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Detection of abnormal energy patterns pointing to gradual conveyor misalignment in a factory automation testbed

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Abstract— **This paper presents a method to detect gradual deterioration of behavior in discrete manufacturing pieces of equipment dedicated to transportation of parts between the processing workstations. Monitored energy patterns are correlated with workload data (number of pallets occupying conveyor segments at a time). Detection of gradual conveyor misalignment relies on checking whether the output of a rule based engine mapping input workload data into classes match with the output of an Support Vector Machine classifier operating on the energy values.**

Keywords-energy awareness, behavioral patterns, monitoring, energy consumption, factory automation, fault detection

I. INTRODUCTION *(HEADING 1)*

Small failures can lead to significant financial losses or hazardous situations. Faults have been e.g. responsible for 3% to 8% decrease in oil production, causing up to $20 billion losses in the US economy [1]. Early detection of faults is therefore critical to prevent serious disruptions to the production process. In addition to vibration, temperature, pressure and humidity data traditionally used in predictive maintenance [2], energy consumption signatures of pieces of equipment are a promising way to detect faults that occur gradually. An example of such fault is such the misalignments of conveyor segments that generally occur as time passes in discrete manufacturing execution systems.

The goal of this work is to characterize the behavior of testbed pieces of equipment from the viewpoint of energy consumption, and use the defined patterns in order to compare producer expectations with data values coming in real time from the line. This paper is organized as follows: Section II presents briefly the theoretical background of this work and related research. Section III describes the testbed used. Section IV gives details on the method used for detecting gradual misalignment of conveyors in the discussed factory automation setting. Section V describes the results obtained. Section VI concludes and outlines future work.

II. BACKGROUND

A. Support Vector Machines(SVM)

Faults are defined as any changes that prevent the system from operating properly. Fault detection is a binary decision making problem (i.e. the system may be operating properly or not).

Fault detection methods can be classified into two main categories: model-based methods and data-based methods. Model-based fault detection uses a mathematical model of the system as a reference to analyze new data. As system complexity increases with each technological advancement, the main challenge of this approach is the ensuring of accuracy.

Data-driven fault detection is based on historical observations of process data. Abnormal system behavior is signaled via mathematical or statistical algorithms, e.g. neural networks or machine learning techniques e.g. Support Vector Machines. The main advantage of the data-driven approach over model-based fault detection is that an accurate mathematical modeling of the system is not essential [3], [4]. 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 data available from condition monitoring. The main challenge here is the need for large quantities of training data of good quality.

Support Vector Machines (SVMs) [5] is a data classifier and a nonlinear function estimation tool. It provides a hyper-plane as a boundary between two classes of data. Using this classifier a model is generated taking a set of data as inputs and allocates each given input to one class or category.

SVMs are generally two-class classifiers (binary classification). Multi-class classification is also accomplishable

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using 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 apart 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. After validation, LS-SVM provides parameters of the model. Here model is defined as the classifier.

B. Related work

State of the art predictive maintenance techniques [10], [11] are of two types: *Passive techniques* either 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.

RT 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 [12]. Failure categorization relies on predetermined failure threshold ISO2372 standard for acceptable vibration levels for three classes of equipment [12].

Carnero [13] employs Factor Analysis to extract essential lubricant and vibration data. The data is integrated and information obtained correlated and alternatives regarding possible failure causes ranked via Analytic Hierarchy Process to identify the preferred maintenance choice and obtain early diagnosis.

Case based fault diagnosis is traditionally supported by large sets of data. Yam and colleagues [14] implemented an intelligent predictive decision support system for condition based maintenance. They used 2 years of data split into 110 sets, 65 dedicated to training and 45 to validation.

III. TESTBED

The testbed used for this research (henceforth denoted as FASTORY) was previously used in a real factory for assembly of mobile phone components. Fig. 1 illustrates the layout of FASTORY. 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).

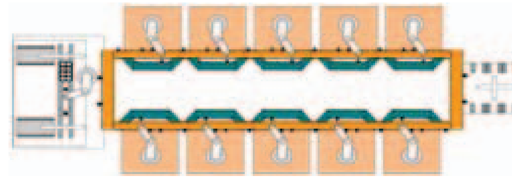

Figure 1. FASTORY testbed layout

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 FASTORY 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 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.

IV. ENERGY PATTERNS FOR DETECTION OF GRADUAL CONVEYOR MISSALIGNMENT

A. Monitoring relevant data

The data relevant for the discussion in this paper is related to *energy consumption* of the piece of equipment, and respectively its workload.

The conveyor belts are running continuously, irrespective of whether the pallets residing on them are stopped via stoppers

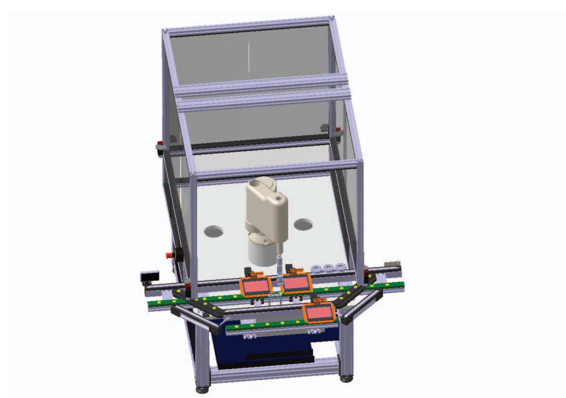

Figure 2. Conveyor system analyzed. Main conveyor hosting 2 pallets. Bypass hosting 1 pallet.

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 FASTORY 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 which provides 3-phase electrical power consumption monitoring (Fig. 3). Phase A is consigned to the robot, phase B is allocated to the cabinet, I/Os and the controller and phase C is assigned to the conveyor system including the main and bypass conveyor. Power measurement is achieved 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.

Equipment workload refers to the number of pallets occupying the conveyor at one time. To monitor this information, inductive sensors are mounted at entrance and exit points of each cell, and CAMX TransferIn/TransferOut notifications coming from the line counted.

B. *Energy based detection of gradual deterioration of expected behavioral signature of equipment pieces*

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:

The *monitored data* (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)) is collected from the testbed workcell.

The energy values are input to an *LS-SVM classifier* who categorizes the one dimensional data into two classes C^m, m is either 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 remained 30 % are utilized for cross

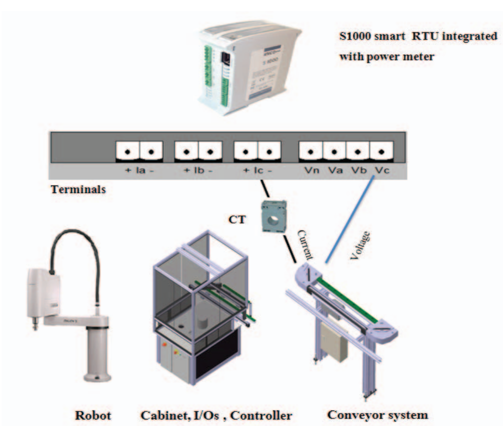

Figure 3. Setting used to monitor energy consumption

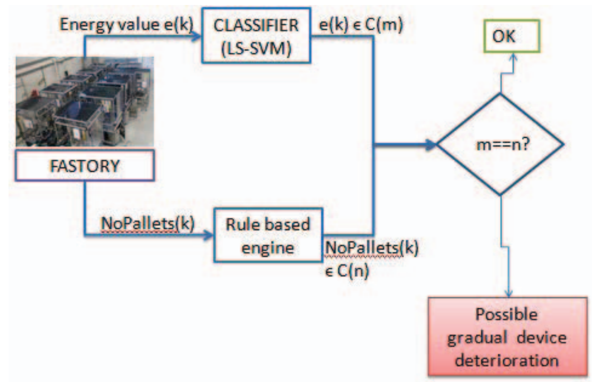

Figure 4. Energy awareness for detection of gradual conveyor miss-alignment

validation. The training set providers 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).

The results coming from the classifier are compared to the results coming from the rule based engine at each time instant considered. Gradual increase in the number of consecutive mismatches between the two outputs would imply 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.

V. Results

A classifier was built to generate a model estimating the class of new energy values based on previous observations.

The power consumption (WATT) of the conveyor system was measured at a sampling rate of 1 second. Fig. 5 depicts the power consumption of the engine rotating the bypass conveyor of FASTORY Cell 5. Increases in engine power consumption are generally correlated with increases in the number of pallets on the conveyor belt.

Fig. 6 shows the data monitored (2500 power consumption data samples) during the operation of the conveyor system (including main and bypass conveyors).

The most significant power consumption change is observed when the number of pallets changes from one to two.

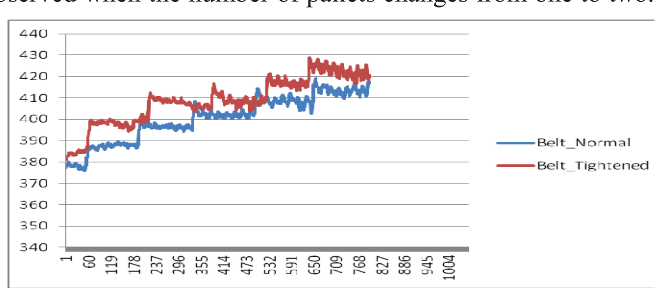

Figure 5: Cell 5 bypass conveyor engine power consumption. Pallet traffic of 0 to 5. In red: data obtained with the belt tightened

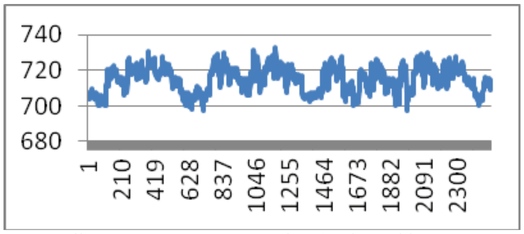

Figure 6: Cell 5 conveyor system engine (main and bypass conveyor) power consumption

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 number of 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 Figure 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. In our experiment, the computed error is 5.56%. This error is achieved by calculating the average percent of the number of unsuccessful estimated classes compared with the classes given by rule based engine. Fig. 7 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 Figures 7 and 8. Such occurrences may influence the value of the calculated error.

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).

As SVMs successfully support regression and classification of high dimensional input spaces, they were used here to provide an implementation backbone for future work.

The classifier produced by SVM was generated by training data values associated with the aligned conveyor belt.

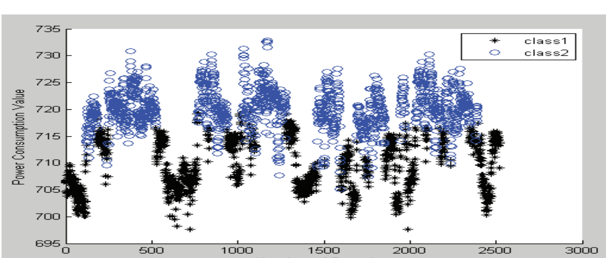

Figure 7: Classes generated by rule based engine and correlated to each sampled data

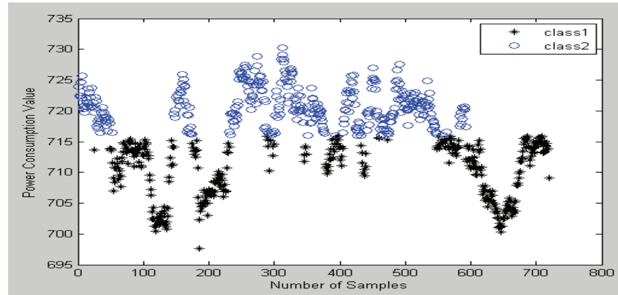

Figure 8: Classified cross validation data generated by LS_SVM

Classification of data values related to missalignment will not match with the classified data provided by Rule-Based engine. The method applied for calculating the error for classifier performance through cross validation data can be applied for fault detection as well.

VI. Conclusions

This paper presents a method to describe expected system behavior from the viewpoint of the energy signature of well behaved processes. In particular, energy consumption values of the transportation system in a manufacturing cell are monitored and classified for a real factory automation testbed. During training phase, the energy 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 pinpoint to possible gradual deterioration of expected behavior. In the presented scenario, such deterioration would translate to a misalignment of conveyor segments.

Acknowledgment

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