented into a data sensors device using a rule-based language. Thus the data sensor represents a virtual sensor which determines the current operating state from the energy data in real-time and outputs it for online monitoring. After successful commissioning, the software was able to validate its reliability. The operating states determined during the tests were compared with the real operating states and an error rate of 0.8% was determined. Therefore, the developed condition monitoring system has a very high reliability. In this application, the virtual sensor was used in transparent mode where no interference with the actual data stream takes place. Due to the permanent monitoring of the production states in real-time, disturbances and irregularities as well as impermissible states or state transitions can be detected. This is important for the development of predictive maintenance applications. The data acquisition and evaluation method describe here can be embedded into any existing data networks.

6. References

[1] Patrick Jahnke: Machine Learning Approaches for Failure Type Detection and Predictive Maintenance, Master Thesis TU Darmstadt, June 19, 2015

[2] Chaitali S. Kalaskar, Vitthal J. Gond: Motor Current Signature Analysis to Detect the Fault in Induction Motor, Journal of Engineering Research and Applications, ISSN : 2248-9622, Vol. 4, Issue 6(Version 1), June 2014, pp.58-61

[3] Festo: Energiemonitoring CP Factory. Systembeschreibung Inbetriebnahme Anwendungsbeispiele, Denkendorf, 11/2015, p. 4.

[4] Festo: Qualifikation für Industrie 4.0, URL:http://www.festo-didactic.com/download.php?name=brochure_Qi4_screen_full_56758de.pdf&c_id=1100&file=brochure_qi4_screen_full_56758de.pdf, p. 10.

[5] Festo: Energiemonitoring CP Factory. Systembeschreibung Inbetriebnahme Anwendungsbeispiele, Denkendorf, 11/2015, p. 1.

[6] Siemens: SENTRON Multifunktionsmessgerät SENTRON PAC3200, Gerätehandbuch, 02/2008, A5E01168664A-04