Embedded Service Oriented Diagnostics based on Energy Consumption Data

Corina Postelnicu, Navid Khajehzadeh, Jose L. Martinez Lastra
Factory Automation Systems and Technology Laboratory
Tampere University of Technology
Tampere, Finland
corina.popescu@ieee.org, navid.khajehzadeh@tut.fi, lastra@ieee.org

***Abstract*—This paper presents a method to identify at an early stage incipient faults in pieces of equipment typically used for transportation of parts in discrete manufacturing settings. The method relies on knowledge of the typical energy consumption of the described devices using different workloads (the energy signature of the machines). At runtime, Support Vector Machines (SVM) are used to classify the input energy data into two pattern descriptions, typical of regular workloads expected on the devices. Consecutive mismatches between the output of the SVM and the workloads observed in real time indicate possibility of incipient failure at device level. The method is implemented using Web Services deploying Service Oriented Architecture in a real multirobot factory automation industrial testbed, originally used for assembly of mobile phones.**

I. Introduction

Significant financial losses and accidents may be caused by gradual equipment failures that are not detected until the effects are serious enough. State of the art predictive maintenance techniques [10], [11] are either passive or active. Passive techniques use the output of existing sensors to verify the performance of the sensors themselves or deploy test sensors onsite to measure directly the parameters of interest and compare measured data with expected 'normal' values. The measured data may refer to vibration, temperature, tribology (lubricating oil analysis and wear particle analysis), or ultrasonics (similar to vibration, but different frequency range) [2]. Active methods inject test signals into the equipment to observe the response of the devices to various modifications in input values in the model used and its inputs.

Quantification of how serious a fault should be to be investigated further implies that thresholds are set for data collected from the equipment, before its utilization in the real factory automation setting of interest. This is done normally by running the devices until the breakdown point is reached, several times, to generate a 'typical failure signature' associated to the parameter of interest. For instance, in [12], real time vibration information is collected until failure to create a vibration based database of suitable amplitudes associated with the bearing defective frequency and its first 5 harmonics.

The assumption is this signature is inherent to the studied device, and cannot be influenced by any other parameters of the world. For processing workstations this may be accurate (a manufacturing process is similar from e.g. a vibration viewpoint; data changes only as time passes by and the utilized equipment pieces wear off; failure categorization relies on predetermined failure thresholds such as the ISO2372 standard for acceptable vibration levels for different classes of equipment [12]). For transportation devices, however, the associated workload is important to infer whether the signature attached to the device is within normal range or not.

In discrete manufacturing settings, adjacent conveyor pieces (Fig. 1) tend to exhibit misalignment in time. The extent to which device segments drift away from each other depends on many factors, including the nature of the production process, pallet weight, total transfer time for a pallet, etc. Data traditionally used in predictive maintenance (vibration, temperature, pressure and humidity [2]) are insufficient to detect gradual device failure, at its beginning.

In this work, energy consumption information regularly associated to a particular workload of the transportation device is repeatedly observed. This information (the expected behavior) is then used in conjunction to the energy consumption and workload information coming in real time from the line, to detect of gradual undesired behavioral changes in the considered equipment piece.

This paper is organized as follows: Section II presents

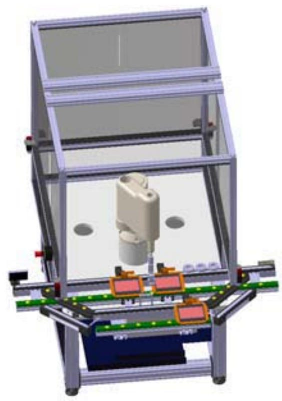

Fig. 1. Conveyor system analyzed. Main conveyor hosting 2 pallets. Bypass hosting 1 pallet.

978-1-4673-1975-1/12/$31.00 ©2012 IEEE ICIAfS'12

briefly the theoretical background of this work and related research. Section III describes the industrial setting utilized for the implementation of the described incipient failure detection method. Section IV gives details on the method employed to categorize device behavior in terms of energy oriented cause-effect relationships, and to timely detect conveyor segments misalignment mismatch. Section V describes the results obtained. Section VI concludes and outlines future work.

II. BACKGROUND

Fault detection methods are either model-based or data-based. Model-based fault detection uses a mathematical model of the system as a reference to analyze new data. The main challenge of this approach is to ensure accuracy is respected with increasing system complexity. Data-driven fault detection is based on historical observations of process data; accurate mathematical modeling of the system is not essential here [3], [4]. Abnormal system behavior is signaled via statistical algorithms and machine learning techniques such as Support Vector Machines. Data-based methods are applied when the physical model of the system is complicated or when the basic system operation principles are difficult to model but there is enough monitored data available concerning the system. This brings us to the main challenge associated to data-based fault detection, i.e. the need of large quantities of good quality training data. In some cases [14] even up to 2 years of are used.

Support Vector Machines (SVM) [5] is a data classifier that provides a hyper plane as a boundary between two classes of data. The classifier generates a model from a set of input data and allocates each given input to one class or category. SVMs are generally two-class classifiers (binary classification). Multi-class classification is also accomplishable via SVMs using a combination of binary classifications and a decision making procedure. In order to have a classification on a dataset consisting of multiple labels (multi-class classification), the most used methods in practice are one-versus-all and one-versus-one classifications [6]. SVMs are capable of classifying non-linearly separable data via kernel functions used to map input data to a higher dimensional feature space in which a clear and wide gap exists to divide data into separate classes.

Least Squares Support Vector Machines (LS-SVM) [7], [8], [9] are a modified version of SVMs. Unlike SVMs, who solve a burdensome quadratic program problem for training, LS-SVM solves linear equations. Usually 70% to 80 % of data are used for learning and the rest applied as cross validation data in order to verify the parameters computed by algorithm.

III. TESTBED

The testbed used for this research was previously used in a real factory for assembly of mobile phone components. Fig. 2 illustrates the layout of the industrial setting. The line was retrofitted to simulate its original operations (assembly of Frame, Keyboard and Screen components) by drawing them. The testbed comprises ten workstations, one static buffer cell and one loading and unloading station. Each workstation includes one main conveyor, one bypass conveyor and one SCARA robot (SONY SRX-611).

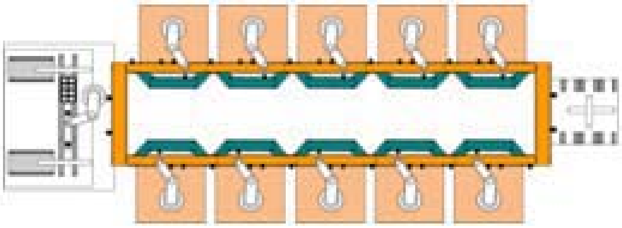

Fig. 2. Testbed layout

The conveyor system of each cell (Fig. 2) consists of one bypass (capacity of one pallet) and one main conveyor (capacity of two pallets). The main conveyor includes two stoppers and the bypass conveyor one stopper. NFC readers installed beside each stopper collect information regarding completed operations from the NFC tags carried by the pallets.

The line is coordinated by a hybrid methodology, using client-server and peer to peer paradigms. The system is composed by the physical devices in the line and a Decision Support System (DSS) located in an external computer. The devices and the DSS functionality are exposed as Web Services. The devices can communicate in a peer to peer fashion and with the DSS. All invocations and notifications are Web Service based. Exposed event notifications (Table I) include information about energy consumption (via S1000 energy meters), CAMX state events (e.g. pallet input to a conveyor piece), quality, and temperature / humidity / light.

TABLE 1
TESTBED GENERATED MESSAGES

No	Message	Description
1	EquipmentChangeState	cell ID, recipe number, device type, pallet ID, the current state, the previous robot state, time stamp.
2	QualityInspection	quality information including pallet ID, the quality of frame, screen and keyboard, the quality of the inspection result and a time stamp.
3	EnergyMeter	Robot/conveyor/controller energy consumption, per each working cell published at a time interval of five seconds.

IV. DETECTION OF INCIPIENT FAILURE IN TRANSPORTATION

A. *Monitoring relevant testbed generated data*

The data relevant for the discussion in this paper is related to energy consumption of the piece of equipment, and respectively its workload (in the analyzed case, the number of pallets occupying the conveyor at one time). The conveyor belts are running continuously, irrespective of whether the pallets residing on them are stopped via stoppers or not. When stoppers are in use, there is an increase in friction between the conveyor belt and the pallet, which results in an observed increase of power consumption in the conveyor engine.

All testbed cells are equipped with energy meters integrated into S1000 processing units (smart Remote Terminal Units). Each energy meter is an E10 Energy Analyzer expansion module [15] which provides 3-phase electrical power consumption monitoring (Fig. 3). Phase A is assigned to the robot, phase B is allocated to the cabinet, I/Os and the controller, while phase C is assigned to the conveyor system (including main and bypass). Power is measured by sampling current and voltage. Fig. 3 depicts the current sampled by a current transformer (CT) connected to +Ia-, +Ib- and +Ic- terminals and the voltage is measured by direct connection of the 3 phases and neutral to the Vn, Va, Vb and Vc terminals of the E10 expansion module.

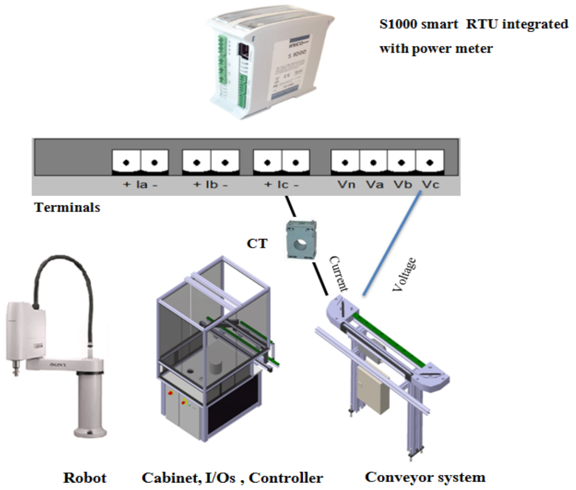

Fig. 3. Monitoring energy consumption in the industrial testbed

To monitor equipment workload, inductive sensors are mounted at entrance and exit points of each cell, and IPC2541 CAMX TransferIn/TransferOut notifications [16] output by the line counted.

B. Detection of incipient failure of transportation equipment

Fig. 4 illustrates the method employed for detection of gradual undesired behavioral changes in the considered equipment piece.

The main actors involved are a monitor, to collect raw values from the line, a classifier for energy data, and a rule based engine defined offline that maps the workload monitored in real time to an expected class of energy consumption. The monitored data includes the energy values e(k) coming from the conveyor, and respectively the device workload NoPallets(k) in number of pallets occupying the conveyor at one moment of time t(k). The energy values are input to an LS-SVM classifier who categorizes the one dimensional data into two classes Cm, m is 1 or 2, corresponding to energy values correlated to 0-1 and respectively 2-3 pallet workload. 70% of data are used as a training set and the remaining 30% are utilized for cross validation. The training set provides the SVM classifier with the model parameters. The model is then verified via the remaining 30% of the data. The Rule-based Engine includes two simple rules defined offline. The rules associate the monitored number of pallets to either class of type 1 (for 0 to 1 pallets detected) or class of type 2 (for 2 to 3 pallets).

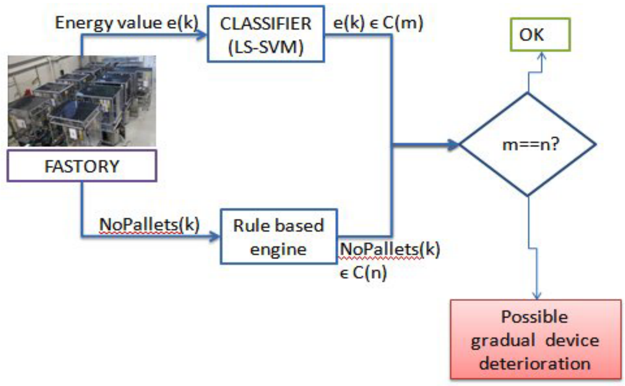

Fig. 4. Detection method of gradual conveyor miss-alignment

The results coming from the classifier are compared to the results coming from the rule based engine at each time instant considered. A gradual increase in the number of consecutive mismatches between the two outputs implies a gradual deterioration of expected behavior in the monitored piece of equipment. The energy values observed no longer correlate as expected to the semantics defined statically, meaning measures must be taken to re-align correctly the transportation segments.

V. RESULTS

A classifier was built to estimate, based on previous observations, the workload-correlated category of each newly monitored energy consumption value.

Fig. 5 depicts the power consumption of the engine rotating the bypass conveyor of testbed Cell 5, at a sampling rate of 1 second. Increases in engine power consumption are correlated with increases in the number of pallets on the conveyor belt.

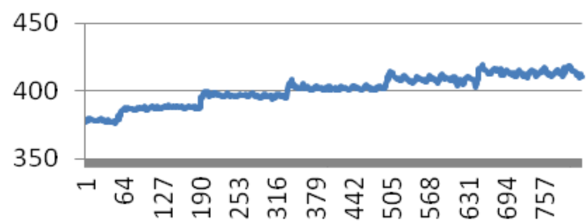

Fig. 5. Cell 5 bypass conveyor engine power consumption (Watt). Pallet traffic of 0 to 5

Fig. 6 shows the data monitored for the entire conveyor system, including both main and bypass conveyors.

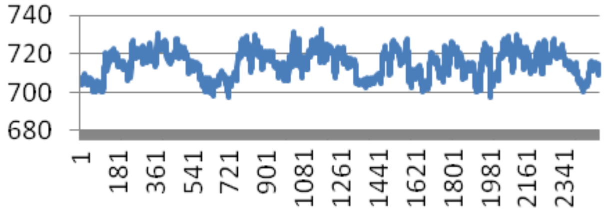

Fig. 6. Cell 5 conveyor system engine (main and bypass conveyor) power consumption

A significant change in power consumption is observed when the pallet workload changes from one to two.

Consequently, the first class corresponds to power consumption values estimated to be representative of zero or one pallet and the second class corresponds to power consumption values representative for two, three or more pallets.

Fig. 7 illustrates the two classes identified by the rule based engine on the sampled data of Fig. 6. The data categories are separated based on observed power consumption values and number of pallets associated to each sampled power value.

A binary classifier algorithm (LS-SVM) with radial basis kernel function was applied to the data shown in Fig. 6. 1800 data samples were used for training, and 700 for validation. The accuracy of the classifier performance is evaluated by computing the error term defined as the fraction of the cross validation examples that were classified incorrectly. The computed error (the average percentage of the number of unsuccessful estimated classes compared with the classes given by rule based engine) is 5.56%. Fig. 8 shows the cross validation data classified into two classes by LS-SVM.

Despite expectations, conveyor power consumption does not change instantly once conveyor workload is modified, but after a short time delay. This delay is responsible for the few outliers visible in Fig. 7 and Fig. 8. Such occurrences may influence the value of the calculated error.

VI. Conclusion

This paper presents a method to describe expected system behavior from the viewpoint of the energy signature transportation processes. In particular, energy consumption values are monitored and classified for a real factory automation testbed. During training phase, the energy

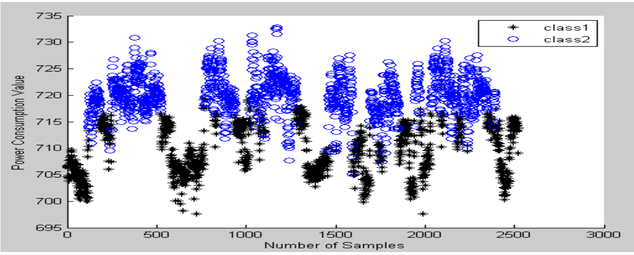

Fig. 7. Classes generated by rule based engine and correlated to each sampled data

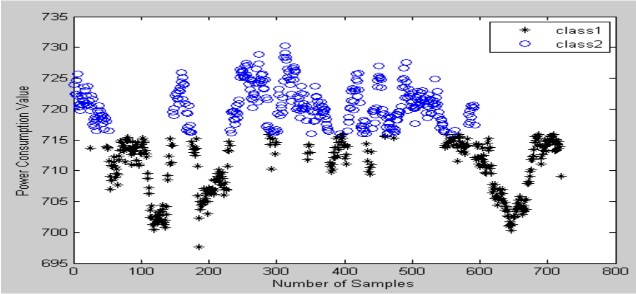

Fig. 8. LS-SVM classifier output

signature of the system components is associated with semantics concerning the workload of the conveyor belts. At validation phase, real time data coming from the line is input to the classifier and the output obtained is compared against the output of a rule based engine defined offline. Chain consecutive mismatches should pinpoint to incipient gradual deterioration of expected behavior. In the presented scenario, such deterioration would translate to a misalignment of conveyor segments.

An important issue of this approach is to avoid the generation of an illusion of causality by an improperly tuned classifier. That is, an inappropriately large classifier error would immediately result in mismatches between the output of the rule based engine and the output of the LS-SVM, mismatches that would not be caused by conveyor deterioration but by the classifier's inability to associate correct categories to the data it is presented with.

Future research will focus on bringing more parameters for analysis, in addition to power consumption, to increase the number of dimensions of the available datasets. Vibration and temperature sensors are available in the testbed, and can be used wherever applicable (e.g. for the robots).

Acknowledgment

This work has received funding from the ARTEMIS Second Call 2009 Programme under Grant Agreement number 100223, correspondent to the project shortly entitled eSONIA Embedded Service Oriented Monitoring, Diagnostics and Control: Towards the Asset Aware and Self Recovery Factory.

References

[1] Wang, H., Chai, TY, Ding JL, Brown M.,"Data Driven Fault Diagnosis and Fault Tolerant Control: Some Advances and Possible New Directions", *Acta Automatica Sinica,* Vol. 35, No.6, pp. 739–747, June, 2009.

[2] Mobley, "An Introduction to Predictive Maintenance", 2nd edition, pp. 99- 113, 2002.

[3] Venkatasubramanian, V., Rengaswamy, R. K. Yin, and S.N. Kavuri. "Review of process fault detection and diagnosis part iii: Process history based methods." *Computers and Chemical Engineering*, vol. 27, pp. 327–346, 2003.

[4] P.M. Frank."Analytical and qualitative model-based fault diagnosis – a survey and some new results", *European Journal of Control* vol. 2, no. 1, pp. 6-28, 1996.

[5] Vapnik, VN, Cortes, C.,"Support Vector Networks", *Machine Learning*, vol. 20, pp. 273-297, 1995.

[6] Naotoshi, S.,"A Comparison of Multi-class Support Vector Machine Methods for Face Recognition", Dec. 2007, Available online: http://note.sonots.com/?plugin=attach&refer=SciSoftware%2FMSVM&openfile=report.pdf

[7] Suykens, J. A. K., Vandewalle, J., "Least squares support vector machine classifiers. Neural Processing Letters", vol. 9 no. 3,pp. 293−300, 1999.

[8] Haifeng W., "Comparison of SVM and LS-SVM for Regression" , IEEE International Conf. On Neural Networks and Brain, vol. 1, pp. 279 – 283, 2005.

[9] Steve R. Gunn, "Support Vector Machines For Classification and Regression" , 1998, Available online: http://users.ecs.soton.ac.uk/srg/publications/pdf/SVM.pdf

[10] Hashemian, H.M., "State-of- the-art predictive maintenance techniques", IEEE Transactions on Instrumentation and Measurement, vol. 60, no. 1 , pp. 226-236, Jan. 2011

[11] Hashemian, H.M., Bean, W.C. "State-of- the-art predictive maintenance techniques", IEEE Transactions on Instrumentation and Measurement, vol. 60, no. 10 , pp. 3480-3492, Oct. 2011

[12] Wu, S.W., Gebraeel, N. Lawley, M. , "A neural network integrated decision support system for condition based optimal predictive maintenance policy", IEEE Transactions on Systems, Man and Cybernetics –Part A: Systems and Humans", vol. 37, March 2007

[13] Carnero, M.C., "Selection of diagnostic techniques and instrumentation in a predictive maintenance program. A case study", Decision Support Systems, vol. 38, pp. 539-555, 2005.

[14] Yam, RCM, Tse, PW, Li, L., Tu, P., "Intelligent Predictive Decision Support System for Condition-based Maintenance", Int. J. Adv. Manuf. Technol., vol. 17, pp. 383-391, 2001.

[15] E10 Energy Analyzer, Inico Technologies Ltd., Available online: http://www.inicotech.com/doc/e10%20brochure.pdf

[16] IPC2541 specification Generic Requirements for Electronics Manufacturing Shop-Floor Equipment Communication Messages (CAMX), Available online: http://webstds.ipc.org/2541/2541pub.pdf