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Model-based wear prediction of milling machine blades

Teemu Mäkiaho[a]*, Henri Vainio[a], Kari Koskinen[a]

[a]Tampere University, Korkeakoulunkatu 7, Tampere 33720, Finland

Abstract

Technological capabilities are enabling the implementation of various prognostic methodologies for industrial assets. Whereas companies are driving for finding new ways to improve asset operation and service offerings to their customers, model-based simulations can be deployed to model machine behavior for instance in usage cases unconventional for the asset. Modern embedded technologies in peripheral milling machines offer asset operation-related data collection and sharing online. Due to this capability, understanding of the asset operational behavior can be assessed remotely, and the data can be used to estimate the wear progress of the milling blades. However, creating a model-based simulation model is not heavily dependent on online data, yet the model construction requires knowledge about asset operation and physical behavior to enable purpose-fit and simple enough simulation construction. In this research, a model-based simulation model is created to predict peripheral milling machine blade wear in terms of average vibration and torque parameters. A blade wear variability in different usage profiles is being tested with a simulation test case. The results are proving that the model-based simulation model can be accurately used to emulate asset physical behavior by the means of torque and vibration parameters. Based on the results, changes in the asset vibration average trend can be distinctly utilized to estimate wear progress on the spindle cutting blades. Further, predicted vibration levels and blade lifetime estimations can be considered in PPX type of business model profitability or lifecycle related calculations where ownership of machines is retained by the manufacturing company.

Peer-review under responsibility of the scientific committee of the 26th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2022)

Keywords: Wear simulation; model-based prognostics; peripheral milling; pay-per-x business models

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1. Introduction

The ability to utilize modern tools to predict optimal blade change interval or monitoring asset availability to perform its intended function is of great importance in milling operations. As an example, worn milling tools will influence the milling quality and the overall economic efficiency of machine usage will be affected in case of the tools are being manually checked or changed in a non-optimized manner. The overview perspective of optimal machine operations can be expressed on the Overall Equipment Effectiveness (OEE) levels, which can be affected by asset operational behavior or maintenance policies [1] such as condition-based maintenance (CBM) [2]–[4]. Predictive maintenance is expected to reduce preventive and corrective interventions as well as to influence the extension of component life [5]. Provision of operational processes such as maintenance performance is in a key role when new service-based pay-per-x (PPX) business models are designed and implemented [6].

The first objective of this study is to evaluate the credibility of peripheral milling blade wear prediction with a model-based simulation model. Previous studies found are concentrating more on illustrating flank wear (Vb) progression on the cutting blade based on the different material properties affecting the wear process and wear increase relative to time. Milling blades and their wear behavior is often based on experimentation measurements [7]–[9] or combined experiments with simulations [10], [11], measuring the progressive loss of material from the tool contact surface. Machine cutting forces are in direct connection with the required electrical power consumption of the asset which in turn is associated with the machine torque values [12]. The connection between cutting forces and vibration signals is developed on a basis of mathematical models. Investigation of the relationship between cutting forces and vibration signals in different cutting conditions by using the standard response surface methodology has been performed as part of [13]. Another objective is to assess how the validated simulation model could be exploited in the PPX context.

The case machine operational data was collected from a peripheral milling machine operating in a maritime industrial environment. The simulation model received input parameters from physical features as well as from the operational parameters from the case machine. With the help of the theoretical foundation, the Simulink-Simscape model was constructed to emulate the mean wear development by simulating the machine vibration behavior and torque parameters. The simulation model was validated against available usage parameters from the real machine behavior. Further, the model was tested with variable simulation inputs to illustrate its applicability in PPX-related case context, although without assessing the actual economic impact of the business making.

* Corresponding author. Tel.: *+358 50 4653384*
E-mail address: teemu.makiaho@tuni.fi

2. Modelling of the milling machine

The simulation model construction is based on the physical phenomena presented in the machine operation. The basic structure of the simulation model was constructed by mathematical equations representing

1) force per tooth calculations that the cutting blades are experiencing when in contact with milling material, and
2) torque calculations are drawn from power consumption calculations.

The input parameters to the simulation model are presented in tables 1 and 2 illustrated in the following sections.

Force per tooth calculations

Force per tooth (F_z) presents the forces the blades are encountering with the given simulation inputs. Certain steps are required to receive the force per tooth value used in the simulation model. Average chip thickness (h_m) [eq.1] is formulated by the blade lead angle (κ) with the milled material, feed per tooth (f_z), multiplied by the product of radial depth of cut (a_e) and 360 (degrees) over the product of contact angle (α), constant pi (π) and spindle diameter (D), as follows. Formulas 1-6 are obtained from [14]:

$$h_m = sin\,\kappa * f_z * \frac{a_e * 360}{\alpha * \pi * D} \tag{1}$$

where,

$\alpha = 180 - \varphi$, and arccos $\varphi = 1 - \frac{2*a_e}{D}$, including conversion of radian into degrees with $(\frac{180° * radians}{\pi})$ (2)

and,

feed per tooth (f_z) is calculated as the given feed velocity (v_f) of the machine with rotational spindle speed (n) and a total number of cutting elements (z) in the spindle, as presented in equation 3.

$$f_z = \frac{v_f}{n * z} \tag{3}$$

Following, the length of cut (b) is resolved by dividing the axial depth of cut (a_p) with sin function of a blade lead angle (κ) as presented in equation [4]. Conversion of radians to degrees applies similarly as in equation 2.

$$b = \frac{a_p}{\sin \kappa} \tag{4}$$

Specific cutting force (k_c) is then resolved by multiplying working material AH36/EH36/S355 specific $k_{c1.1}$ value (Sandvik P1.2.Z.HT) with average chip thickness (h_m) exp by the inverse of (mc), as illustrated in eq.5.

$$k_c = k_{c1.1} * h_m^{-mc} \tag{5}$$

The force per tooth (F_z) value is received by multiplying earlier received values of average chip thickness (h_m), specific cutting force (k_c), and length of cut (b) presented in equation 6 below:

$$F_z = h_m * k_c * b \tag{6}$$

The F_z is presented in Newtons, illustrating force for individual tooth of the spindle when in contact with the milled material. The force per tooth parameter was found most convenient to represent the changes in the forces in correlation to variable simulation model inputs.

Torque calculations

Net power (P_c) calculation requires several previously presented parameters: axial depth of cut (a_p) feed velocity (v_f), specific cutting force (k_c) and variable radial depth of cut (a_e). The equation for net power is presented in eq.7. Formulas 7 and 8 are obtained from [15].

$$P_c = \frac{a_e * a_p * v_f * k_c}{60 * 10^6} \tag{7}$$

Further, the motor torque (M_c) is then calculated by utilizing the net power (P_c) calculations, constant pi (π) and spindle rotational speed (n), as in equation 8 below.

$$M_c = \frac{P_c * 30 * 10^3}{\pi * n} \tag{8}$$

A variety of simulation model input parameters are obtained as static values given by machine in-build capabilities and physical dimensions of components received from manufacturer specifications. Table 1 represents the inputs and their values received from machine technical specifications. Also, certain feed material parameters ($k_{c1.1}$and mc) were used in the simulation mathematical formulae.

Table 1. Simulation model input parameters from technical specifications

Specification input parameter	Value	Unit	Variability
Spindle diameter, (D)	496	mm	Static
Spindle number of effective teeth, (Zc)	18	pcs	Static
Electric motor nominal power, (P)	45	kW	Static
Gear unit ratio, (i): (HSS/LSS ratio)	7.88	ratio	Static
Low speed shaft nominal torque, (Tg)	2290	Nm	Static
Lead angle, (k)	90	degrees	Static
Feed material parameter, (Kc1.1) (Sandvik P1.2.Z.HT)	1820	N/mm^2	Static
Feed material parameter, (mc)	0.25	-	Static

Simulation model input parameters from the case machine operation are presented in table 2 below. Radial depth of cut (a_e) values are variating within the illustrated value range. Other parameters in table 2 with values are considered as static inputs in the validation of the simulation model. However, the simulation model was constructed to derive variability from machine operational parameters for illustrative case research purposes presented in chapter 4.

Table 2. Simulation model validation input parameters from case machine operation

Machine operation parameter for test simulation	Value	Unit	Variability
Radial depth of cut, mill depth set value (ae)	2.0-3.035	mm	Variable
Axial depth of cut, profile thickness (ap)	5	mm	Static
Table feed, (Vf):	7995.8733	mm/min	Static
Cutting speed (Vc): (m/min)	377,34	m/min	Static
Spindle speed, (n): (rpm)	241.7821	rpm	Static
Tool rows average milled meters: (m)	<2000	m	Validation
Tool rows milled time: (s)	<15000	s	Validation

Tool rows average milled meter and milled time parameters were used in the model validation as simulation reference due to approximated operational lifetime of the milling blades. These values are based on the actual usage profile of the case machine.

2.1. Real machine operation data collection and pre-processing

In the case machine setup, the data was collected by the embedded programmable logic controller (PLC) system, and the raw data is further transferred to the cloud for data collection and pre-processing. Figure 1 below illustrates the simplified schematics of the relevant milling machine section and related vibration sensor position. Vibration and motor torque values are presented in the validation table, chapter 3 validation table 4. The complete list of case machine operational parameters from PLC is listed in figure 2, under chapter 2.2.

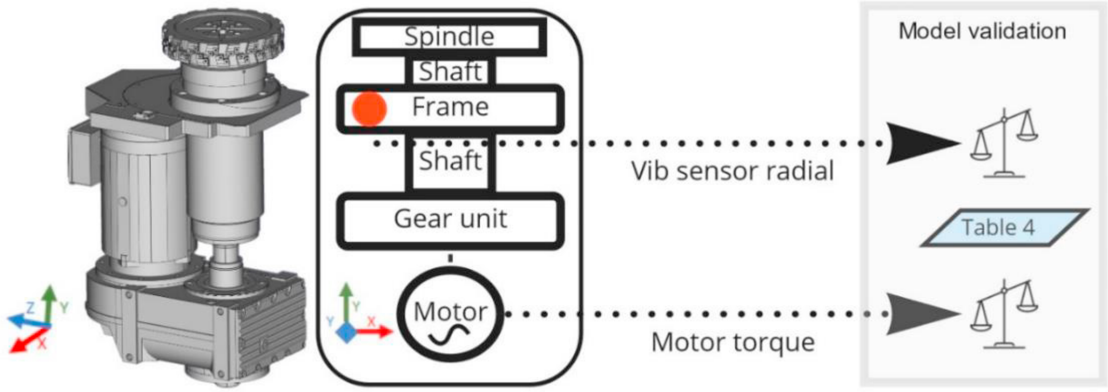

Fig 1. Simplified illustration of the case machine

In total, the data collection period consisted of twenty-four (24) days of operation including nine (9) complete blade change intervals. Change interval means the 90-degree rotation resulting in new cutting surface usage or a complete change of the active cutting blades. In both instances, an indicated blade change is always describing that a new contact surface is present once the milling process begins and milling meters calculators are being reset. Table 3 illustrates the raw dataset information available for this study as well as the amount of data filtered and utilized to create the test dataset for the simulation purposes.

Table 3. Raw dataset details including the subset details of Ap5 (5mm plate thickness) data

Lenght (days)	Data rows	Ap 5 data rows	Ap 5 % of all data rows
24	632193	451352	71,39%

First, pre-processing of the raw dataset was performed. Feed rate error % -value was calculated from the raw data to receive actual milling operation time when cutting blades are operational with physical cutting contact. It is calculated by comparing the set feed rate and actual feed rate measured from the machine operational parameters. Used Feed rate error percentage of 95% is used, therefore the rest of the stored data is filtered out to reduce noise and increase the veracity of the data. Next, filtering a comparable sample set was essentially associated with the fact that each individual blade usage trend received from raw data consists of several usage profiles. Therefore, the most adapted milling profile thickness, ap (5mm) was considered most applicable due to its existence of 71,39 percent of the whole population of raw data.

2.2. Simulation model creation

The creation of the model-based simulation model was initiated based on the theoretical findings applicable to the research study environment, including milling technique, material properties, and prognostic nature of scientific experiments. The simulation model structure was initiated based on machine-related static input parameters and further developed by the operational parameters from the case machine as presented earlier in tables 1 and 2. Figure

2 gives the overall picture of the elements affecting the simulation model construction and the calculated simulation model outputs that are either directly or indirectly used for the data validation phase.

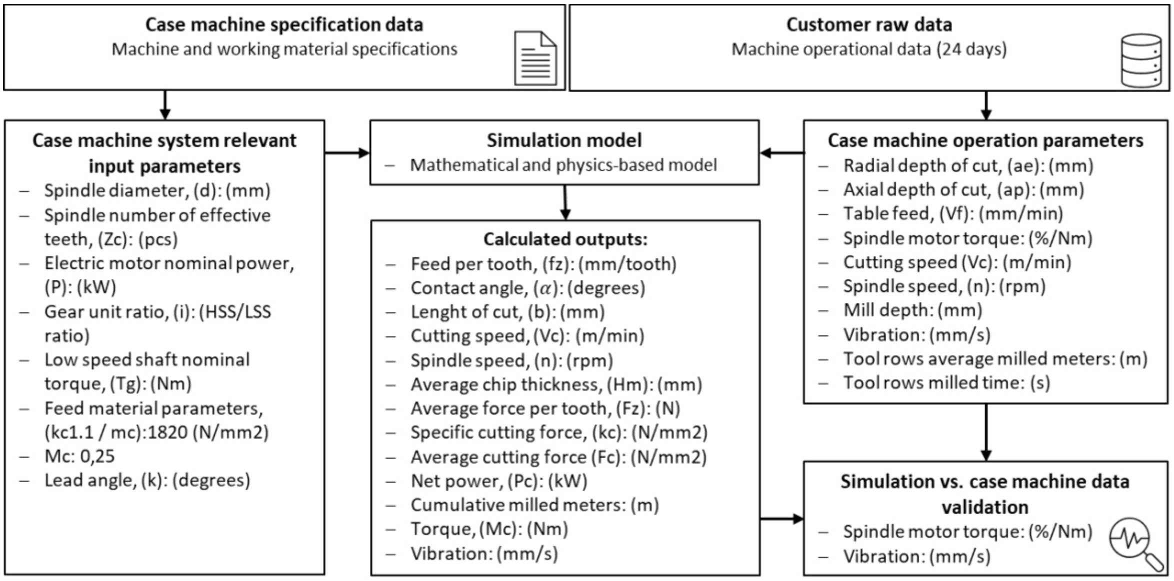

Fig 2. Simulation model inputs and outputs

Force per tooth (F_z) values from the simulation model mathematical base are further connected to a sinusoidal signal to receive repetitive oscillation to the output signal given by the Simulink-Simscape libraries. The vibration mass, spring, and damper coefficients are adjusted to represent the case machine raw data average amplitude values of the signal, therefore giving sufficient accuracy for the simulated vibration outcomes per the given inputs. The wear effect was simulated by Boolean type of simple rule functions including if-then-else like conditions based on machine operational parameters. A simplified simulation model structure from model inputs to the model validation phase is presented in figure 3 below.

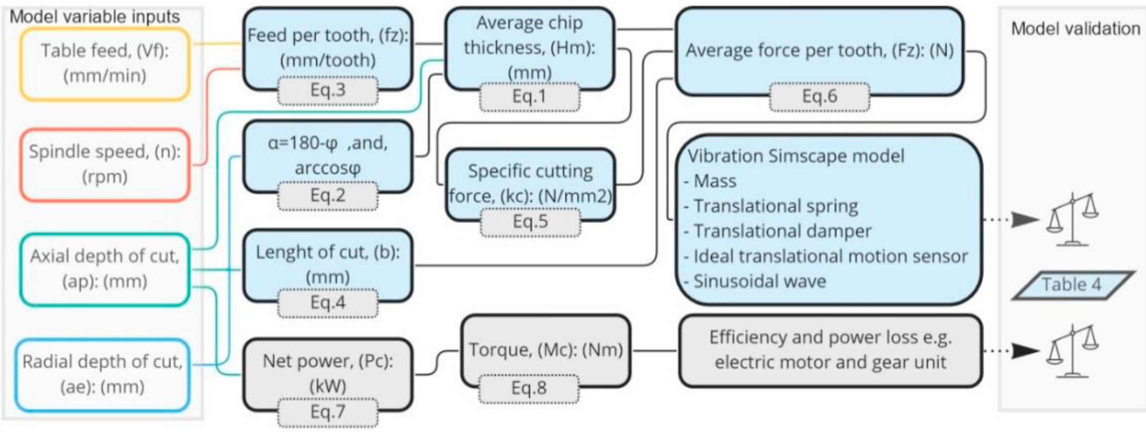

Fig 3. Simplified simulation model structure to data validation

Torque outputs from the simulation model are presented as a percentual share of electric motor nominal values, as the validation data from the case machine illustrates the parameter in the presented format. Torque efficiency and power losses are considered in the simulation model by a separate factor. The losses consider the functional mechanical and electrical elements of the asset power train, including electric motor, gear unit components (i.e. gears, bearings), shaft, coupling, spindle, and cutting blades.

3. Validation of the simulation model

The simulation model results are compared against the validation test set with real machine torque and vibration values. Based on the results, a physical simulation model can be effectively used to replicate peripheral milling machine outputs with the given inputs. The literature review indicated that increased wear on the cutting blades would be visible in the increased vibration and motor torque values. By observing the case machine operational data, the wear symptoms of the peripheral cutting blades can be primarily connected to increased vibration averages collected by the milling machine PLC system. However, the study case data manifests that increased wear does not correlate to machine torque parameter values, although, the received case study mass dataset only presented machine operation from 24 days of usage. Yet, the case study results illustrate no visible ascending effect in the motor torque trend curve parallel with the increased usage time of the milling blades. Despite this fact, the results will discuss both parameters due to their identified potential to illustrate wear symptoms from the machine-related data.

Simulated torque values are presented in figure 4 in relation to the actual torque values from the case machine raw data. The raw data and simulated data have slight variation in the test setup results, however, the averages trend curves are corresponding sufficiently. Motor torque results can be more accurately simulated compared to vibrations due to their more direct mathematical foreground based on the power consumption calculations. Also, motor torque results have minor connectivity to environmental noise. A more accurate comparison of simulation data and raw data is presented in the next chapter, table 4.

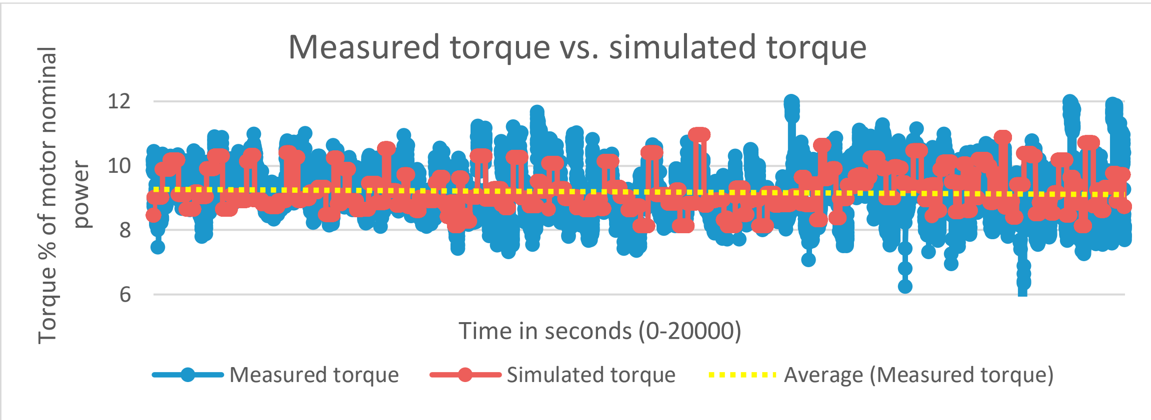

Fig 4. Simulated torque averages vs. measured machine torque and related average trend curve

The observations from the case machine raw data represent that the vibration average trend correlates to the linear wear stages on the blades. Average trend monitoring filters out the majority part of the process-related noise from the data, which may be considered significant in peripheral milling types of environments. The case machine data consisted vast amount of noise including vibrating chip removing feature, therefore simulation of machine vibration averages was deemed reasonable for wear imitation. Figure 5 below represents the simulated vibration average trend curve in relation to actual machine vibration values and the dotted line represents the average of real measured vibration values.

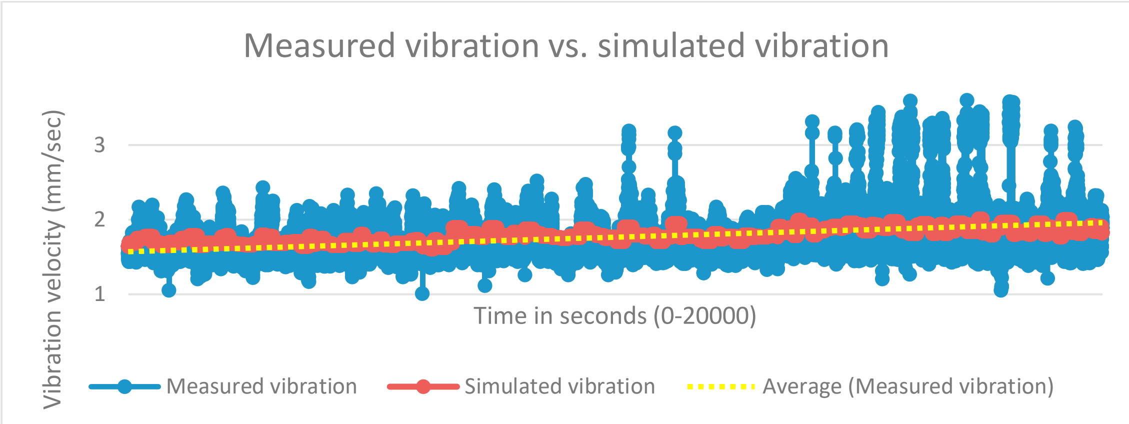

Fig 5. Simulated vibration averages vs. actual machine vibration and related average trend curve

The simulation model was constructed and evaluated only based on realized, real-life blade change intervals and not the actual flank wear progress monitoring. This leaves the simulation model utilization imperfect for accurate wear phenomena prognosis, but adequate information about the model parameter applicability can be obtained. Overall, the simulation model outputs may be adjusted to meet the machine system output data averages in close approximation. Table 4 illustrates the actual measured machine average values in accordance with the variation in milled depth values and wear stage categorization (phases 1-3). To simplify the model, the wear phenomena was constructed to the simulation model based on the theoretical approach where initial- (phase 1), linear- (phase 2), and final (phase 3) wear stages are recognized. More accurate wear modeling could be initiated by using interpolation or extrapolation techniques or integrating wear modeling calculations such as Colding or Archard models. However, utilization of the techniques would increase the complexity of the model construction and was not seen to improve the research results significantly. Therefore, a simplified simulation of torque and vibration parameters and their average increase over time was seen adequate instead of simulating progressive loss of material from the contact surface based on separate wear models. The average deviations of the model results can be considered accurate enough to estimate the torque and vibration parameter development in relation to time and milled meters as illustrated in table 4 below.

Table 4. Validation results table. Case machine and simulated average values on each mill depth category in correlation to initial/Phase 1 (<500m)-, linear/Phase 2 (>500<1500m)- and final/Phase 3 (>1500m) wear stages

Milled meters	Mill depths		Torque	Simulated torque	% torque difference	Average deviation %	Vibration	Simulated vibrations	% vibration difference	Average deviation %
Phase 1:	>2,0	<2,3	9.130986396	8.8544047	-0.031923931	-3 %	1.564394179	1.671888775	0.064233099	6 %
<500m	>2,3	<2,6	9.79222222	9.762841468	-0.003520882	0 %	1.745667871	1.743632042	-0.001081833	0 %
	>2,6	<3,1	9.927489712	10.5518538	0.057245716	6 %	1.82799392	1.802850758	-0.014130946	-1 %
Phase 2:	>2,0	<2,3	8.845816349	8.777725559	-0.008881036	-1 %	1.660198442	1.765976918	0.059951148	6 %
>500m<1500m	>2,3	<2,6	9.27071816	9.47889323	0.021921282	2 %	1.777842131	1.825388165	0.026813217	3 %
	>2,6	<3,1	10.04196401	10.47849447	0.040561107	4 %	2.055047633	1.906248835	-0.077829351	-8 %
Phase 3:	>2,0	<2,3	8.815767422	8.73871425	-0.009447227	-1 %	1.823832906	1.827802232	0.001890616	0 %
>1500m	>2,3	<2,6	9.817712987	9.743601773	-0.008172692	-1 %	1.957427364	1.915868561	-0.022192464	-2 %
	>2,6	<3,1	9.528823048	10.50577193	0.0926771	9 %	1.932770621	1.979191275	0.023649941	2 %

The model's overall average deviation outputs were differing from actual machine system outputs on average as follows: torque simulations +2%, and vibration simulations +1%. Minimum and maximum deviations are not presented due to their irrelevance on the wear stage estimation where statistical average increase is being simulated. Simulation model outputs are also incapable to create process or usage environment-related noise or impact like amplitudes, which can be considered significant in the case machine operation. Therefore, comparing minimum and maximum values are filtered out from the table 4 results, which do not indicate the overall progress of the wear process of the milling blades. In general, the physical simulation model results can be exploited in a prognostic manner due to the acquired accuracy and confidence in the results.

4. Simulation model utilization in pay-per-x (PPX) business model planning

Prediction of machine operational outputs such as vibrations is considered important from various perspectives. The simulated vibration information can be exploited to verify machine capability to operate in a specified environment in case the machine is making its debut appearance in new applications or being driven with pre-inexperienced usage parameters. Understanding normal operational vibration levels in different phases of wear is also beneficial and such information can be used to monitor exceeding average vibrational stresses for the asset once in use. Such predicted information about the machine operation benefits not only R&D people considering machine operational capabilities but such data can be exploited from a life cycle and business strategy perspective as well. Model-based simulation data can be utilized in PPX-related business model designs where extensive usage data of machine behavior does not always exist. Predicting wear effect based on variating inputs is of the essence in business models where ownerships or life cycle responsibilities are retained by the product manufacturer.

The simulation model constructed as part of this research is utilized to predict vibration outputs for normal operational phases as well as to calculate reduced operational figures when increased cutting forces are applied. The following cutting event input parameters in table 5 are used in the simulation study. The inputs are deducted from the milling machine technical specifications and real machine operational parameters for different plate thicknesses.

Table 5. Different plate thicknesses and their input parameters to the simulation model

Plate thickness: (mm)	Radial depth of cut avg, (ae):(mm)	Cutting speed (Vc): (m/min)	Spindle speed, (n): (rpm)	Table feed, (Vf): (mm/min)
5	2.315	377	242	8000
6	2.132	376	241	7500
10	1.501	377	242	7500
15	1.553	369	236	7000
20	1.769	345	221	5000

The results from the simulation study are illustrated in table 6 below. It is noteworthy to state that the simulated results herein only indicate a linear reduction of operational time and referenced cutting meters. The reduction in operational durability could be utilized in business case profitability calculations when considering inexperienced customer requirements such as new milling profiles. The simulation model could also be used to simulate constantly variating operational settings such as different milling recipes would be tested. In such a case, the simulation results would be used to approximate the consumption of milling blades per dedicated milling recipe.

Table 6. Referenced vibration averages, operational time, and cutting meters

Plate thickness: (mm)	Vibration avg Phase 1: mm/s	Vibration avg Phase 2: mm/s	Vibration avg Phase 3: mm/s	Operational time until reference forces: (sec)	Operational meters until reference forces: (m)	Reduction to reference meters: (%)
5	1.704	1.806	1.872	15000	2000	-
6	1.894776811	2.007255375	2.082865795	13524	1691	18 %
10	2.760106343	2.924709698	3.034424219	9258	1157	73 %
15	4.057196192	4.30155897	4.461340737	6434	751	166 %
20	4.635905709	4.914891013	5.096789204	6023	502	298 %

Vibration averages are differentiated into three categories: phases 1, 2, and 3. These phases indicate the normal average vibration levels per wear stage in velocity format (mm/sec) per dedicated usage profiles (plate thickness, ap 5-20mm). Reduction to reference values is compared to validated simulation model values i.e. plate thickness ap5, blade change interval of 2000 meters, and operation time of 15000 seconds with the model validation setup. As an example, the linear wear maximum for plate thickness ap10 (mm) is received after 1157 milled meters in 9258 operational seconds. The averaged vibration levels of 3,03 mm/sec would be expected for the ap10 near the need for a blade change.

The simulation model results given through this example present model-based wear stage relations between different linear milling profiles. Such information may be beneficial when performing risk mitigation actions and cost calculations in ownership retaining business making.

5. Conclusions

The creation of model-based wear prediction simulation model requires a comprehensive understanding of the asset operation and behavior, as well as condition monitoring and data analysis knowledge. In this paper, a physical simulation model is created based on the case machine's static and variable parameters. The first objective of this research was to examine the blade wear in peripheral milling blade wear stage estimation. The result illustrates that vibration average trend simulations can be used in peripheral milling machine linear wear recognition rather accurately. However, creating a simulation model matching real machine inputs and outputs is rather a time consuming and complicated. Simulation model creation to meet certain fixed machine inputs is rather simple to construct, but the more variable inputs are present, the more complex the simulation model creation becomes. The usage of the validated model was demonstrated in a PPX business-related study where multiple input parameters were changed to illustrate the estimated wear effect based on contact forces affecting the spindle blades. Based on the accuracy of the validation results, trust towards utilizing the created model in business case design or profitability calculations is viable.

Actual blade wear research including microscopic wear monitoring was not conducted as part of the study. However, such investigation could be seen highly beneficial for the case company to increase the accuracy of the simulation model results as the actual level of flank wear could be investigated in relation to time and milled meters based on variating input values. Also, the simulation model can be further developed by examining the data interrelations with different machine learning techniques and evaluating remaining useful lifetime (RUL) values for the asset operational cycles. Model-based and data-based prognostic methods utilization in PPX-related design is also seen beneficial in future research.

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