Model-based predictive maintenance techniques applied to automotive industry

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ABSTRACT

In automotive industry, and generally in the mass production world, maintenance is a very critical issue requiring special attention since every single stop causes a huge loss in term of item produced due to very small cycle time.

Basing on this observations, in the last years, a lot of efforts has been put in failure prevention and condition based maintenance; as an example in Fiat Chrysler Automobiles (FCA) the WCM (World Class Manufacturing) became part of its culture and the area dedicated to Professional Maintenance makes possible many step forwards. The ways WCM reaches the zero breakdown are Time Based Maintenance (TBM) and Condition Based Maintenance (CBM) but further improvements can be reached with focus on cost reduction and by optimizing the component usage without arriving to a fault.

In this paper, after an overview of maintenance techniques adopted in FCA plants worldwide, a model-based approach is suggested for a COMAU hemming tool named RHEvo (Roller Hemming Evolution). After the development of a simplified model, we try to estimate the actual status of internal components making use of Neural Network.

Focusing on the internal springs, the aging affects the elastic coefficient because of fatigue phenomena. As will be shown, under certain assumptions the cracks presence affects the nominal elastic coefficient; therefore, starting from the estimation coming from the Neural Network, it is possible to model an equivalent crack length. Finally, basing on stochastic crack growth model proposed by Yang and Manning an estimation of internal spring's Remaining Useful Life Estimation (RULE) is calculated.

The proposed approach and the obtained results could be used for a variety of devices that make use of springs; indeed helical tension and compression springs have numerous uses, notably automobile suspension systems, gun-recoil mechanisms, and closing valves on engines.

1. MAINTENANCE IN FCA

World Class Manufacturing (WCM) is a structured, rigorous and integrated production methodology adopted at FCA plants worldwide, which involves the entire organization, from safety to environment, maintenance, logistics and quality. WCM is focused on continuous improvements and the source of decision making is cost deployment which uses systematic analyses to address costs to losses.

The WCM is structured in pillars that cover all the manufacturing area and focus on different aspect of production work cycle. A "7-step" approach is then applied to determine Root Cause and prevent reoccurrence, moving the organization from a reactive to preventative and ultimately proactive approach (FCA 2016).

Professional maintenance is responsible for preventive maintenance, equipment classification and for economical justifications of maintenance systems (FCA, 2010); it tries to maximize the equipment availability at an economical cost, to eliminate unplanned maintenance and to reduce the number of production stops to zero. As for the other pillars, we have seven step to be run in order to reach the maximum WCM level in professional maintenance (Image 1).

In FCA, when a new Plant is started, usually the first three steps are automatically reached after ramp-up phase; instead when an old plant wants approach to WCM, it starts from first step.

The step three means that all the maintenance procedure provided by the machine suppliers are inserted in a standard maintenance plan. Many of these plan are very conservative and brings to over-maintenance and extremely high cost. On the other end this step brings already to machine zero breakdown, is very important that all the further steps will result in cost saving but the zero stop condition must be respected.

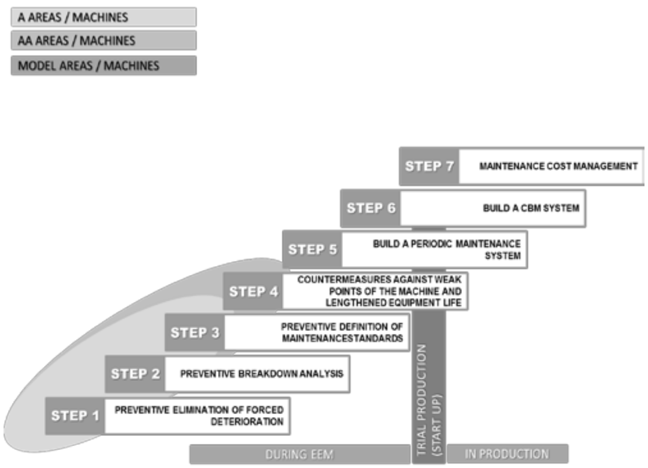

Figure 1- PM steps

Inside the step three, the most common approach to activity plan is the TBM (Time Based Maintenance) that does not optimize the usage of component because is based on nominal production and does not take in account the real working hour of that component .

The simpler cost reduction is made counting the working cycles of component in order to have a real estimation of remaining useful time basing on MTBF. This is the step five of Professional Maintenance named HBM (Hit Based Maintenance).

Going further with the optimization we arrive to step six where a key parameter of the component life is monitored and make possible to estimate the machine efficiency in real-time. This kind of maintenance is named CBM, Condition Base Maintenance.

The last step in component usage optimization and maintenance cost reduction is the predictive approach that brings to a complete maintenance activity schedule tailored on each component health status.

2. COMAU RHEVO

COMAU (*COnsorzio MAcchine Utensili*) is part of FCA Group and has its headquarter in Grugliasco-Turin. Comau specialization is the industrial automation with an international network of 35 operative centers, 15 manufacturing plants and 5 innovation centers worldwide.

One of COMAU products is RHEvo, a robotic tool for hemming process; in this work a model based approach for its predictive maintenance is proposed.

Hemming is a process that bent edge of a metal sheet giving a neat and compact joint even if less strong than a welded joint (Jonkers, B.,2006).

One of the most diffuse processes is robot roller hemming where a robot guides a roller parallel along the flange.

RHEvo Roller Hemming Head is the COMAU solution for robot hemming process and consist in a double spring mechanical structure that permits to use a single tool for Push and Pull applications. Thanks to the internal springs a full force control is possible over the path with a total force range of ± 2200 [N] .

The RHEvo includes two load cells for remote force monitoring in order to make easier the setup phase, and monitor the force, one of the technological parameters of the hemming process.

Figure 2- Comau RHEvo

Run a FMECA before the modelling phase is very important in order to define the simulation level we want to reach and components we want to include in it.

Starting from the maintenance manual and the experience of process technology experts we can extract information about failure mode, effects and obtain Risk Priority Number (RPN) calculation as an alternate method to criticality analysis. The RPN is a result of a multiplication of detectability (D) x severity (S) x occurrence (O).

The scales used for each parameter are:1-6 for Detectability where 1 means fault is Certain and 6 fault undetected, 1-5 for Severity where 1 means no relevant effect on reliability or safety and 5 catastrophic effects, 1-5 for occurrence where 1 means extremely unlikely and 5 frequent.
Once collected the failure modes and the effects they lead, an evaluation of just reported factors has been made; in the table below you can see the failure modes of RHEvo already sorted by Risk Priority Number.

Table 1. RHEvo FMECA

Failure mode	**Effect**	**S**	**O**	**T**	**RPN**
Spring characteristic change	Different Robot torque requirement	4	4	3	48
Bushes wear	Friction increasing	3	3	4	36
Pad wear	Friction increasing	3	3	4	36
Bearings wear	Vibrations increase	3	2	3	18
Finger roll wear	Less hemming pressure	4	4	1	16
Roller wear	Vibrations increase	4	4	1	16
Preload change	Different Robot torque requirement	3	2	2	12
Roller dirty	Quality process loss	2	5	1	10
Robot Alteration	Quality process loss	3	1	3	9

3. RHEVO PHYSICAL MODEL

Analyzing the FMECA it is evident that the main problems can arise in relation with springs characteristic changes and internal components wear (pad and brushes); therefore we assumed to focus on this two phenomena including in the model the two spring-dump components and the friction caused by pad and brushes. As a first extreme simplification the Roller Pack mass is concentrate in a point between two spring-dumper systems connected with fix frame.

Friction due to internal pads and bushes has been modeled as a unique coulomb & viscous friction.

As a first step we started from nominal values for friction and spring parameters; combining all the forces acting on the concentrated mass we reach the model expressed by Eq.1 :

$$M\ddot{x} = \sum F = -F_{ub} - F_{uk} - F_{lb} - F_{lk} + F_g + F - F_f \qquad (1)$$

Where F is the force exerted by the robot, F_{ub}, F_{uk}, F_{lb}, F_{lk} are the elastic and dumping forces from the upper and lower springs, F_g is the gravitational force and F_f is the friction force.

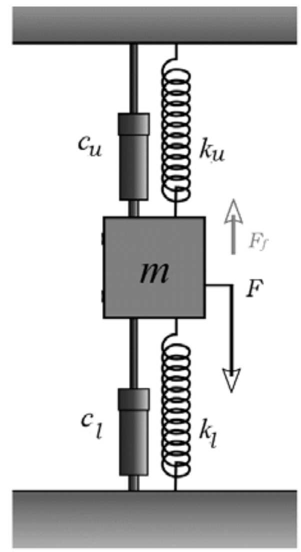

Figure 3- RHEvo model

The outputs of the model in Equation (1) are the forces acting on the springs which can be measured directly from the load cells.

The input of the model is the force from Robot F; assuming the tool acting on a single direction, all the force applied by the robot's TCP (Tool Center Point) z-axis is reported directly on the Hemming tool.
The robot's forces can be estimated from the motor's currents that are directly related to the torques then to the Cartesian forces.
The adopted robot model is based on the classical Euler-Lagrange approach that brings to the following formula (Siciliano, Sciavicco, 2009):

$$M(\theta)\ddot{\theta} + C(\theta,\dot{\theta})\dot{\theta} + N(\theta,\dot{\theta}) = \tau \qquad (2)$$

where τ is the vector of actuator torques , $N(\theta,\dot{\theta})$ includes gravity terms and other forces which act at the joints and matrices M and C summarize the inertial properties and the Coriolis matrix of the manipulator. This is a second-order vector differential equation for the motion of the manipulator as a function of the applied joint torques.
If we know all the characteristic matrix of the robot (usually we do in phase of robot construction) we can start from measured currents and calculate the torque for each joint.

Once done that we can use the kineto-static duality between generalized (Cartesian) forces and Cartesian velocities that makes use of geometric Jacobian:

$$\tau = J^T F \tag{3}$$

4. AGING EFFECTS

In this paragraph we will focus on how to model the effects of wear on the modeled components inside the RHEvo.

Time-dependent increase of frictional strength, or frictional aging, is a widely observed phenomenon both at macro and nanoscales. Even if many studies demonstrate and describe the logarithmic trend of frictional aging (Zhiping Yang, 2008), in this study it was decided to focus just on the effect of aging on RHEvo internal springs.

4.1. Wear effects on Spring

The common usage of the Hemming tool puts under cyclical stress the internal spring. It is well known that at pulsated stress below the yield strength of the spring materials, the materials can break because of fatigue.

A spring fatigue problem starts with the development of a micro fatigue crack which grows for every pulsation. When the stress in the remaining material reaches the ultimate tensile strength the spring will break (Sinan Korkmaz, 2008).

In (Yang & Minning, 1990) the authors propose a stochastic crack growth model for predicting the statistical crack growth damage accumulation in metallic structures; starting from this model, under certain assumption it is possible to predict the Remaining Useful Life Estimation (RULE) of the spring.

The micro fatigue crack propagates radially starting from an initial surface defect and progressively reduce the useful section of the material twist; on the other hand the Hook law shows that the spring rate depends directly from the fourth power useful diameter (Hooke, 1678):

$$\mathrm{k} = \frac{\mathrm{G \cdot d^4}}{\mathrm{8 \cdot N_a \cdot D^3}} \tag{4}$$

$$\mathrm{G} = \frac{\mathrm{E}}{\mathrm{2(1+v)}} \tag{5}$$

where: d is the wire diameter, D outer the outer diameter, D is the mean diameter (D outer - d), E the Young's Modulus of Material, G is the Shear Modulus of Material, k is the spring rate (spring constant), Na is the number of active coils and v is the Poison's ratio of material.

Let’s introduce the concept of spring’s equivalent useful diameter on the mean circular area without cracks along the spring’s length.

Basing on this observations, we can say that with aging and occurrence of fatigue crack the spring’s equivalent useful diameter reduces, therefore the spring rate will reduce.

5. HEALTH STATUS ASSESSMENT ALGORITHM

Once the model has been defined and implemented in Simulink an approach to detect faults and estimate the health status has been proposed.

The approach is based on simulation with a defined input force pattern: once reached a baseline running the simulation with nominal parameters this has been changed randomly in a realistic range.

The range of applicable frequencies is bounded from the real one deployable with robot therefore we assumed a 100 s long vector (sample time Ts=0.001) composed of steps with different amplitude (500,-1500, 2000, -2000 N) and sinusoid with amplitude 1800N and different frequencies (1, 2, 5, 7, 10 Hz).

After saved the output as a simulation baseline (spring’s output forces) three percentages that represent respectively the change of spring’s elastic constant (assumed to be up to 30%) and friction’s gain (assumed to be up to 50%) has been introduced. A large training dataset (100 Experiments) has been obtained running the Simulink model setting randomly the parameters deviation percentages.

By observing the outputs simulated the following features has been defined:

- Freq. peaks differences→calculated the spring force’s signals FFT and detected the magnitude at the stimulation frequencies, the differences with baseline are estimated (Figure 5); then, the differences between estimated values for upper and lower spring are assumed as feature. It is made by five values because input force contains five different frequencies;
- Phase→ Considering the input step subparts and detected the overshoot in the output, the times between the input step and output steps are calculated and the average is made (one value for spring);
- Overshoot→ Starting from the step input, the overshoot’s difference between baseline and output is calculated (four values for spring).

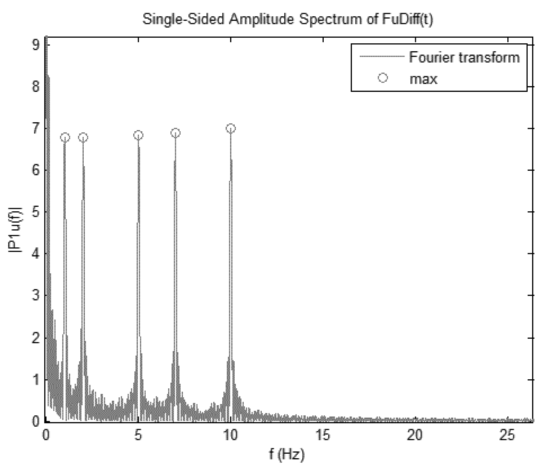

Figure 5- FFT Output signal difference with baseline

Starting from the features vector (with total dimension is fifteen) the decisional algorithm must be able to estimate the parameter's change percentages. Neural Network has been chosen as fitting tool; the two-layer feed-forward network with sigmoid hidden neurons and linear output neurons has been trained with Levenberg-Marquardt backpropagation algorithm, starting from the simulated set of one hundred examples.
In detail the training, Validation and Test sets has been respectively composed by seventy, fifteen and fifteen experiments where the NN's output is the one composed by the three percentage representing the model parameter change. The input of NN is the features vector.

In order to assess the dimension of NN that perform better, many trainings has performed varying the dimension of hidden layer. As performance kpi the following has been adopted:

- Mean Squared Error (MSE), the average squared difference between outputs and targets Lower values are better. Zero means no error;
- Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.

The Table 2 includes the training results, and shows that a hidden layer with thirty neurons is the most performing.

Table 2. NN training results.

N Neurons	Set	MSE	R
10	Training	4,57E-04	0,99
	Validation	1,81E-03	0,95
	Test	7,73E-04	0,98
20	Training	7,05E-04	0,998
	Validation	1,30E-04	0,999
	Test	1,24E-04	0,999
30	Training	7,02E-04	0,998
	Validation	7,45E-06	0,999
	Test	4,08E-05	0,999
35	Training	5,35E-04	0,985
	Validation	1,63E-03	0,997
	Test	1,79E-05	0,996
40	Training	4,32E-04	9,982
	Validation	6,53E-04	0,973
	Test	1,57E-03	0,984

6. SPRING RULE ALGORITHM

Once obtained, as NN's output an estimation of deviation from the nominal parameters of springs and friction, in this paragraph we will focus on the remaining useful life estimation for the springs.

The nominal diameter of adopted spring can be obtained from datasheet data and brings to an equivalent diameter of 5.6 mm.

Starting from the estimated deviation ratio and using Eq 4:

$$\frac{K_{act}}{K} = K_{\%} = \frac{\left(\frac{G\cdot {d_{act}}^4}{8\cdot N_a\cdot D^3}\right)}{\left(\frac{G\cdot d^4}{8\cdot N_a\cdot D^3}\right)} = \frac{{d_{act}}^4}{d^4} \rightarrow d_{act} = d\sqrt[4]{K_{\%}} \quad (7)$$

The equivalent diameter is assumed as the mean along the entire spring length of the section diameter. Let's assume that the defect affects just the 10% of the entire length (L), this means that in that section the useful diameter is the difference between the nominal one and the crack length:

$$d_{act} = \frac{0.9\cdot L\cdot d + 0.1\cdot L(d - d_{crak})}{L} = d\sqrt[4]{K_{\%}}$$
$$\rightarrow \quad d_{crak} = \frac{d\left(1-\sqrt[4]{K_{\%}}\right)}{0.1} \quad (8)$$

Defining as C_{PR} the crack propagation ratio, we can use the quadratic relation between the number of cycles and crack length proposed by (Yang & Minning, 1990) as follows:

$$d_{crak} = (C_{PR}\cdot N_{act})^2 \quad (9)$$

The crack propagation rate depends from different values but in initial propagation phase a likely value could be $C_{PR} = 10^{-6}\left[\frac{mm}{Cycle}\right]$ (C.D. Beachem,1976). Assuming as a limit value for crack length the half of the nominal spring's diameter, it can be represented as:

$$d_{crak\_Lim} = 0.5 \cdot d = \left(C_{PR} \cdot N_{act_{Lim}}\right)^2 \qquad (10)$$

Therefore we can estimate the Remaining Useful Life Estimation (RULE) as:

$$N_{resid} = N_{act\_Lim} - N_{act} = \frac{1}{C_{PR}}\sqrt[2]{\frac{d}{2}} - \frac{1}{C_{PR}}\sqrt[2]{d_{crak}} = =\frac{1}{C_{PR}}\sqrt[2]{\frac{d}{2} - 10d\left(1-\sqrt[4]{K_{\%}}\right)} \qquad (11)$$

Finally the Remaining Useful Life Estimation (RULE) has been plotted (Figure 6) on the function proposed by Yang and Manning that put in relation number of cycles and crack length.

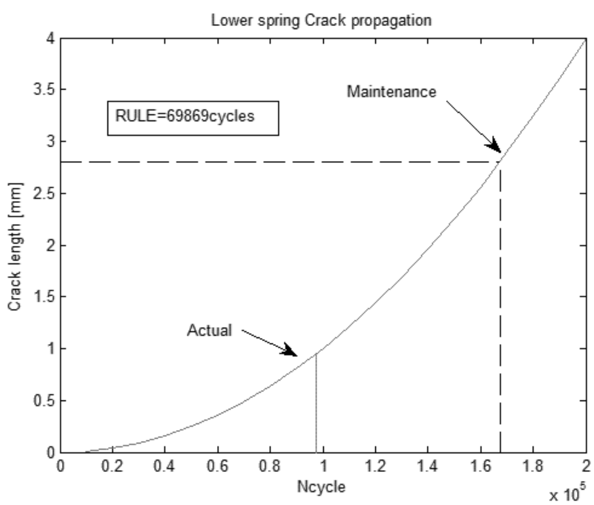

Figure 6-Matlab routine RULE representation

7. EVALUATION

In order to validate the result of the remaining useful life estimation, dedicated endurance tests are required.

More in detail, due to the fact that this formalization focus on the springs it is possible to create a simplified setup that goes beyond the Comau RHEvo.

A dedicated setup can be composed by a spring, a load cell and an adjustable oscillator in order to modulate the acting force. Reproducing the simulated test and leading the spring to the appearance of cracks, it is possible to validate the obtained relation between spring wear and elastic coefficient.

8. CONCLUSIONS

In this paper a model based approach for COMAU RHEvo predictive maintenance has been developed.

RHEvo is a tool for hemming, mainly composed by mechanics part like springs, rollers, pads, bearings and pads and has as unique measurement two load cells on the springs.

After a simplified model development a routine for fault classification and health status assessment based on Neural Network has been developed.

Once obtained the deviation from a baseline, the Remaining Useful Life Estimation has been obtained for the two springs basing on metals crack propagation theory.

An implementation of the suggested algorithm in a real case will need a model's parameter identification with dedicated experiments. After that, efforts can be done in order to avoid usage of dedicated cycle and using as baseline the normal production. Finally models for friction aging present in the literature could be studied and adopted.

Once validated, the results obtained for RHEvo's internal springs, can be reused for predictive maintenance on a variety of devices that make use of springs.

NOMENCLATURE

K	spring constant
d	Spring diameter
G	Shear Modulus of Material
D	mean spring's diameter
N_a	number of active coils
E	Young's Modulus
V	Poison's ratio
K_{act}	Actual spring constant
d_{act}	Actual useful spring diameter
L	Spring Length
d_{crak}	Crack length
C_{PR}	crack propagation ratio
N_{act}	number of cycles
$N_{act_{Lim}}$	Limit number of cycles
d_{crak_Lim}	Limit crack length

ACRONYMS

FCA	Fiat Chrysler Automobiles
WCM	World Class Manufacturing
TBM	Time Based Maintenance
CBM	Condition Based Maintenance
RHEvo	Roller Hemming Evolution
RULE	Remaining Useful Life Estimation
HBM	Hit Based Maintenance
PM	Professional Maintenance
RPN	Risk Priority Number
FMECA	Failure Mode, Effects and Criticality Analysis

TCP Tool Center Point
FFT Fast Fourier transform
NN Neural Network

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