DE GRUYTER OPEN

Management Systems in Production Engineering

2017, Volume 25, Issue 3, pp 183-190

Date of submission of the article to the Editor: 10/2016
Date of acceptance of the article by the Editor: 04/2017

DOI 10.1515/mspe-2017-0027

AGGREGATION OF ELECTRIC CURRENT CONSUMPTION FEATURES TO EXTRACT MAINTENANCE KPIs

Victor SIMON, Carl-Anders JOHANSSON, Diego GALAR
Luleå University of Technology

Abstract:
All electric powered machines offer the possibility of extracting information and calculating Key Performance Indicators (KPIs) from the electric current signal. Depending on the time window, sampling frequency and type of analysis, different indicators from the micro to macro level can be calculated for such aspects as maintenance, production, energy consumption etc. On the micro-level, the indicators are generally used for condition monitoring and diagnostics and are normally based on a short time window and a high sampling frequency. The macro indicators are normally based on a longer time window with a slower sampling frequency and are used as indicators for overall performance, cost or consumption. The indicators can be calculated directly from the current signal but can also be based on a combination of information from the current signal and operational data like rpm, position etc. One or several of those indicators can be used for prediction and prognostics of a machine's future behavior. This paper uses this technique to calculate indicators for maintenance and energy optimization in electric powered machines and fleets of machines, especially machine tools.

Key words: *fingerprint, operational data, condition based maintenance (CBM), condition monitoring (CM), energy optimization, machine tool*

INTRODUCTION

Today's business environment sets ever-higher requirements on reliability, availability and economic performance of plants and equipment. Loss of production due to machine damage, especially if it occurs unexpectedly, diminishes the economic success of an enterprise and must, therefore, be prevented. In recent years, emphasis in maintenance has shifted to using emerging technology to measure machine condition and predict maintenance requirements. Key words like preventive, predictive and condition-based maintenance reflect this tendency. If plant personnel can always make an accurate assessment of the condition of their machines and plant assets, they can plan and introduce appropriate maintenance measures promptly, before larger and more serious damage and associated unplanned machine downtime occur. The bottom line benefits include gaining experience and learning relevant mechanisms or correlations to better control production processes. To achieve an accurate prediction of failure, however, it is essential to have an effective method of monitoring the status of an item or system. Clearly the ideal technique is one in which the condition of the equipment is known at all times and which accurately predicts any potential failure on demand. Condition Monitoring (CM) attempts to fulfill these requirements.

Maintenance strategies are methodologies able to create and/or optimize a maintenance plan for an overall system, with information from the maintenance preprocessing level as input and maintenance decisions at the next decision-making level as output.

Maintenance actions are defined, planned and prioritized according to the criteria and objectives of each available maintenance strategy. Generally speaking, maintenance actions, whenever possible, should attack the components' failure modes. The success of these actions depends largely on the time required to execute the action, the priority of the action, and the desired reliability to be achieved.

In this context, the two main maintenance strategies are:

1. Event Based Strategies: reactive and/or preventive maintenance, based on maintenance records, alarms and fault logs.
2. Measurement Based Strategies: predictive maintenance and/or Condition-based Maintenance (CBM) and/or Prognostic and Health Management (PHM), using condition monitoring variables and all related post- processed information.

Event Based Strategies are common in industry, while Measurement Based Strategies are the best option when a short-time maintenance plan is needed and the failure mode can directly be detected by health condition monitoring.

In Event Based Strategies, the most common maintenance model applied in industrial asset maintenance analysis, classic preventive maintenance information can be used to make good maintenance decisions, analyze assets and make fleet comparisons. Based on such analyses, an operator learn which assets are "better or worse" maintained and gain an initial idea of the effectiveness of the maintenance plan based on fleet comparison.

Preventive time-based maintenance strategies use the historical information of events and the analysis of reliability parameters to estimate the optimum Mean Time Between Maintenance (MTBM) or Mean Time To Maintenance (MTTM), used to prepare the asset maintenance plan. In this context, the Weibull Distribution Maintenance Model is one of the most commonly used lifetime distribution models in industrial applications. The Weibull Distribution and its parameters can be easily fitted to various maintenance lifetime distribution cases, mainly when the maintenance rate changes during the asset life.

As mentioned in the beginning of this section, the results from event based strategies could help the system operator to understand what assets are "better or worse" maintained and to get an initial sense of how efficient the maintenance plan is based on fleet comparison. Moreover, because input data to these models are usually available for any industrial asset under a preventive maintenance plan, the long-term maintenance actions can be rescheduled according to the real asset life historical behavior.

Preventive time based maintenance strategy analysis demonstrates that much of the information available in events data could help in maintenance rescheduling and decision- making; in general, such information is available without requiring a cost increase in data acquisition.

Nevertheless, when short-term analysis is needed and when the asset is under different working conditions and regimes, the mean behavior evaluated, based on the events data, is not the best information source to estimate and schedule the "next" maintenance actions. In this context, measurement based maintenance strategies should be used.

Measurement based maintenance strategies use the available data on asset measurements to predict when a maintenance action needs to be carried out. CBM and PHM are the best known examples of these strategies.

To rationalize failure prevention through predictive maintenance actions, measurement pre-processing results (based on both machine level and component level) can be applied to adopt either a CBM model, where the physical variables determining fault symptoms have been monitored, or a PHM model, where the focus is on incipient fault detection, current system health assessment and prediction of the remaining useful life in a component.

It is important to understand that the event information is only used to determine the critical components and failure modes and to define the normal behavior time periods used as a "baseline" for the health condition assessment. Based on these ideas and considering that the monitored condition is available to a measurement based strategy, we only need to define the Maintenance Threshold (MT), i.e., the asset state or condition when the predictive maintenance action is carried out. The main drawbacks of measurement based strategies are the implementation cost (monitoring system, expert knowledge for health condition models, etc.) and the fact that incipient faults and "bad" health conditions cannot always be detected and/or predicted.

To achieve and maintain good asset condition and operation, it is important to launch maintenance actions even when the health condition thresholds are not reached, thus guaranteeing the efficacy of all asset functions. This implies having a maintenance threshold that differs from the health condition threshold.

Maintenance information includes unit life plans, job cataloguing, etc. for each unit in two different categories: preventive and corrective maintenance. These data are characterized by their identification (record numbers), by the parameters characterizing them (category, activities involved, impact, date), by the resources that imply their deployment (man/hours, equipment), and by outputs in terms of active maintenance time and downtime.

Recording maintenance actions is crucial for successful knowledge extraction at some later date.

The normal strategy to keep production systems in good condition is to apply preventive maintenance practices, with a supportive workforce being "reactive" in the case of obvious malfunctions, as these have an impact on quality, cost and productivity. The uncertainty of machine reliability at any given time also has an impact. For example, a worn-out mechanism can have higher energy consumption.

The use of intelligent predictive technologies could improve the situation, but these are not widely used in the production environment. Often sensors and monitors needed in the production environment are non-standard and require costly implementation.

Monitoring and profiling the electric current consumption in combination with operating data which describe the way the machine is used (the context) is an easy way to implement Green Condition Based Maintenance (Green CBM) to improve overall business effectiveness. Green CBM takes a triple perspective:

1. Maintenance: Optimizing maintenance strategies based on the prediction of potential failure, scheduling maintenance operations in convenient periods and avoiding unexpected breakdowns.
2. Operation: Managing energy as a production resource and reducing its consumption.
3. Product reliability: Providing the machine tool builder with real data about the behavior of the product and its critical components.

Green CBM opens up the possibility of creating new business models for maintenance and service providers.

The Green CBM technique can be applied to many types of machines, but in this paper, we concentrate on machine tools.

The paper is part of the Power Consumption Driven Reliability, Operation and Maintenance Optimization (Power OM) project (http://www.power-om.eu/), now in the middle of collecting operating and fingerprint data. The paper is, therefore, mostly conceptual and concentrates on possible techniques and methods to determine and predict the condition of machine tools and fleets of machine tools, especially problems/faults in the spindle drive train and linear axis. The proposed method for Condition Based Maintenance (CBM), based on fingerprint and operating data, gives information about both operating conditions and power consumption without increasing the complexity and can be seen as a Green Condition Based Maintenance platform (Green CBM) [1] for both CBM and energy optimization.

CONDITION MONITORING OF MACHINE TOOLS

It perhaps goes without saying that knowing and predicting the condition of an asset is valuable. During the last 40 years, numerous diagnostic techniques have been developed, many based on signal analysis and statistical methods.

For stationary operating conditions, even prognostics of the failure work well, but the methods often require costly installation of transducers and signal analysis equipment handled by skilled personnel.

For some time, there has been increasing interest in methods based on available operating data that do not require costly equipment or skilled personnel. This is especially relevant for those with a fleet of similar equipment where methods and experience can be reused, for example, producers and owners of windmills, airplanes, ships, cars & trucks, elevators, packing machines and, in our case, machine tools.

Machine spindle defects are responsible for frequent and cost-intensive downtimes in machine tools, so these are normally a focus of condition monitoring. But a machine tool consists of many sub-systems that also can be supervised.

In the Power OM project, we concentrate on the spindle and the linear axis (Figure 1).

The main technique for detecting mechanical and electrical problems uses vibration analysis or Motor Current Signature Analysis (MCSA) in combination with context data. In the Power OM project, we use both, but in this paper we concentrate on MCSA in combination with context data. MCSA uses the electric motor as a transducer, allowing the user to evaluate the electrical and mechanical condition of the motor control and, by extension, of the machine. The basic idea is that any load or speed variation within an electro- mechanical system produces correlated variations in current and voltage. The resulting time and frequency signatures reflect loads, stresses, and wear throughout the system, but seeing these requires a mapping process or pattern recognition. Comparing a reference, electric signature of equipment in good condition (the fingerprint), and equipment under monitoring supports fault identification.

There are a number of commercial products in this area, including the ARTESIS system (www.artesis.com). The methods described in this paper are similar to those used in other systems but are more focused on other context data than is available in current, voltage and vibration signals.

Power monitoring with a torque sensor is evaluated in [2]. Other work uses power analysis to detect production machine failures with current signals [3, 4] and machine internal signals [5].

As we learn from [6, 7], several failures can be detected using induction motor current analysis. The controlled values, for example, of a gearbox failure, can be compared in the stator current spectrum, because several peaks are related to shaft and gear speed (see Figure 2). Characteristic gearbox frequencies can be detected in the stator current spectrum.

Current-based diagnosis of mechanical faults, such as imbalance and misalignment, can be performed in the same way. It is also possible to control the rotating movement of the machine; in addition, some work has been done on linear movement. For example, Electro Mechanical Actuators (EMA) are widely used in aeronautic systems; the use of Health Monitoring is widespread [8, 9, 10] as well. Similar actuators are used in machine tools.

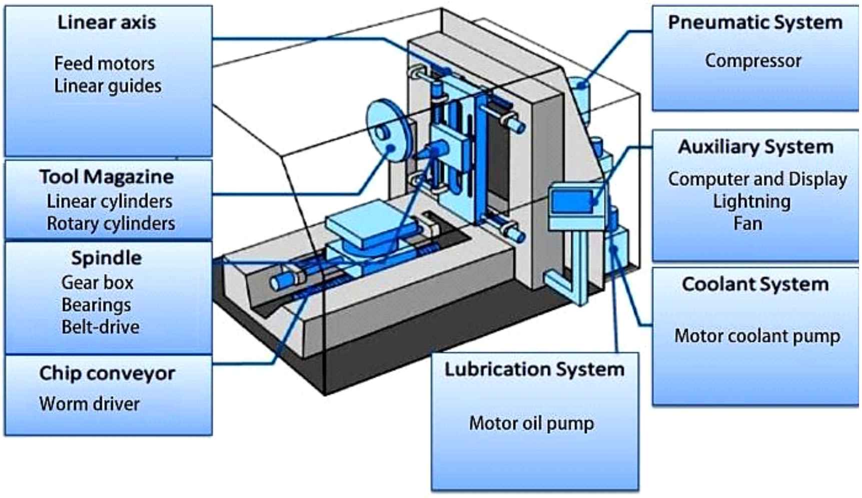

Fig. 1 Main sub-system of a CNC Machine
Source: Siemens.

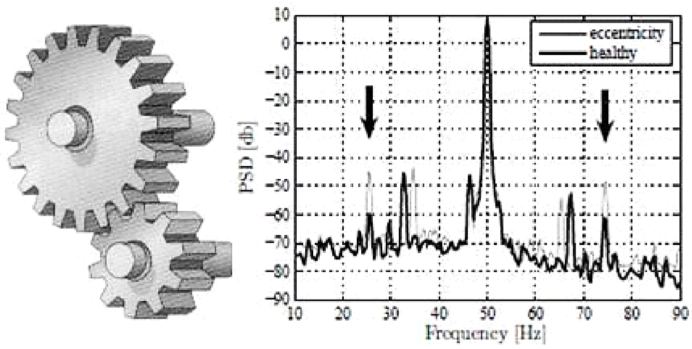

Fig. 2 Gear Failure detection with current signal

From testing to data collection

Condition monitoring methods, such as vibration or acoustic monitoring, usually require expensive sensors. The application of Electrical Signature Analysis includes the diagnostics of electrical machines. Several authors have applied this technique to detect induction motor failures [11]. Others [12] have detected other failures using the induction motor current signature analysis. The controlled values, for example, of a gearbox failure, can be compared in the stator current spectrum, because certain peaks are related to shaft and gear speed. Characteristic gearbox frequencies can be detected in the stator current spectrum. Current-based diagnosis of mechanical faults, such as imbalance and misalignment, can be performed in the same way.

Good maintenance policies lead to less energy consumption by assets, as stated by [13]. However, the relationship between an electric signal and wear for any complex electro-mechanical system, for instance, a machine-tool spindle, is less evident. The potential correlation has to be learned based on experimental research. The use of test benches allows us to identify a machine´s operating condition, to analyze and describe its various failure modes, to pinpoint the most significant signal to be used in tests for failure, and to design and execute a test plan for fault detection and prognosis.

Laboratory research gives us the ability to run components to failure, working in a controlled failure environment. This helps us relate current and power signal analysis to the selection of features for failure diagnosis.

To achieve statistical consistency, during the first phase of testing, i.e. failure diagnosis, various faults should be tested, along with the nominal one [14].

A local CBM module may consist of two main components based on Condition Monitoring (CM) techniques: first, the fingerprint to be used for the health assessment of the critical elements of the machine and second, operational data to infer the use of the machine.

A health monitoring system helps avoid component defects; consequently, it can prevent poor performance or even breakdowns. In the case of the spindle, component defects include bearing damage, defects in rotary transmission, clamping malfunction, imbalance, stator error, and alignment error. Operational data (i.e. feed, speed) can be used for energy and reliability management. An example is the different usage ratios of the machine: loads, speeds, etc. Note that the collection of operational data (real- and non-real-time) and fingerprint collection do not need to be performed simultaneously.

A fingerprint executed on a periodic basis (weekly, monthly etc...) generates raw data. These data are integrated with available inputs from the operational data to give information on the usage of the machine. These mixed data are pre-processed to obtain a set of relevant features that will be further analyzed for the nowcasting process. In parallel, data obtained from the machine are pre-processed to register the usage of the machine. The three main components of this process are operational data, fingerprints, and health assessments (the latter belong to data management).

Monitoring working conditions (operational data)

Determining the usage of the machine by the end user yields a more holistic understanding of the real status of a machine's critical components. The historical use of the machine is found in the operational data. The main reason to collect operational data is to determine the operating environment of the machine with the purpose of finding possible reasons for malfunction or failure and optimizing reliability through the proper selection of component or machining parameters. Depending on the already installed or optional sensors, the solution may vary, but in any case, the required data rate should not be high (tens of Hertz). In modern Computer Numerical Control (CNC) systems, several configurations are available: sensors can be connected to the CNC or digital drive system or to specialized hardware (for accelerometers or main power monitoring). In any event, there are two options to obtain operational data from the machine. The first is dialoguing with the CNC using specific hardware; this facilitates higher acquisition speed and detailed data, enabling some pre-processing. The second procedure requires the use of CNC internal data accessible through various links, like OPC servers, libraries, etc.; this limits the information available on how the machine is being used to showing only its acquisition rate.

Some processing is done to extract all the information from the data, using it to uild a historical register of the use of the machine and to obtain the data required for further service implementation.

Co-relating operational data and machine condition data using the correct algorithms can guide component maintenance, help change working conditions to extend component life or even help select a different component, more appropriate for the real machine use.

Operating data are collected with a sampling frequency between 1-100 Hz. The data are collected via interfacing with the Computer Numerical Control (CNC) controller of the Machine Tool (see Figure 3). In the Power-OM project, the research toolbox GEM OA (Open Architecture) hardware from Artis is used for the data collection [15].

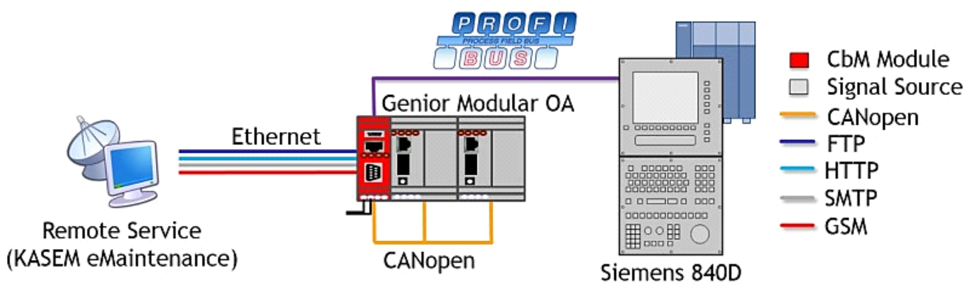

Fig. 3 Local data collection unit GEM OA (Artis)

Typical data collected are:
- spindle power and rpm,
- motor power and position for linear axis,
- difference between commanded and actual position,
- temperatures,
- programme number,
- tool number,
- alarms (sampled from the CNC or taken from the log file).

The operating data describe the way the machine has been used between the fingerprints.

Machine fingerprint

The term fingerprint has been coined to denote the electrical signature of a machine in a specific time domain.

To obtain the main fingerprint features, machines are run in a pre-defined test cycle in a no-load condition to achieve better failure detection and to remove any noise that could affect the normal machine process load. Condition monitoring data are based on the fingerprints obtained from the machine. In the first stage, data analyzed during the experimentation phase may help in the selection of the type of sensors, acquisition rates and tests to be performed on the machine in the production plant. The idea behind the fingerprint is that any load and speed variation within an electro-mechanical system produces correlated variations in current and voltage. The resulting time and frequency signatures reflect loads, stresses, and wear throughout the system, but identifying them requires a mapping process or pattern recognition. Comparing the electric signature of equipment in good condition and equipment under monitoring facilitates fault identification. Note that Signature Analysis is only applicable to cases where the principal cause-effect is verified and modelled.

Fingerprint data are collected in a standardized way every day/week/month using a test procedure. As part of this standardized procedure, the machine runs a special CNC programme every time the fingerprint is collected.

There is also a possibility of using standard sequences in ordinary production programmes like tool changing for part of the fingerprint collection.

The data are collected with a sampling frequency between 100 Hz and 50 kHz, depending on the type of data.

Typical data collected and synchronized in time are:
- vibration,
- motor power for spindle and linear axis (current signal and motor current signature analysis),
- RPM and speed for spindle and linear axis and axis position.

The data can be analyzed in both time and frequency domains [16], and a number of features (Table 1) can be calculated for each signal. In the frequency domain, the system follows the vibration levels on known frequencies like gear mesh frequencies, bearing frequencies, rotational speed etc. and their harmonics.

For faults/problems in the gear train, such as the bearing and gear problem, the most sensitive features are chosen through the use of a test bench (see Figure 4) where different types of faults can be simulated and by using faulty components sent in by customers for repair (see Figure 5).

Normally, the spindle rotates clockwise, but in certain operations, like threading and some milling, it operates counter clockwise. The latter operation normally has less power/torque. Therefore, comparing the difference in feature values in different rotational directions gives valuable information.

Table 1
Time domain feature

Feature	Definition
Peak Value	$Pv = \frac{1}{2}[\max(x_i) - \min(x_i)]$
Root Mean Square	$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i)^2}$
Standard Deviation	$Std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$
Kurtosis Value	$Kv = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{RMS^4}$
Crest Factor	$Crf = {}^{Pv}/_{RMS}$
Clearance Factor	$Clf = \frac{Pv}{(\frac{1}{n}\sum_{i=1}^{n}\sqrt{\lvert x_i \rvert})^2}$
Impulse Factor	$Imf = \frac{Pv}{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i \rvert}$
Shape Factor	$Shf = \frac{RMS}{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i \rvert}$
Normal Negative Likelihood value	$NNL = -lnL;\ L = \prod_{i=1}^{N} f(x_i, \mu, \sigma)$

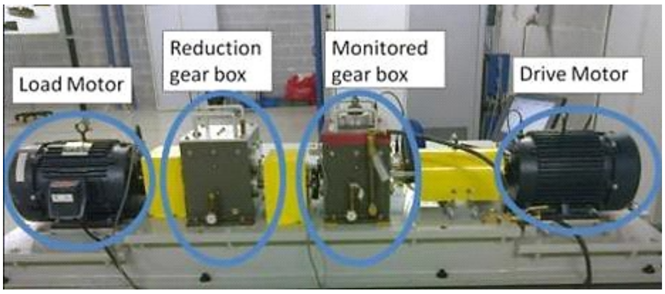

Fig. 4 Test bench for gear train

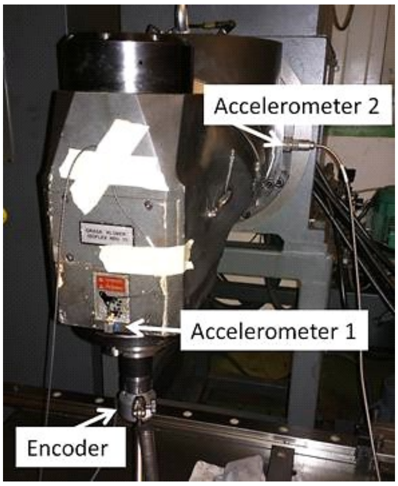

Fig. 5 Spindle head in test bench

Table 2 shows the testing of a spindle head before and after repair in both rotational directions. As the table shows, the degradation is greater in the "normal operation" direction (clockwise).

Table 2
Motor Current Analysis of the Spindle Motor showing the difference in behavior for a spindle head rotating in different diretions. CCW is the normal rotating direction

Feature	Value	Rotational direction	Spindle Status
Crest Factor	1,96	Counter clockwise	Repaired
	2,24	Counter clockwise	Faulty
	1,96	Clockwise	Repaired
	1,96	Clockwise	Faulty
Rotational Frequency sideband	3,56	Counter clockwise	Repaired
	12,7	Counter clockwise	Faulty
	4,73	Clockwise	Repaired
	4,64	Clockwise	Faulty

For the linear axis, there can be problems with the drive train (motor/gearbox/ball screw/nut/rack/pinion) and the linear bearings (see Figure 6).

Fig. 6 Linear guides ball screw/nut

For the drive train, the machine tool axis dynamics is an important factor; it can be analyzed by looking at the position/speed/acceleration and jerk values and by comparing differences in commanded and actual position [17].

With high resolution power or vibration measurements on the linear axis, it is possible to isolate problems in the ball screw/nut, rack/pinion, hydraulic counter balance system, and linear bearings [18].

KPI calculation

From the operating data, a number of KPIs can be calculated for both condition monitoring and energy optimization. Some examples are:

- number of starts/stops/accelerations/retardations,
- total travelled length for linear axis and distribution over the axis or 'travelled load' calculated from power need during acceleration of the axis,
- mean power/torque for spindle and axis and distribution over the axis,
- difference in behavior in different rotational directions for both spindle and linear axis,
- running time in different rpm, direction and power intervals,
- number of alarms per type/group,
- total energy used for a certain product/programme in a certain machine,
- total energy used for a certain tool.

For each machine/component in the fleet, typical faults/problems are identified, and the most sensitive fingerprint features and KPIs are chosen for each. This means each machine/component has a number of faults, and each fault has a number of features and KPIs that can be traced in a multi-dimensional space to estimate the condition of the machine/component. The threshold for the estimation is based on the results of tests with known faults using a test bench, tests of faulty components (for repaired and faulty spindle heads in this case) and the experience of this or similar machines in the fleet.

To begin, the estimation can be based on the history of the machine tool, including:

- age of component/machine tool,
- designed lifetime of component/machine tool,
- type of production/use (8h/24h/7d, heavy, medium, low),
- maintenance history,
- experience of similar machines in the fleet.

After a while, however, the estimation can be based on results from fingerprint and operating data.

The change in value of features between fingerprints indicates the degradation of the component; degeneration depends on both the previous condition and the way the machine has been used.

This means that the future condition, the feature value Fn, is a function of previous condition value Fn-1 and subsequent operating data.

$$F_n = f(F_{n-1}, Operational\ data) \tag{1}$$

ENERGY OPTIMISATION

A recent Directive of the European Parliament on Energy using Products [Directive 2009/125/EC] establishes a framework for the eco-design requirements of energy-using products. The European Commission has published a working plan [Working plan for 2009-2011 under the Eco design Directive] with a list of energy-using product groups it has prioritized. Machine tools represent one of ten product groups.

As a result, the machine tool sector is beginning to change. An example is the German Machine Tool Builder Association (VDW) which has developed the label Blue Competence.

In short, energy saving measures is increasingly relevant, especially in the machine tool sector for metal working production, as this sector requires 15% of the entire electric power consumption (German statistics).

Figures 7 and 8, extracted from an ISW study [20], show with more detail where energy is lost in the use of a machine tool and the share of energy consumed by each of its main components. Motor losses and idle running comprise 35% of the energy loss; spindle and drives consume more than 30%.

Power is normally optimized in machine tools in one of the following ways:

- limiting power output by optimizing production planning,
- minimizing the use of energy by putting subsystems like cooling fluid, hydraulic pumps, cooling fans etc. into idle/sleep mode,
- minimizing the use of energy by optimizing CNC programmes and processing paths,
- reducing power consumption for deep whole machining with an adaptive pecking cycle, which executes pecking as needed by sensing cutting load,
- reducing power consumption by synchronizing the spindle acceleration/deceleration with the feed system at rapid traverse stage,
- minimizing the use of energy by cutting parameters and optimizing tool selection,
- reducing power consumption for drilling and face/end milling by setting the cutting conditions high, yet within a value range which does not compromise tool life and surface finish, thereby shortening machining time,
- minimizing the cost for energy by optimizing production planning based on different energy prices at different times of the day.

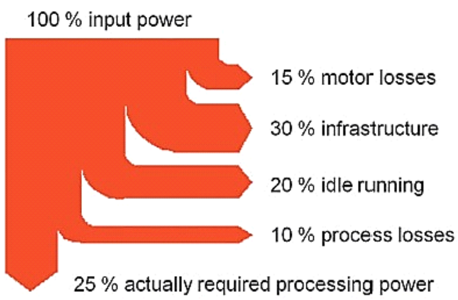

Fig. 7 Machine tool power flow diagram
Source: Translated from [19].

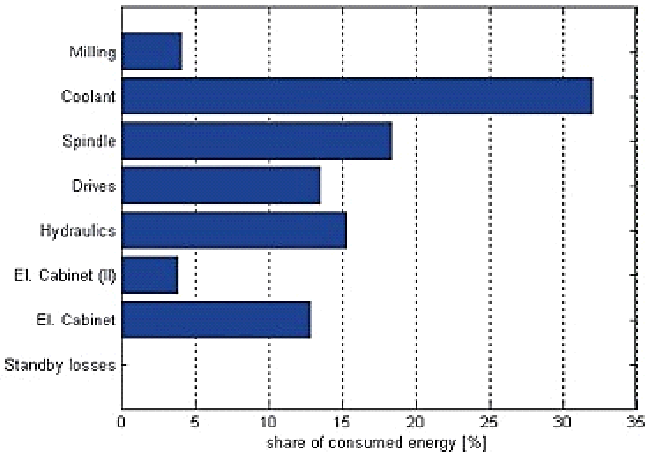

Fig. 8 Share of energy consumed by each Machine Tool component

The energy efficiency (η) of a machine tool operation can be calculated in one of the following ways:

$$\frac{Spindle\ used\ Energy}{Total\ Energy} \quad (2) \quad \text{or} \quad \frac{Total\ Energy}{RMV} \quad (3)$$

where:
RMV= Removed Material Volume [cm^3]

CONCLUSION

The analysis of data from existing sensors and information about a machine's power consumption and operating conditions permit the use of a new, easy to implement, Green Condition Based Maintenance platform (Green CBM).

For each machine/component in the fleet, typical faults/problems are identified, and the most sensitive fingerprint features and KPIs are calculated for each. The calculation is based on data extracted from the electric current signal through MCSA in combination with context data.

Green CBM does not increase the complexity and can be used for many types of manufacturing machines. By integrating all the information from individual machines, the fleet of machines, and even between companies, the Green CBM platform can act as a hub of technology, providing the different user profiles (Machine Tool users, Maintenance Service Providers and Machine Tool Manufacturers) with services for Maintenance and Energy Optimization and increased machine Reliability.

REFERENCES

[1] C-A. Johansson, D. Galar, R. Villarejo and M. Monnin, "Green Condition based Maintenance – an integrated system approach for health assessment and energy optimization of manufacturing machines", in *The 10th Int. Conf. on Condition Monitoring and Machinery Failure Prevention Technologies*, Kraków, Poland, 2013, pp. 1069-1084.

[2] J.L. Stein and C-H. Wang, "Analysis of Power Monitoring on AC Induction Drive Systems", *Journal of Dynamic Systems, Measurement, and Control*, vol. 112, no. 2, pp.239-248, 1990.

[3] F. Zhao, X. Mei, T. Tao, G. Jiang and Y. Zhou, "Fault diagnosis of a machine tool rotary axis based on a motor current test and the ensemble empirical mode decomposition method", *Journal of Mechanical Engineering Science*, vol. 225, no. 5, pp. 1121-1129, 2011.

[4] K. Chinmaya and A.R. Mohanty, "Vibration and current transient monitoring for gearbox fault detection using multiresolution Fourier transform", Journal of Sound and Vibration, vol. 311, no. 1-2, pp. 109-132, 2008.

[5] M. AbuAli, J. Lee and W. Zhao, *Methods and Systems for Energy Prognosis*, United States Patent Application Publication, no. US8527223 B2, 2013.

[6] E.L. Bonaldi, L.E.L. Oliveira, J.G. Borges da Silva, G. Lambert- Torres and L.E. Borges da Silva, "Detecting Load Failures using the Induction Motor as a Transducer", in *10th Int. Conf. on Control, Automation, Robotics and Vision*, Hanoi, Vietnam, 2008, pp. 196-199.

[7] H.B. Attia, "Détection et localisation de défauts mécaniques d'un entraînement électrique à vitesse variable", Ph.D. dissertation, Institute National Polytechnique de Toulouse, Toulouse, France, 2003.

[8] S. Curran, T.E. Walters and A.J. Chirico, "Health monitoring and prognostics for electro mechanical actuation", in *Proc. of the Int. Conf. on Recent Advances in Aerospace Actuation Systems and Components*, Toulouse, France, 2010, pp. 47-55.

[9] C.S. Byington, M. Watson and D. Edwards, "Data-driven neural network methodology to remaining life predictions for aircraft actuator components", in *Proc. IEEE Aerospace Conf.*, Big Sky, MT, USA, 2004, pp. 3581-3589.

[10] E. Balaban, P. Bansal, P. Stoelting, A. Saxena, K.F. Goebel and S. Curran, “A diagnostic approach for electromechanical actuators in aerospace systems”, in *Proc. IEEE Aerospace Conference*, Big Sky, MT, USA, 2009, pp. 1-13.
[11] M. Messaoudi and L. Sbita, “Multiple Faults Diagnosis in Induction Motor Using the MCSA Method”, *International Journal of Signal and Image Processing*, vol. 1, no. 3, pp. 190-195, 2010.
[12] E.L. Bonaldi, L.E.L. Oliveira, J.G. Borges da Silva, G. Lambert-Torres and L.E. Borges da Silva, ”Detecting Load Failures using the Induction Motor as a Transducer”, in *10th Int. Conf. on Control, Automation, Robotics and Vision*, Hanoi, Vietnam, 2008, pp. 196-199.
[13] UNE-EN 15341:2008.
[14] I. Bravo-Imaz, A. Garcia-Arribas, S. Ferreiro, S. Fernandez and A. Arnaiz, “Motor current signature analysis for gearbox health monitoring: Experiment, signal analysis and classification”, in *2nd European Conf. of the Prognostics and Health Management Society*, Nantes, France, 2014, pp. 1-5.
[15] A. Alzaga, E. Konde, I. Bravo, R. Arana, A. Prado, C. Yurre, M. Monnin and G. Medina-Oliva, “New technologies to optimize reliability, operation and maintenance in the use of Machine-Tools”, in *Euro-Maintenance Conference*, Helsinki, Finland, 2014.
[16] D. Galar, U. Kumar, J. Lee and W. Zhao, “Remaining Useful Life Estimation using Time Trajectory Tracking and Support Vector Machines”, in *25th International Congress on Condition Monitoring and Diagnostic Engineering*, Huddersfield, United Kingdom, 2012, pp. 1-10.
[17] J.J. de Santiago-Pérez, R.A. Osornio-Rios, R.J. Romero-Troncoso, G. Herrera-Ruiz and M. Delgado-Rosas, “DSP algorithm for the extraction of dynamics parameters in CNC machine tool servomechanisms from an optical incremental encoder”, *International Journal of Machine Tools and Manufacture*, vol. 48, no. 12-13, pp. 1318-1334, 2008.
[18] B. Huang, H. Gao, X. Mingheng, X. Wu, M. Zhao and L. Guo, “Life Prediction of CNC Linear Rolling Guide Based on DFNN Performance Degradation Model”, in *7th International Conference on Fuzzy Systems and Knowledge Discovery*, Yantai, China, 2010, pp. 1310-1314.
[19] Gloor Engineering. (2014, July 31). Druckluftanlagen [Online]. Available: http://www.energie.ch/themen/industrie/infel/druckluft.htm
[20] B.V. Dasarathy, “Information Fusion. What, Where, Why, When, and How? Information Fusion”, Information Fusion, vol. 2, no. 2, pp. 75-76, 2001.

Victor Simon, MSc, Carl-Anders Johansson, prof. Diego Galar
Luleå University of Technology
971 87 Luleå, SWEDEN
e-mail: victor.simon@ltu.se
carl-anders.johansson@ltu.se
diego.galar@ltu.se